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DISSERTATION

Extending the Working Lives of Older Workers

The Impact of Social Security Policies and Labor Market

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This document was submitted as a dissertation in June 2010 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of Nicole Maestas (Chair), Pierre-Carl Michaud, and Michael Hurd.

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Published 2010 by the RAND Corporation
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Acknowledgements

The first person I should thank is Nicole Maestas, the chair of my dissertation committee. She has been my primary advisor, mentor, and project supervisor since my first year at RAND. As a researcher trained and developed under her wing, I cannot find enough words to express my gratefulness to her. Her endless patience, consistent encouragement and invaluable advices have changed my life.

I am also deeply indebted to Pierre-Carl Michaud and Michael Hurd. It has been a great privilege for me to have them on my dissertation committee and learn from their scholarship, expertise and experience. The completion of this dissertation would not be possible without their continuous guidance and support throughout the years.

I would like to thank Hugo Benítez-Silva, the outside reader of this dissertation, for his insightful and helpful comments. At earlier stages of the dissertation process, Seo Yeon Hong, Alan Gustman, Yuhui Zheng, Mark Duggan, and numerous seminar participants contributed their time and knowledge to the first and the third chapters of this dissertation. I am thankful to them as well.

This dissertation was generously supported by the Social Security Administration (through Michigan Retirement Research Center under grants UM06-21 and UM08-21), Kip and Mary Ann Hagopian and the National Institute on Aging (under grant P01 AG022481-01). I am very grateful for their contributions to my research.

During the past six years, numerous professors, researchers, staff, fellows at RAND and PRGS have helped me to grow professionally or personally. They include Julie Zissimopoulos, Arie Kapteyn, Darius Lakdawalla, David Loughran, Diana Malouf, Steven Popper, Julie Kim, Patricia StClair, Jacob Klerman, Lionel Galway, Robert Klitgaard, John Graham, Susan L. Marquis, Rachel Swanger, Ira Krinsky, Maggie Clay, Mary Parker, Ze Cong, Yuhui Zheng, Nailing Xia, Yang Lu, Yuyan Shi, Seo Yeon Hong, Baoping Shang, Bogdan Savych, Haijun Tian, Florencia Jaureguiberry, Ricardo Basurto, Shi Lu, Arkadipta Ghosh, John Fei, Xiaohui Zhuo, Ying Liu, Qian Gu, Brian Weatherford, Meenakshi Fernandes, and many others. I owe a thank you to all of them.

Finally, I want to thank my family for their unconditional love to me.

Dissertation Abstract

(Dissertation Title: Extending the Working Lives of Older Workers: The Impact of Social Security Policies and Labor Market

Dissertation Author: Xiaoyan Li)

This dissertation addresses several issues related to public policies that encourage the extension of working lives of the elderly in the United States. It consists of three chapters.

The first chapter and the second chapter of the dissertation evaluate the impacts of the increase in the Social Security Full Retirement Age (FRA) from age 65 (for those born before 1937) to age 66 (for those born between 1943 and 1954).

As the FRA rises, the relative generosity of Social Security disability benefits in comparison to retirement benefits is rising, increasing the incentive for insured people to apply for disability benefits. The first chapter uses the Health and Retirement Study (HRS) to estimate this spillover effect. I find that an average four-month increase in the FRA modestly increases the two-year disability benefits application rate by 0.34 percentage points. The effect is greater (0.77 percentage points) among those with a work-limiting health problem.

The increase in the FRA also creates an incentive for older workers to increase their labor supply. Using the Basic Monthly Current Population Survey 1994-2009, the second

chapter estimates that the labor force participation rate of men aged 62-65 increased by 3.5-4.5 percentage points in response to a one-year increase in the FRA.

The third chapter of the dissertation answers the question, “To what extent can the elderly readily find suitable jobs if they want or need to work?” This chapter shows that the employment transition rates are relatively low for older job searchers in the Health and Retirement Study: only half of older searchers successfully attain jobs. A negative age gradient in job attainment is estimated from a set of reduced-form econometric models, which although not conclusive, corroborates other evidence in the literature of statistical age discrimination in the labor market for older workers.

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Chapter 1. Increased Applications for Disability Benefits: An Effect of Increasing the Full Retirement Age

Chapter Abstract

As the Social Security full retirement age (FRA) rises, the relative generosity of Social Security disability benefits in comparison to retirement benefits is rising, increasing the incentive for insured people to apply for disability benefits. This paper uses the Health and Retirement Study (HRS) to estimate this effect based on the exogenous variation in the FRA across cohorts born between 1935 and 1940. I find that an average four-month increase in the FRA modestly increases the two-year disability benefits application rate by 0.34 percentage points. The effect is greater (0.77 percentage points) among those with a work-limiting health problem.

1.1 Introduction

The rise in the Social Security full retirement age (FRA)—from age 65 for individuals born before 1938 to age 67 for those born in 1960 or later—is equivalent to a universal cut in Social Security retirement (SSR) benefits. For example, those who claim at the earliest eligibility age (EEA), currently set at 62, receive 80 percent of their full SSR benefit when the FRA is at age 65, 75 percent when the FRA is set at age 66, and just 70 percent when the FRA is set at age 67.[1] While some individuals might choose to work longer to compensate for the reduction in expected lifetime wealth, for those who cannot work or who experience physical discomfort at work, the increase in the FRA could reduce their well-being.

The FRA increase creates an incentive for individuals with a certain degree of disability to switch from Social Security's Old Age Insurance program to the Social Security Disability Insurance (SSDI) program.[2] Because the SSDI benefit equals the full SSR benefit and is not reduced when claimed early, the generosity of the SSDI benefit rises relative to the SSR benefit. The magnitude of any such "spillover" effect from the Old Age Insurance program to the SSDI program is central to accurately estimating the financial and welfare consequences of the rise in the FRA and forecasting the potential effects of policy proposals that seek to accelerate or extend the rise. If many retirees

[1] SSR benefits are reduced by an actuarial factor equal to 5/9th of 1 percent per month for the first 36 months before the FRA and 5/12th of 1 percent per month thereafter.

[2] When Social Security benefits are reduced as the FRA rises, those struggling to get by may apply for means-tested programs like the SSI (Supplemental Security Income) as a last resort. However, non-disabled, non-blind people can only get SSI after reaching age 65. The data used in the study do not make up a large enough sample for me to examine policy-induced SSI applications.

alternatively secure SSDI benefits, planned savings associated with the FRA increase might be somewhat offset. Additionally, the financial well-being of early retirees who cannot work might be protected by the availability of alternative SSDI benefits.

In this paper, I investigate the potential substitution between these two retirement channels—SSR versus SSDI—with a theoretical model that generates two hypotheses: the rise in the FRA encourages SSDI application; and the effect is greater among those with more severe disabilities. A longitudinal sample of older individuals born between 1935 and 1940 in the Health and Retirement Study (HRS) is used to test these two hypotheses. Identification comes from exogenous variation in the FRA across birth cohorts. I find that individuals born after 1937 (i.e., those with higher FRAs) are more likely to apply for SSDI after controlling for a rich set of observables that are potentially correlated with individual propensities to apply for SSDI (e.g., age, calendar year, SSDI benefit level, and the presence of a work-limiting health problem). Consistent with the hypotheses, I find that the average 0.33-year rise in the full retirement age for people born between 1938 and 1940 has resulted in a 0.34 percentage point increase in the SSDI application rate; the increase is even higher (0.77 percentage points) among individuals with health problems that limit their ability to work.

The estimated effect is similar to those in previous studies that imply a modest behavioral response, in terms of seeking SSDI benefits, to the FRA increase. According to my estimate, the expected savings in Social Security expenditures resulting from the two-year FRA increase will only be reduced by 3.2 percent through induced entry into the SSDI program. From the perspective of older people for whom delayed retirement would be a hardship as the generosity of retirement benefits declines, retiring with unreduced disability benefits would only occasionally be an alternative option.

I begin with an explanation of the potential causes of the spillover effect and a summary of the results of previous studies on this subject in Sections 1.2 and 1.3. In Section 1.4, I devise a model to show the mechanism by which the FRA affects SSDI application decisions. In Section 1.5, I describe the data and the analytical approach. Section 1.6 presents the results, and Section 1.7 concludes the paper.

1.2 The Relationship between the Full Retirement Age and SSDI Applications

To be fully insured for SSR benefits, an individual must have accumulated at least one quarter of work in covered employment for every year that has elapsed since she was 22 years of age, up to a maximum of 40 quarters. If at least 20 of those quarters were earned within the last 10 years, she is also insured for SSDI benefits. [3] As a result of this recency requirement, SSDI insured status is less universal than SSR insured status (Mitchell and Phillips, 2001). Any possible spillover effect between the two Social Security programs can only be driven by people who are dually insured for both programs. It is worth noting that people who are insured for SSDI are always insured for SSR benefits as well (while the reverse is not true). Therefore, SSDI application behavior can be interpreted as an individual's choice between the two retirement channels. If an individual is insured for SSDI but never applies before reaching the FRA, she will receive SSR benefits.

[3] Special eligibility requirements apply to workers younger than 31: those who became disabled before age 24 need at least 6 quarters of coverage earned within the past 3 years; those who became disabled between age 24 and age 31 need at least 2 quarters of coverage earned for each year that has elapsed since they reached the age of 21.

Although the FRA has risen, the earliest possible age at which one can claim SSR benefits has remained fixed at 62. To maintain the actuarial equivalence of expected lifetime benefits at every claiming age, the Social Security Administration (SSA) has increased the reduction in the SSR benefit amount at claiming ages preceding the FRA. Because the SSDI benefit is *not* actuarially reduced along with claiming age, it becomes relatively more generous in comparison to the SSR benefit when the FRA rises; this change in relative generosity could cause some individuals to substitute toward SSDI retirement channel (Section 1.4 will discuss this mechanism in more detail). In addition, because SSDI benefits automatically convert to SSR benefits when SSDI beneficiaries reach their FRA, an increase in the FRA also means that people gain the option of applying for SSDI during the period between the original FRA and their new FRA. This might also lead to an increase in SSDI applications. SSDI beneficiaries become eligible for Medicare after they have received SSDI benefits for two years; thus, a SSDI award before age 63 is linked to additional value for people who need health insurance coverage. If the Medicare eligibility age were raised along with the FRA, older people with the option to apply for SSDI would have an even greater incentive to do so (GAO, 1999).

Besides the increase in the FRA, there have been two other recent changes in the Social Security Old Age Insurance program: the abolition of the earnings test above the FRA in the year 2000,[4] and the increase in the delayed retirement credit across cohorts.[5]

[4] The earnings test effectively defers SSR benefits for people whose earnings are above an exempt amount. It applies to people between the ages 62 and 70 before the year 2000 and between 62 and the FRA in 2000 or later.

Those two policy changes apply to individuals in the age range beyond the FRA and are less relevant to the SSDI application decisions because SSDI benefits are converted to SSR benefits at the FRA.

Although there are other direct or indirect links between the Social Security Old Age Insurance program and the SSDI program, this paper focuses on how increasing the FRA affects SSDI applications through the most direct mechanism: decreasing the relative generosity of SSR benefits in comparison to SSDI benefits by widening the gap between the monthly SSR and SSDI benefit amounts.

1.3 Previous Research

The disability retirement channel has been frequently omitted in studies of the retirement behavior of elderly Americans, perhaps because the fraction of people retiring through this channel is much lower in the United States than in some European countries. Among the studies that do mention the possible interaction between the two Social Security programs, some provide only rough estimates or upper and lower bounds for the size of the effect. In many cases, these estimates are based on aggregate statistics that include the proportion of people who claimed SSR benefits at the earliest eligibility age who also had work-limiting health problems (Panis et al., 2002) and the new SSDI award rate at or after the earliest eligibility age (Gustman and Steinmeier, 2005). To date, only three groups of researchers (Mitchell and Phillips, 2000; Duggan, Singleton, and Song,

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[5] The delayed retirement credit is the percentage increase in the SSR benefit amount for each year of delayed claiming after the FRA. It gradually increases from 3 percent for people born in 1917-1924 to 8 percent for people born in 1943 and after.

2005, 2007; Bound, Stinebrickner, and Waidmann, 2009) have provided model-based estimates of this effect.

Mitchell and Phillips (2000) use the first four waves of the HRS (the corresponding range of years is 1992-1998) to estimate a conditional logit model of the choice between three retirement paths for workers born between 1931 and 1935: retirement with SSDI, retirement with reduced SSR benefits, and retirement with full SSR benefits. They simulate the consequence of reducing the present value associated with the early SSR retirement path by $25,000 (an experiment not exactly equivalent to the two-year rise in the FRA, [6] which makes their results hard to compare with the others) and find that the fraction of people choosing the SSDI path would increase by 0.6 percentage points under those conditions.

Also using the first four waves of the HRS, Bound, Stinebrickner, and Waidmann (2009) develop a dynamic programming model that includes detailed modeling of the SSDI application decision for single working men in the original HRS cohort (b.1931-1941). In their model, a simulated two-year increase in the FRA to age 67 would increase the one-year labor force exit rate through the SSDI application channel by 0.2 percentage points. This effect would vary by health status—1.3 percentage points among people in very poor health (at least one standard deviation below average) and 0 percentage points among other individuals.

[6] According to Duggan, Singleton, and Song (2007), the reduction in the present value of the SSR benefits at age 62 caused by the increase in the FRA from age 65 to age 67 is about $18,000 for men and $13,000 for women based on the average benefit amounts for people claiming SSR benefits in 1999. Mitchell and Phillips's simulated cut is much larger in magnitude than either of those reductions in value.

Duggan, Singleton, and Song (2007) critique the two papers described above for not explicitly using actual behavioral responses to the ongoing exogenous policy change represented by the FRA increase to estimate the spillover effect. Using Social Security administrative data, they create a large sample of potential beneficiaries who were between ages 45 and 64 sometime during 1984 through 2005. They estimate a linear regression model of age-/year-specific SSDI enrollment rates, with identification coming from policy-induced reductions in the present value of SSR benefits across birth cohorts and age. Controlling for calendar year and age, they find a larger spillover effect than that reported in the two studies mentioned above: a 1.3 percentage-point increase among male beneficiaries and a 2.0 percentage-point increase among female beneficiaries in the SSDI enrollment rate at age 64 as a result of a simulated two-year increase in the FRA. [7] In an earlier version of the paper (Duggan, Singleton, and Song, 2005) with the ratio of the SSR benefit to the SSDI benefit as the independent policy variable used in the model, the effect is predicted to be 1.6 percentage points among 63- and 64-year old male beneficiaries. One limitation of these two papers is that the dependent variable they use is the SSDI enrollment rate (the fraction of people on SSDI), which captures not only the flow of new awards but also the stock of past awards, as well as the SSA's subjective decisions regarding whether or not to approve an application. A cleaner measure of the individual behavioral response to the policy change would be an individual's decision to newly apply for SSDI. Another limitation of these studies is that the Social Security administrative data they use include limited information about individual characteristics,

[7] These two estimates are derived by multiplying the average present value reduction in SSR benefits at age 64 (in Table 1.1 of the paper) by the corresponding coefficients that they recommend for use (in column (1) and (5) of Table 1.3 in the paper).

which prevents them to include richer controls for the differences in observables across cohorts.

In summary, current estimates of the size of the spillover effect vary across these studies, but differences in methodology, especially with respect to the definition of the outcome variable, make comparisons across studies difficult. In any event, none has examined actual changes in decisions to apply for SSDI in response to the rise in the FRA. This paper attempts to fill that gap.

1.4 A Theoretical Model of SSDI Application

1.4.1 The Setup of a Discrete Choice Model

In this section, a simple theoretical model is formulated to present how the increase in the FRA affects an individual's decision to apply for SSDI by increasing the value of the SSDI retirement channel in relative to the SSR retirement channel. This model is illustrative but captures aspects that are important to the linkage between the FRA and the SSDI application decision. In another work (Maestas, Michaud, Li, and Shi, 2010), this simple framework is extended to create a dynamic structural model that accounts for additional aspects of the relationship between economic incentives embedded in institutions and the retirement behavior of individuals in both the United States and the United Kingdom.

Suppose that a potential SSDI applicant[8] is working at age t (which is below the full Social Security retirement age T_{FR}) with an annual real wage rate w constant over her life cycle. She needs to maximize her expected lifetime utility at $t+1$ over a discrete

[8] A potential SSDI applicant is anyone who is insured for both SSR and SSDI benefits but is not currently receiving either of them.

choice APP_t, which will take the value of 1 if she decides to apply for SSDI and 0 if she does not. The outcome of an SSDI application is uncertain and will be revealed at age $t+1$. Probability p_t exists that the individual's application will be approved and she will become a SSDI recipient ($REC_{t+1} = 1$). Otherwise, she will become a rejected SSDI applicant ($REC_{t+1} = 0$). The probability of her receiving an award conditional on her application $p_t = p(d_t)$ is an increasing function of the severity d_t of her disability at t ($p'_d > 0$).

To illustrate this setup, Figure 1.1 delineates the decision tree for SSDI application and describes how the income y_s and utility u_s at any age s above t ($t < s \le T_D$, where T_D is a hypothetical maximum possible age) are supposed to vary by each branch of the decision tree.

The upper panel of Figure 1.1 presents different flows of annual income y_s at age $t+1$ and forward for three hypothetical individuals— a SSDI recipient (with $APP_t = 1$ and $REC_{t+1} = 1$), a rejected SSDI applicant (with $APP_t = 1$ and $REC_{t+1} = 0$), and a non-SSDI applicant (with $APP_t = 0$) under certain simplifying assumptions about labor supply and Social Security benefit receipt.[9] A SSDI recipient will stop working at $t+1$

[9] The key assumption is that individual's labor supply, earnings and Social Security benefits received at each age are determined based on the choice of whether to apply for SSDI and the uncertain outcome of the application process, which is the only uncertainty in the model. Other decisions (e.g., saving, claiming a private pension), uncertainties (e.g., SSDI benefit termination, job separation for reasons other than SSDI application), and income sources (e.g., asset income, private pensions, workers' compensation, unemployment benefits and income from one's spouse) are abstracted from the model.

and receive SSDI benefits every year from $t+1$ until her death. [10] The annual SSDI benefit amount $PIA(w)$ is equal to the full value of an individual's Primary Insurance Amount (PIA) multiplied by twelve. [11] A rejected SSDI applicant will stop working at $t+1$ [12] and claim SSR benefits[13] at $t_{OA} = \max(t+1,62)$, the earliest age when those benefits become available. [14] Before the age of 62, a rejected SSDI applicant will receive government transfer from means-tested welfare programs. The annual transfer amount will be equal to $c_{\min}$, a "consumption floor" covering her basic needs. At the age of 62 or thereafter, the annual SSR benefit amount will equal $a_{t_{OA}}(T_{FR})PIA(w)$, where $a_{t_{OA}}(T_{FR})$ is an actuarial factor less than 1 that permanently reduces the full value of the PIA when the claiming age t_{OA} is below the FRA. As the ratio of the SSR benefit to the SSDI benefit at t_{OA}, the actuarial factor declines as the FRA increases ($\frac{\partial a_{t_{OA}}(T_{FR})}{\partial T_{FR}} < 0$). A non-SSDI

[10] Labor market withdrawal and benefit receipt are both absorbing states in the model. SSDI recipients generally do not work because their SSDI benefits will be completely terminated if their earnings are above a very low threshold called the substantial gainful activity (SGA) amount. The exit rate from SSDI due to recovery from disability is also very low as one approaches the retirement age and can be ignored (Hennessey and Dykacz, 1989; Blau, 2008).

[11] The PIA is a piecewise linear function of the average indexed monthly earnings (AIME). The AIME is determined by one's earnings history between age 21 and the benefit start age. I assume that the individual has continuously worked since the age of 21 with a constant wage profile and that therefore, the PIA only depends on wage w and does not vary by age t.

[12] Rejected SSDI applicants, especially those who are older, have limited employment rates because they are considered to suffer a large wage penalty after a certain duration of non-working time as required by the application process (Halpern and Hausman, 1986; Bound, 1989; von Wachter, Song and Manchester, 2009).

[13] I omit modeling appeals and reapplications potentially made by rejected SSDI applicants.

[14] Age 62 is the most common age for claiming SSR benefits. In each year since 1985, more than 50% of the SSR awards have been initially claimed at age 62 (Social Security Administration, 2009).

applicant will receive wage w every year until she stops working and claims SSR benefits at age t_{OA}.[15]

The bottom panel of Figure 1.1 describes the variation in the utility flow u_s across the three hypothetical individuals. At age s, the flow utility u_s is assumed to take the following form dependent on the values of APP_t and REC_{t+1}:

$$u_s(APP_t, REC_{t+1}) = u(y_s(APP_t, REC_{t+1})) - c_s(APP_t, REC_{t+1}) \tag{1.1}$$

where $u(y_s(APP_t, REC_{t+1}))$ represents the indirect utility of the income y_s (the function u is strictly increasing and concave, $u' > 0$, $u'' < 0$), and $c_s(APP_t, REC_{t+1})$ captures any potential additive utility cost. Two types of utility cost c_s are included in the model: $e(d_t)$ for the expected annual cost of exerting effort at any age above t when the agent is working[16] and $h_t(w)$ for a one-time upfront hassle cost of SSDI application applied to the age $t+1$ utility.[17]

1.4.2 Deriving the Condition for the Choice of SSDI Application

Evaluating this decision problem requires the derivation of the discounted present value of the lifetime utility from $t+1$ forward for each of the three hypothetical individuals. Summing up their age-specific utility u_s in Figure 1.1 with survival probability and time preference taken into account yields the following expressions:

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[15] Most people, especially those who have stopped working at or after 62, have retired and claimed benefits at the same age (Coile et al., 2002). Empirical studies also find that the retirement hazard rate is highest at age 62 (Panis et al., 2002; French, 2005).

[16] The term $e(d_t)$ can also be interpreted as the value of leisure relative to working and will be greater for a person with a more severe disability at t ($e'_d > 0$).

[17] The disutility term $h_t(w)$ incorporates the hassle cost, stigma cost and other disutility associated with the SSDI application process, including the waiting period. The hassle cost is greater for people with higher wages ($h'_w > 0$).

$$U_t(APP_t = 1, REC_{t+1} = 1) = \sum_{s=t+1}^{T_D} \pi_{s,t} \delta^{s-t} u(PIA(w)) - h_t(w) \tag{1.2}$$

$$U_t(APP_t = 1, REC_{t+1} = 0) = \sum_{s=t+1}^{t_{OA}-1} \pi_{s,t} \delta^{s-t} u(c_{\min}) + \sum_{s=t_{OA}}^{T_D} \pi_{s,t} \delta^{s-t} u(a_{t_{OA}}(T_{FR}) PIA(w)) - h_t(w) \tag{1.3}$$

$$U_t(APP_t = 0) = \sum_{s=t+1}^{t_{OA}-1} \pi_{s,t} \delta^{s-t} (u(w) - e(d_t)) + \sum_{s=t_{OA}}^{T_D} \pi_{s,t} \delta^{s-t} u(a_{t_{OA}}(T_{FR}) PIA(w)) \tag{1.4}$$

where $\pi_{s,t}$ represents the probability of living to age s given survival up to age t and δ is a subjective discount factor.

The expected net present value of the lifetime utility when the agent applies for SSDI, $U_t(APP_t = 1)$, is the probability-weighted sum of the utility value when her application is approved (with probability $p(d_t)$) and the utility value when her application is rejected (with probability $1 - p(d_t)$):

$$\begin{aligned} U_t(APP_t = 1) &= p(d_t) U(APP_t = 1, REC_{t+1} = 1) + (1 - p(d_t)) U(APP_t = 1, REC_{t+1} = 0) \\ &= p(d_t) \sum_{s=t+1}^{T_D} \pi_{s,t} \delta^{s-t} u(PIA(w)) \\ &+ (1 - p(d_t))[\sum_{s=t+1}^{t_{OA}-1} \pi_{s,t} \delta^{s-t} u(c_{\min}) + \sum_{s=t_{OA}}^{T_D} \pi_{s,t} \delta^{s-t} u(a_{t_{OA}}(T_{FR}) PIA(w))] - h_t(w) \end{aligned} \tag{1.5}$$

The individual will choose to apply for SSDI only when the expected lifetime utility value if applying for SSDI is greater than the lifetime utility value if not applying, which means that the following condition must be satisfied:

$$\begin{aligned} \Delta U_t &= U_t(APP_t = 1) - U_t(APP_t = 0) \\ &= p(d_t)\{\sum_{s=t+1}^{t_{OA}-1} \pi_{s,t} \delta^{s-t} u(PIA(w)) + \sum_{s=t_{OA}}^{T_D} \pi_{s,t} \delta^{s-t} [u(PIA(w)) - u(a_{t_{OA}}(T_{FR}) PIA(w))]\} \\ &- h_t(w) - \sum_{s=t+1}^{t_{OA}-1} \pi_{s,t} \delta^{s-t} [u(w) - e(d_t) - (1 - p(d_t, \kappa)) u(c_{\min})] > 0 \end{aligned} \tag{1.6}$$

This condition can be rewritten as follows:

$$p(d_t)\{\sum_{s=t+1}^{t_{OA}-1}\pi_{s,t}\delta^{s-t}u(PIA(w))+\sum_{s=t_{OA}}^{T_D}\pi_{s,t}\delta^{s-t}[u(PIA(w))-u(a_{t_{OA}}(T_{FR})PIA(w))]\}$$
$$>h_t(w)+\sum_{s=t+1}^{t_{OA}-1}\pi_{s,t}\delta^{s-t}[u(w)-e(d_t)-(1-p(d_t,\kappa))u(c_{\min})] \tag{1.7}$$

The left-hand side of the Inequality 1.7 represents the expected benefit of SSDI application, which equals the summation of the discounted utility stream from SSDI benefits before the age of 62 ($\sum_{s=t+1}^{t_{OA}-1}\pi_{s,t}\delta^{s-t}u(PIA(w))$) and the gain in the discounted utility stream at or after the age of 62 when the individual is receiving full (SSDI) benefits rather than reduced (SSR) benefits ($\sum_{s=t_{OA}}^{T_D}\pi_{s,t}\delta^{s-t}[u(PIA(w))-u(a_{t_{OA}}(T_{FR})PIA(w))]$), weighted by the SSDI award probability $p(d_t)$.

The right-hand side of Inequality 1.7 expresses the costs of SSDI application, which consist of the hassle cost $h_t(w)$ plus the discounted utility stream from forgone earnings before the age of 62 ($\sum_{s=t+1}^{t_{OA}-1}\pi_{s,t}\delta^{s-t}u(w)$) adjusted for the disutility from work efforts ($\sum_{s=t+1}^{t_{OA}-1}\pi_{s,t}\delta^{s-t}e(d_t)$) and the utility of the consumption floor for rejected SSDI applicants ($(1-p(d_t))\sum_{s=t+1}^{t_{OA}-1}\pi_{s,t}\delta^{s-t}u(c_{\min})$) during that period.

Inequality 1.7 suggests that an individual's decision to apply for SSDI can be affected by many factors: age, wage, the PIA, the severity of disability, survival probability, etc. An empirical model of SSDI application should take all of these factors into account.

1.4.3 The Effect of the FRA on the Choice of SSDI Application

The individual will only apply for SSDI at t if the expected benefits of application exceed the cost of application ($\Delta U_t > 0$). She will be more likely to apply for SSDI as the difference between the benefit and the cost (ΔU_t) increases. Therefore, the effect of raising the FRA on SSDI application at t will take the same sign as the first-order derivative of ΔU_t with respect to T_{FR}:

$$\frac{\partial \Delta U_t}{\partial T_{FR}} = -p(d_t)\sum_{s=t_{OA}}^{T_D} \pi_{s,t}\delta^{s-t}u'(a_{t_{OA}}(T_{FR})PIA(w))PIA(w)\frac{\partial a_{t_{OA}}(T_{FR})}{\partial T_{FR}} \tag{1.8}$$

Given that $u' > 0$ and $\frac{\partial a_{t_{OA}}(T_{FR})}{\partial T_{FR}} < 0$, the sign of the derivative is positive, suggesting that the individual will be more likely to apply for SSDI as the FRA increases. [18]

According to Inequality 1.7 and Equation 1.8, the mechanism of this effect is straightforward: the rise in the FRA reduces the actuarial factor $a_{t_{OA}}(T_{FR})$ of the SSR benefit, generating an increase in the utility gain of receiving SSDI benefits rather than SSR benefits at or after the age of 62 ($\sum_{s=t_{OA}}^{T_D} \pi_{s,t}\delta^{s-t}[u(PIA(w)) - u(a_{t_{OA}}(T_{FR})PIA(w))]$) and eventually an increase in the expected benefit of SSDI application.

[18] This analysis assumes that the SSR benefit-claiming age t_{OA} does not vary as the FRA increases. Recent studies (Benítez-Silva and Yin, 2009; Mastrobuoni, 2009; Song and Manchester, 2009) have suggested that older workers will delay retirement and SSR benefit claims when the FRA rises, which means that the average t_{OA} will be higher as a result of the FRA increase. When SSR beneficiaries increase their claiming age t_{OA}, the policy-induced reduction in the generosity of the SSR benefit will be offset to a certain degree. Incorporating this behavioral response into my model will not qualitatively change the results, although the magnitude of the effect of the FRA increase on SSDI application will decrease.

It is obvious that the first-order derivative of ΔU_t with respect to T_{FR} (Equation 1.8) will increase as the approval probability $p(d_t)$ increases. Thus, the effect of the FRA increase will be greater among those with greater disability severity d_t because they have a higher chance of receiving an SSDI award conditional upon their application.

The primary motivation of the following empirical analysis is testing two hypotheses suggested by this simple theoretical model: (1) that individuals are more likely to apply for SSDI when the FRA increases; and (2) that the impact of the FRA increase on individuals' propensity toward SSDI application is larger among those with a higher degree of disability.

1.5 Data and Sample

The empirical data I use comes from the Health and Retirement Study (HRS). The HRS currently has up to eight biennial interview waves (from 1992 to 2006) for a nationally representative sample of individuals born between 1931 and 1941 (so-called age-eligible respondents in the original HRS cohort). As illustrated in Table 1.1, those born between 1935 and 1937 are chosen as the "control" cohort for this analysis because their FRA remains unaffected at age 65; those born between 1938 and 1940 are the "treatment" cohort because their FRA has been raised above age 65 by 2 months (if they were born in 1938), 4 months (if they were born in 1939) or 6 months (if they were born in 1940). On average, the FRA for the "treatment" cohort is 0.33 years (or four months) higher than that of the "control" cohort. I exclude from the sample those attrited from the HRS before reaching their FRA. This sample restriction leaves a total of 4,026 individuals—2,050 of them in the "control" cohort (born before 1938) and 1,976 of them in the “treatment” cohort (born in or after 1938). I apply an additional sample restriction in which I drop everyone without matched SSA earnings records[19] because insured status for SSDI benefits (which is not universal) can only be derived using historical records of annual earnings before the HRS baseline wave in 1992. The SSA match rates are similar across the two cohorts in my sample: 85 percent in the “control” cohort and 84 percent in the “treatment” cohort, leaving 1,748 respondents in total who are unaffected by the FRA rise and 1,666 affected respondents.

The fourth through sixth columns of Table 1.1 illustrate how the difference in the FRA across the two cohorts leads to a difference in the relative generosity of SSR and SSDI benefits. The SSR/SSDI benefit ratio at age 62 drops from 80 percent for the “control” cohort to 77.5 percent for the youngest members of the “treatment” cohort (those born in 1940). The age 62 SSR/SSDI benefit ratio is also a valid approximate measure of relative generosity for individuals who apply for SSDI before age 62, given that most SSR beneficiaries claim SSR benefits at this earliest eligibility age. Compared to the cross-cohort difference in the SSR/SSDI benefit ratio at age 62, that difference is even higher at ages 63 and 64 (with 3.3 percent vs. 2.5 percent as the results for the “control” cohort and those born in 1940, respective).

I next compare SSDI application and receipt outcomes across the “treatment” and “control” cohorts. The observations used in this set of comparison exercises are those for individuals at or above age 56 but below the FRA. In the first panel of Figure 1.2, I plot

[19] Kapteyn, Smith and van Soest (2006) and Michaud and van Soest (2008) find that the matching of Social Security earnings records does not lead to a biased sample for the original HRS cohort.

the percentage of people who ever applied for SSDI[20] by age separately according to whether their FRA is 65 or greater than 65. Interestingly, the "treatment" cohort has a significantly higher chance of ever pursued SSDI application. The average probability of having ever applied for SSDI between the ages of 56 and 63 is 14.1 percent for the "control" cohort and 17.7 percent for the "treatment" cohort.[21] This large difference in the stock of past SSDI applications implies that a significant part of the recent rapid growth in the SSDI caseload (Autor and Duggan, 2006; Duggan, Singleton, and Song, 2005, 2007) might be driven by individuals who apply for and receive awards well before their mid-50s. The second panel of Figure 1.2 confirms this implication, showing that the cohort difference in the SSDI enrollment rate already exists at age 56 (with 3.8 percent for the "control" cohort and 7.0 percent for the "treatment" cohort) and does not notably increase at later ages. In that sense, I argue, the outcome variable used by Duggan, Singleton, and Song (2005, 2007) (the stock of beneficiaries as a percentage of the insured population) might capture changes in behavior among prime-age workers in addition to those approaching retirement. It is certainly possible that the "treatment" cohort might have responded to the rise in the FRA by increasing the number of SSDI applications submitted well before their mid-50s; however, individuals much younger than 62 should be less responsive to the policy-induced reduction in the SSR benefit

[20] The HRS did not ask separate survey questions regarding SSDI and SSI application before Wave 5. SSI is generally considered a disability program for people who are not insured for SSDI and who are younger than 65. Because the outcome measure (the SSDI application rate, described later) of the analysis is conditional on one's being insured for SSDI, most applications in my sample should be only associated with SSDI.

[21] The respondents in the "treatment" cohort enter the HRS at younger ages (52-54) and are likely to be more "experienced" with interviews when reporting previous SSDI applications at ages above the mid-50s. One might worry about potential bias caused by this cohort difference; however, Weir and Smith (2007) argue that the so-called panel-conditioning effect is small in the context of the HRS.

amount, because they are less likely to have severe disabilities and less willing to forego their expected labor income in exchange for potential gains in post-age-62 Social Security income, as can be inferred from the theoretical model in Section 1.4.[22] An alternative explanation for the rise in SSDI applications among middle-aged Americans is the rising prevalence of disability due to obesity and associated health problems (Lakdawalla, Bhattacharya and Goldman, 2004; Goldman et al., 2005).

The large cohort difference in the stock of previous SSDI applications does not necessarily imply a large difference in the flow of new SSDI applications, which is the key outcome variable in this paper. Because the HRS is a biennial survey, I define the SSDI application rate as the fraction of people who applied for SSDI between time t (or wave w) and time $t+2$ (or wave $w+1$) conditional on their having the option of applying for SSDI at time t. To correctly identify the pool of people who can apply for SSDI in the interval between two waves, I exclude people who were not insured for SSDI (due to insufficient numbers of total or recent quarters of coverage) in the earlier wave from the denominator. In the third panel of Figure 1.2, I plot the age profile of SSDI-insured status by cohort.[23] Strikingly, respondents in the "treatment" cohort are more likely to be insured for SSDI. For individuals between the ages of 56 and 63, the average SSDI coverage rate is 70.8 percent for those in the "treatment" cohort compared to 67.4 percent for those in the "control" cohort. This cohort difference in SSDI-insured status reflects

[22] Similar explanations can also be found in Duggan, Singleton, and Song (2005).
[23] I combine the SSA earnings records and annual employment/earnings information in the HRS core survey to determine the total number of quarters of coverage during one's lifetime and in the last 10 years. SSDI insured status at each wave is computed using the estimated history of annual quarters of coverage before the wave.

the reversal of the early retirement trend in recent years (Gustman and Steinmeier, 2009) and the stronger labor force attachment of later birth cohorts (Maestas, 2007).

Besides dropping time *t* to time *t+2* transitions associated with time *t* non-insured status, I also exclude transitions from respondents who were already receiving or had already applied for SSDI at time *t*. Applying all the restrictions described above, I end up with 4,314 time *t* to *t+2* transitions from the "control" cohort and 4,145 transitions from the "treatment" cohort remaining in the analysis sample.

1.6 Results

1.6.1 Cross Cohort Comparison of SSDI Application Rate

In the fourth panel of Figure 1.2, the two-year SSDI application rate is presented by cohort. Surprisingly, the "treatment" cohort, which exhibits a higher average FRA and also a higher probability of having previously applied for SSDI, does not seem to have a significantly higher SSDI application rate. In reality, the average two-year SSDI application rate for individuals between age 56 and age 63 is 2.8 percent for both cohorts.

The fifth panel of Figure 1.2 shows the SSDI application rate by cohort and a dichotomous measure of disability severity at time *t*. The measure is assigned on the basis of responses to the HRS work limitation question, "Do you have any impairment or health problem that limits the kind or amount of paid work you can do?" [24,25] As

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[24] In Wave 7, if re-interviewees had previously reported having a work-limiting health condition, they were assumed to still have the condition and the survey question was skipped. Using the hot-deck method based on demographic characteristics, socioeconomic status, and health status, I impute the values of the work limitation variables for those observations. The imputation is based on answers given by all respondents between Waves 5 and 8 who provided a valid ("yes" or "no") response to the work-limitation questions. Another important cross-wave difference is that beginning in

expected, people who are experiencing a work-limiting health problem at time *t* are much more likely to apply for SSDI between *t* and *t+2*. The average application rate for individuals between ages 56 and 63 conditional on their having a work limitation at time *t* is about 11.2 percent compared to 1.6 percent among those without work limitations at time *t*. In other words, most SSDI applications come from individuals with health problems that limit their work ability. Among those without work limitations, SSDI application rates are almost the same across the "treatment" and "control" cohorts. Among those with work limitations, the "treatment" cohort displays lower SSDI application rates for individuals between ages 56 and 60 but slightly higher SSDI application rates at ages 61-63 (when the SSR benefits are available sometime during the time range *t*-*t+2*).

When one puts the fourth and the fifth panels together, the treatment effect does not seem to consistently have expected sign (that is, a higher SSDI application rate for the cohort with higher FRA). However, these contrasts control only for age and the presence of a work limitation. Because respondents are not actually randomly assigned to each cohort, there are likely to be some cohort differences with regard to other characteristics

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Wave 7, "not working" is added as a possible response category. I use a similar imputation method to assign "yes" or "no" to the observations with those "not working" missing values.

[25] Benítez-Silva and his colleagues (1999, 2004, 2006) have shown that HRS responses to this question and a follow-up question asking whether this limitation prevents the individual from working altogether can be considered a sufficient approximate statistic of "true" disability status (in the sense that other health variables add very little additional predictive power once the work limitation variable is included in models predicting SSDI application and the outcome of an application) and an unbiased indicator of the SSA's ultimate SSDI award decisions. Because I am interested in SSDI application, not awards, I use the work limitation variable rather than the work prevention variable to measure disability severity. See Burkhuaser, Butler, and Gumus (2004) for a dynamic programming model of SSDI application that assumes that workers start to make SSDI application-timing decisions after the onset of a work limitation.

that may be related to the propensity toward SSDI application and thus confound the true effect. The existence of such cohort differences can be inferred from the first three panels in Figure 1.2—for example, differences in past SSDI application experience, labor force attachment, and health measures other than the dichotomous work limitation variable.

1.6.2 Cross Cohort Comparison of Other Related Variables

An examination of cohort differences in observable characteristics is presented in Table 1.2. The sample means (or medians for the monetary variables) are compared across "treatment" and "control" cohorts in terms of measures for SSR/SSDI relative generosity, SSDI benefit level, health and disability status, demographics, socioeconomic status and labor force attachment.

The primary policy variable of interest in this empirical analysis is the ratio of the SSR benefit to the SSDI benefit[26] at time $t+1$, which is identical to the actuarial factor at the earliest age when SSR benefits become available after t in the theoretical model. The SSR/SSDI benefit ratio at 62 is linked to time t to $t+2$ transitions when the age at time t is no older than 61. SSR/SSDI benefit ratios at age 63/64 are, respectively, associated with transitions when the age at time t is 62/63. Almost all of the variation in the SSR/SSDI benefit ratio originates from the difference in birth year. The "treatment" cohort has an

[26] I use the SSA administrative earnings file for the original HRS cohort to compute SSR and SSDI benefits. The SSA administrative earnings file indicates HRS respondents' annual Social Security covered earnings from 1951 to 1991. I forecast earnings by averaging the two highest of the respondents' last five years of earnings for which the SSA records are available (i.e., 1987-1991 for the original HRS cohort) and then project the average forward assuming zero real annual growth. The respondents' earnings data are fed into a set of Social Security benefits computation SAS macros developed by Dr. Nicole Maestas. The macros calculate retirement benefit amounts or disability benefit amounts for a given benefit start age.

average SSR/SSDI benefit ratio of 80.5 percent, which is significantly lower than that for the "control" cohort (82.3 percent).

The monthly SSDI benefit amount itself (the PIA) is also compared across cohorts. The "treatment" cohort, with a higher SSDI-insured rate as shown before, also has significantly higher PIA ($1,194 vs. $1,075), which is additional evidence of its higher lifetime labor force participation level.

It is interesting to see that the mean of the dichotomous disability severity measure is similar across the cohorts despite the large difference in past SSDI application experience. The time t fraction of people with work limitations is 12.5 percent in the "control" cohort and 12.7 percent in the "treatment" cohort.

Although the incidence rates of work limitations look similar, there could be other differences in the degree and types of disabilities experienced across cohorts that could lead to different levels of propensity to apply for SSDI. A battery of objective and subjective health measures available in the HRS is examined, including (1) the sum of ADLs (Activities of Daily Living) and other functional limitations (using a 0-13 index counting the number of activities that the respondent reports having some difficulty performing),[27] (2) self-reported fair or poor health, (3) the sum of major health conditions (a 0-8 index),[28] (4) whether the individual is often troubled with pain,[29] (5)

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[27] These activities include walking across the room, dressing, bathing, eating, getting in/out of bed, walking one block, walking several blocks, sitting for about 2 hours, getting up from a chair after sitting for a long period, climbing one flight of stairs without resting, climbing several flights of stairs without resting, stooping/kneeling/crouching, and pushing/pulling large objects.
[28] These conditions include high blood pressure, arthritis, mental health problems, cancer, stroke, lung disease, diabetes, and heart problems.
[29] See Kapteyn, Smith, and van Soest (2008) for a study of the relationship between pain and disability.

whether the individual is obese (with corrected BMI equal to or above 30),[30] and (6) the ratio of the subjective probability of the individuals' living to age 75 to the corresponding life table probability (which can be considered a proxy for survival information as known to the individual but unobservable to the econometrician). The obesity measure is labeled as "corrected" because I adjusted the self-reported BMI using height and weight measured with devices during the "enhanced face-to-face interviews" for one randomly chosen half of the households interviewed in the HRS Wave 7 and Wave 8. In this, I followed the approach described in Cawley and Burkhuaser (2008).[31]

Respondents in the "treatment" cohort experience more functional limitations (1.43 vs. 1.31) and have more major health conditions (1.25 vs. 1.11) than those in the

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[30] See Burkhauser and Cawley (2004) for a study of the relationship between obesity and SSDI enrollment.

[31] When measuring body mass index (BMI), the HRS core survey only records respondents' self-reported height and weight, both of which are subject to a large degree of measurement error according to Cawley and Burkhauser (2008). In general, people tend to underreport their weight and overreport their height, leading to an underestimate of the obesity rate. Cawley and Burkhauser (2008) have used a data set (NHANES III) that includes both self-reported and measured height and weight to estimate a prediction equation for measured height and weight. Although some researchers (e.g., Michaud, van Soest, and Andreyeva, 2007) have directly applied these coefficients to the HRS, applicability of these coefficients is questionable. (Questions arise because the mode of the NHANES III survey is face-to-face, while many other surveys, including the HRS, are generally conducted via telephone; also, the estimation sample in Cawley and Burkhauser (2008) does not include people older than 65, and the NHANES III covers the period from 1988 to 1994, which is earlier than most HRS waves.) Because the HRS itself includes measured height and weight data for a random group of respondents in Wave 7 and Wave 8 (about 8,000 wave-respondent observations), it is more appropriate to use the HRS-based measured height and weight to correct for the measurement error in the HRS self-reported height and weight. Therefore, I estimate a regression model of measured weight/height with self-reported weight/height fully interacted with gender and race as controls using the HRS Wave 7 and Wave 8 data. I also include self-reported fair or poor health, education, and self-reported BMI as covariates of this model. The predicted BMI is about 1.3 units higher than self-reported BMI. Cleaned obesity prevalence is about 8 percentage points higher than that based on self-reported height and weight. Detailed estimates are available from the author upon request.

“control” cohort. They are also more frequently troubled with pain (21.2 percent vs. 19.3 percent) and are more likely to be obese (36.1 percent vs. 31.2 percent) than are their counterparts. These comparisons suggest that their underlying disabilities may be more severe.

The past SSDI application experience is also included in this comparison exercise as a proxy for the unobserved disability level. In comparison to the “control” cohort, the “treatment” cohort features a similar fraction of people who have applied for and received SSDI before *t* (1.2 percent vs. 1.3 percent) but a significantly higher fraction of people who have applied for but failed to receive SSDI before *t* (3.1 percent vs. 2.2 percent). It is sensible to expect that SSDI application decisions are serially correlated—those who applied before time *t* should be more likely to apply between time *t* and *t+2* because they might be suffering from a more severe underlying disability, exhibit a weaker attachment to the labor force, experience a lower level of perceived hassle cost when applying for SSDI, or feature other unobservables that make them more likely to apply for social welfare programs.[32] Benítez-Silva et al. (1999) have shown that having previously applied for SSDI is a strong predictor of current SSDI application.

Based on a comparison of the demographic and socioeconomic status (SES) variables, respondents in the “treatment” cohort are much better educated, are more racially diverse, and enjoy higher labor income and higher net worth[33] at time *t*. Generally speaking, those born after 1937 have a higher SES level, which might decrease

[32] In addition, former beneficiaries who have had their benefits terminated for earnings above the substantial gainful activity threshold can reinstate benefits during a three-year Extended Period of Eligibility should they stop working and continue to be disabled.
[33] Net worth is the sum of assets (primary residence, other real estate, vehicles, businesses, IRAs, stocks, bonds, checking accounts, CDs, and other assets) less liabilities (mortgages, other home loans, and other debt).

their propensity to apply for SSDI. According to Inequality 1.7 in Section 1.4, the cost of SSDI application is larger among high-SES people because they experience a greater opportunity cost of applying (forgone earnings) and may perceive greater hassle or stigma cost associated with the take-up of government benefits labeled "disability" benefits.

The last variable compared in Table 1.2 is a direct measure of labor force attachment—lifetime total quarters of coverage based on the SSA earnings records. On average, the "treatment" cohort has worked in covered employment for about 3 quarters more than the "control" cohort by time *t* (131.5 vs. 128.5). The stronger labor force attachment of the "treatment" cohort is another factor that might potentially offset the increase in the propensity toward SSDI application as induced by the increase in the FRA.

In summary, cross-cohort differences do exist with respect to other observables that are potentially correlated with an individual's propensity to apply for SSDI: in particular, SSDI benefit level, disability severity, SES and labor force attachment. In the next section, I present estimates of the effect of the FRA increase on the SSDI application rate that control for these factors. Because the HRS data is linked to administrative SSA records, I am able to control for the PIA and lifetime total quarters of coverage with very little measurement error. In addition, the richness of the HRS allows me to control for multiple dimensions of underlying disability and past SSDI application experience, which have both been shown to be clearly different across cohorts according to Figure 1.2.

1.6.3 Regression Estimation Results

I estimate two probit models of SSDI application based on the analysis sample with 8,312 time *t-t+2* observations. The estimation results are shown in Table 1.3. The dependent variable is whether the individual has applied for SSDI between time *t* and *t+2*.[34] Every two columns in Table 1.3 present estimation results (coefficients and standard errors) based on one specification of the model. The standard errors are clustered by respondent.[35]

For each specification, I include the SSR/SSDI benefit ratio at time *t+1*, the SSDI benefit level, and health and disability status, demographics, socioeconomic status and labor force attachment measures at time *t*. A flexible set of age dummies (one dummy for each age between 56 and 60 plus an additional dummy for ages 61 and above) is added to control for any variation in age-specific SSDI application propensity, especially the difference based on whether the age at *t+1* is equal to or greater than age 62, the earliest eligibility age for SSR benefits. Interview dummies (one dummy for each interview wave) are also added to control for macroeconomic conditions and the variation in the SSDI award probability across calendar years.

The benchmark specification (1) directly tests whether the FRA increase encourages SSDI application through the reduction in the relative generosity of the SSR versus the SSDI program (as measured by the SSR/SSDI monthly benefit ratio).

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[34] Following the spirit of the theoretical model, individual's labor supply decision and Social Security retirement benefit claiming decision are abstracted from this reduced-form empirical model.

[35] In a similar specification, Duggan, Singleton, and Song (2005) cluster the standard errors by birth year because the variation in the SSR/SSDI benefit ratio mostly originates from the difference in the FRA by birth year. I do not employ their approach because my sample only includes 6 birth years (standard errors clustered by a small number of clusters might be downward biased according to Wooldridge (2003)). The standard error estimates do not change much when clustered by birth year or obtained through bootstrapping.

According to the theoretical model, I hypothesize that the effect might differ for individuals with and without work limitations. To test this hypothesis, in specification (2), I include an interaction term for the SSR/SSDI benefit ratio and an indicator for having a work limitation at time *t*.

In specification (1), the coefficient of the SSR/SSDI benefit ratio is negative and significant, suggesting that the decline in SSR/SSDI relative generosity does encourage insured individuals to apply for SSDI. In specification (2), the interaction term is significant but the SSR/SSDI benefit ratio main effect becomes insignificant, implying a larger effect among people with work-limiting health problems and a smaller (if any) effect among those without work limitations.

Most of the coefficients for the other covariates included in the model have the expected signs as discussed in Section 1.6.2. Most health and disability measures have strong and positive associations with SSDI application in both specifications. A rejected SSDI application before time *t* is strongly and positively correlated with SSDI application after *t*. Among the demographics and SES variables, the number of schooling years has significant and negative associations with the SSDI application rate, suggesting that SSDI application is more likely to be selected as a retirement path by a relatively disadvantaged group.

To better interpret the regression estimates, I compute the marginal effect of the SSR/SSDI benefit ratio and its interaction with the presence of a work-limiting health problem at time *t*. This is particularly important because the sign and significance of the coefficient for an interaction term in a nonlinear model do not necessarily match the sign and significance of the marginal effect of the interaction term (Ai and Norton, 2003).

The Stata module "inteff" (Norton, Wang, and Ai, 2004) is used to compute the corrected average marginal effect for the interaction term in specification (2). The average marginal effect of the SSR/SSDI benefit ratio in specification (1) is estimated using the Stata module "margeff", which is developed by Bartus (2005). These results are shown in the top panel of Table 1.4, where each row gives the marginal effect of interest for one of the two specifications. A one percentage-point decrease in the SSR/SSDI benefit ratio is estimated to increase the average SSDI application rate by 0.189 percentage points among all individuals and by 0.449 percentage points among people with work limitations.

In the second and third panels in Table 1.4, I present two sets of "treatment effect" estimates, those implied by each of two "treatments"—raising the FRA by 0.33 years and 2 years (from age 65). Here the "treatment effect" is defined as the predicted change in the SSDI application rate in response to a change in the FRA. 0.33 years is the average FRA increase actually experienced by the "treatment" cohort, whereas 2 years is the legislated increase in the FRA when this policy change is fully implemented for people born in 1960 or later. I use the "treatment" cohort sample for this exercise and also report the treatment effects for a subsample of those with work limitations.

The second column in each of the two panels presents the simulated changes in the average SSR/SSDI benefit ratio arising from one indicated "treatment" among individuals born between 1938 and 1940. Assuming a simple linear dose-response relationship between the increase in the FRA and the induced increase in the SSDI application rate,[36] I can multiply a simulated change in benefit ratio by the corresponding average marginal effect in the first panel to derive the treatment effect of a given change in the FRA on the two-year SSDI application rate.

The average treatment effect in terms of the two-year SSDI application rate resulting from the actual FRA increase ("0.33 year" increase) is 0.34 percentage points for the "treatment" cohort and 0.77 percentage points for those with work-limiting health problems in this cohort. If the FRA for everyone in the cohort was increased to 67, the average two-year treatment effect among them would be 1.02 percentage points.

1.6.4 Discussion of the Results

It is interesting to compare my estimate to those reported in previous studies. Based on a structural dynamic programming model, Bound, Stinebrickner, and Waidmann (2009) estimate a 0.2 percentage point increase in the one-year SSDI application rate in response to a simulated two-year FRA increase among single working men born in 1931-1941. Their estimate is different from mine (0.51 percentage points as the one-year (time t-$t+1$) treatment effect[37] of the two-year increase in the FRA, as shown in the third panel of Table 1.4) for the following two possible reasons. First, their estimate is not explicitly based on exogenous variation in Social Security rules. It might be subject to endogenous bias to the extent that it depends on cross-individual variation in the Social Security benefits and retirement path. Second, their sample only includes working men, who might be less responsive to the rise in the FRA because they face a

[36] The validity of this assumption is of course questionable for the treatment effect estimate based on a simulated 2-year-increase in the FRA, given the fact that the estimate does not come from a structural model and is subject to the Lucas Critique (Lucas, 1976).
[37] In the second and the third panels of Table 1.4, the one-year treatment effect is converted from the two-year treatment effect assuming that the effect does not vary across two adjacent years.

higher opportunity cost of applying for SSDI in comparison to women or those out of the labor force.[38] The similarity of the two studies lies in the findings about the heterogeneity of the effect based on health and disability status: the induced-SSDI application rate increase caused by the rise in the FRA is estimated to be larger for those with worse health (in Bound, Stinebrickner, and Waidmann, 2009) and with more severe disabilities (in this study).

The outcome variable in Duggan, Singleton, and Song (2005, 2007) is the SSDI enrollment rate (a stock measure) at each age between 45 and 64. It is difficult to transform my estimate into something similar to theirs without some arbitrary assumptions about the functional form of the SSDI application hazard in terms of age and SSDI award probability. As a simplifying approximation, I assume that the SSDI enrollment rate at age 64 is a linear function of the average one-year SSDI application rate before age 64. The slope coefficient in the function is assumed to be a constant 2.82.[39] With this assumption, the change in the SSDI enrollment rate among 64-year-old individuals would constitute a 1.44 percentage-point increase in response to a two-year-increase in the FRA based on the corresponding one-year treatment effect on the SSDI application rate (0.51 percentage point). Duggan, Singleton, and Song's estimates are of a similar magnitude: a 1.6 percentage point increase among men at ages 63-64 (in their 2005 paper) and a 1.3 (2.0) percentage point increase among men (women) at age 64 (in

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[38] Duggan, Singleton, and Song (2005, 2007) suggest that the spillover effect is larger for women "because of their longer life expectancy and because of the lower average opportunity cost of applying for benefits resulting from their lower labor force participation".

[39] It is the ratio of the difference in SSDI enrollment rate between age 56 and 64 (4.0 percent=11.0 percent-7.0 percent) to the average yearly SSDI application rate between age 56 and 63 (1.42 percent) observed among the "treatment" cohort in the analysis sample.

their 2007 paper) caused by a two-year increase in the FRA. Richer controls for cohort differences (especially those for past SSDI application experience) in my paper might be a possible explanation for the discrepancy between the estimates given in the two papers.

The inferred estimate regarding the policy-driven increase in the age-64 SSDI enrollment rate can also be used to examine the extent to which the projected savings from the FRA increase would be offset by rates of induced entry into the SSDI program. When I use an approach similar to that of Duggan, Singleton, and Song (2005), the offset rate is predicted to be only 3.2 percent when the scheduled two-year FRA increase is fully phased in under the following simplifying assumptions: that the PIA and life expectancy are constant across individuals, that there are only two retirement paths—either receiving SSDI benefits or claiming SSR benefits at age 62, and that the behavioral response of younger cohorts is similar to that of the 1938-1940 cohorts.[40]

1.7 Conclusion

As the full retirement age rises, the generosity of the Social Security disability benefits increases relative to that of retirement benefits, resulting in an incentive for

[40] This estimate is derived as follows assuming that everyone has a PIA equal to $1,000. Among 10,000 hypothetical people in the "treatment" cohort, 1,052 will receive SSDI benefits (equal to $1,000/month) and 8,948 will claim reduced SSR benefits (equal to $800/month) assuming that the FRA is age 65 for everyone. The fraction of SSDI beneficiaries (10.52 percent) in this scenario is equal to the observed SSDI enrollment rate at age 64 (11 percent) minus the effect caused by an average 0.33-year increase in the FRA (0.48 percent). When the FRA increases to age 67, 1,196 will receive SSDI (equal to $1,000/month) and 8,804 will claim further reduced SSR benefits (equal to $700/month), reflecting the estimated 1.44 percentage-point increase in the SSDI enrollment rate (1,196-1,052=144). Ignoring the policy-induced increase in SSDI enrollment, the total savings in expenditures associated with the two-year FRA increase should be ($800-$700)*8,948=$894,800/month. The induced SSDI entry effect leads to an increase in expenditures equal to ($1,000-$800)*144=28,800/month, which only accounts for 3.2 percent of 894,800.

people to apply for disability benefits as an alternative way to exit the labor force. This paper examines the actual behavioral response to this policy change by comparing the SSDI application rates of two birth cohorts in the Health and Retirement Study, one (b.1935-1937) unaffected by the change and the other (b.1938-1940) affected by the change.

A theoretical model of SSDI application predicts that the cohort affected by the change will exhibit a higher SSDI application rate and that this spillover effect will be greater among the subsample of people with work limitations. Consistent with the theoretical model, a set of reduced-form models of SSDI application is estimated with controls for other covariates that potentially affect the decision to apply for SSDI, especially health and disability status, past SSDI application experience, labor force attachment, socioeconomic status, age, and calendar year. The estimated treatment effect of the FRA increase (ranging from 2 months to 6 months, with an average of 4 months) on the two-year SSDI application rate among people born between 1938 and 1940 is 0.34 percentage points. Even though the effect is significantly larger (0.77 percentage points) among those with health problems that limit their work capacity, those people only account for about 13 percent of the sample. Taking into account this spillover effect will not significantly affect the magnitude of the projected budgetary savings for the Social Security system that would result from increasing the FRA.

One important policy worry with regard to the increase in the FRA is the potential harm to older individuals who are unable or unwilling to extend their working lives. The magnitude and heterogeneity of the effect estimated in this study imply that applying for SSDI benefits would only be an effective option for a small fraction of people (in particular, those who are severely disabled) in offsetting the potential policy-induced economic hardship caused by the FRA increase. One possible reason for this, suggested by Bound, Stinebrickner, and Waidmann (2009), is that most people are "too healthy" to meet the SSA's definition of disability. For those who have limited work capacity but are not medically eligible for SSDI, what seems necessary is an alternative source of public support to address the potential adverse impacts of the FRA increase on their economic well-being.[41]

[41] One example of such a policy option is the proposed Employment Support for the Transition to Retirement program, put forth by Stapleton (2009).

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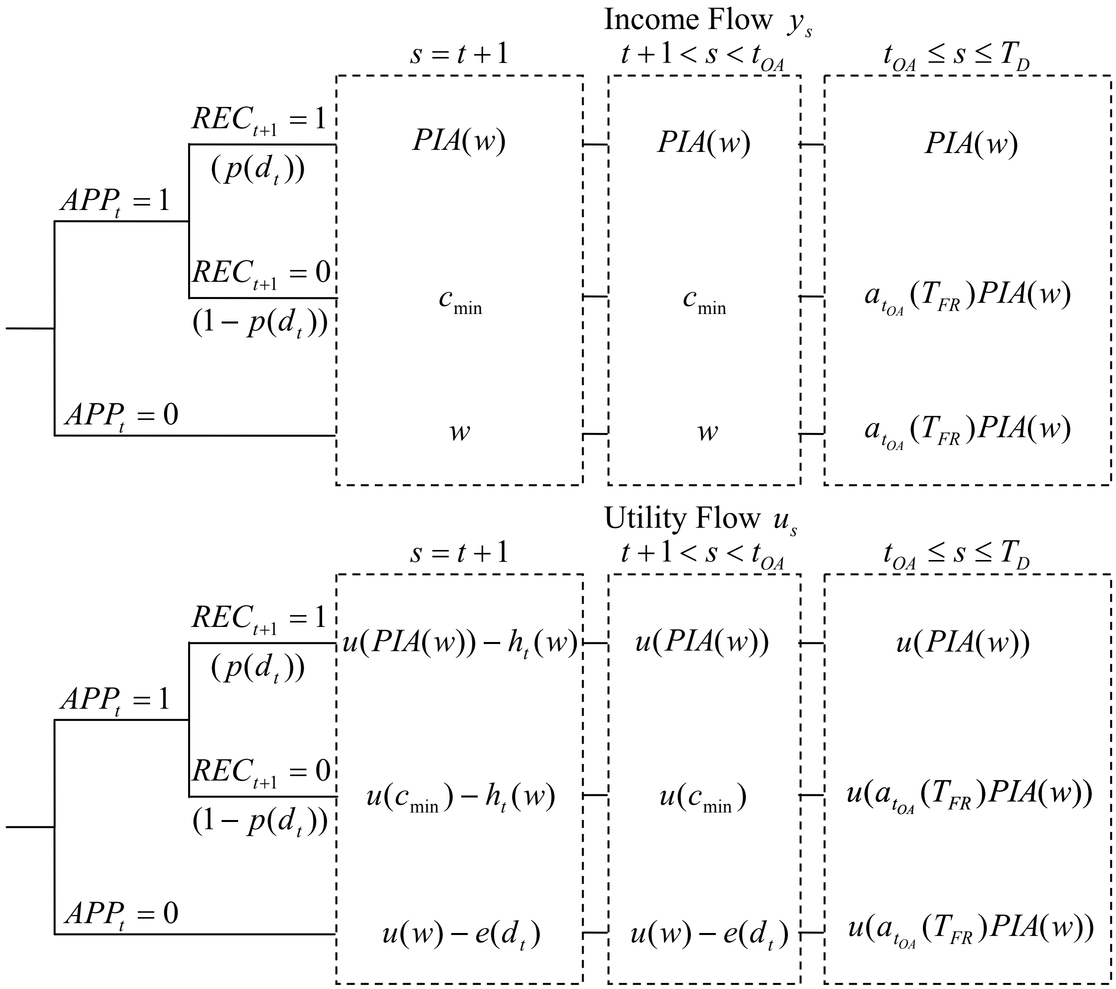
Figure 1.1 The Income Flow and Utility Flow by the Decision to Apply for SSDI and Its Outcome



APP_t: Whether applies for SSDI at age t (1: yes, 0: no)

REC_{t+1}: Whether an application is approved (1: approved, 0: denied)

$p(d_t)$: SSDI award probability as an increasing function of one's disability severity d_t

s: Any age above t

t_{OA}: The earliest age when SSR benefits become available, $t_{OA} = \max(t+1, 62)$

T_D: The maximum possible age an individual might live up to

u: A strictly increasing and concave utility function of income

w: Annual wage rate

$PIA(w)$: Annual SSDI benefit amount

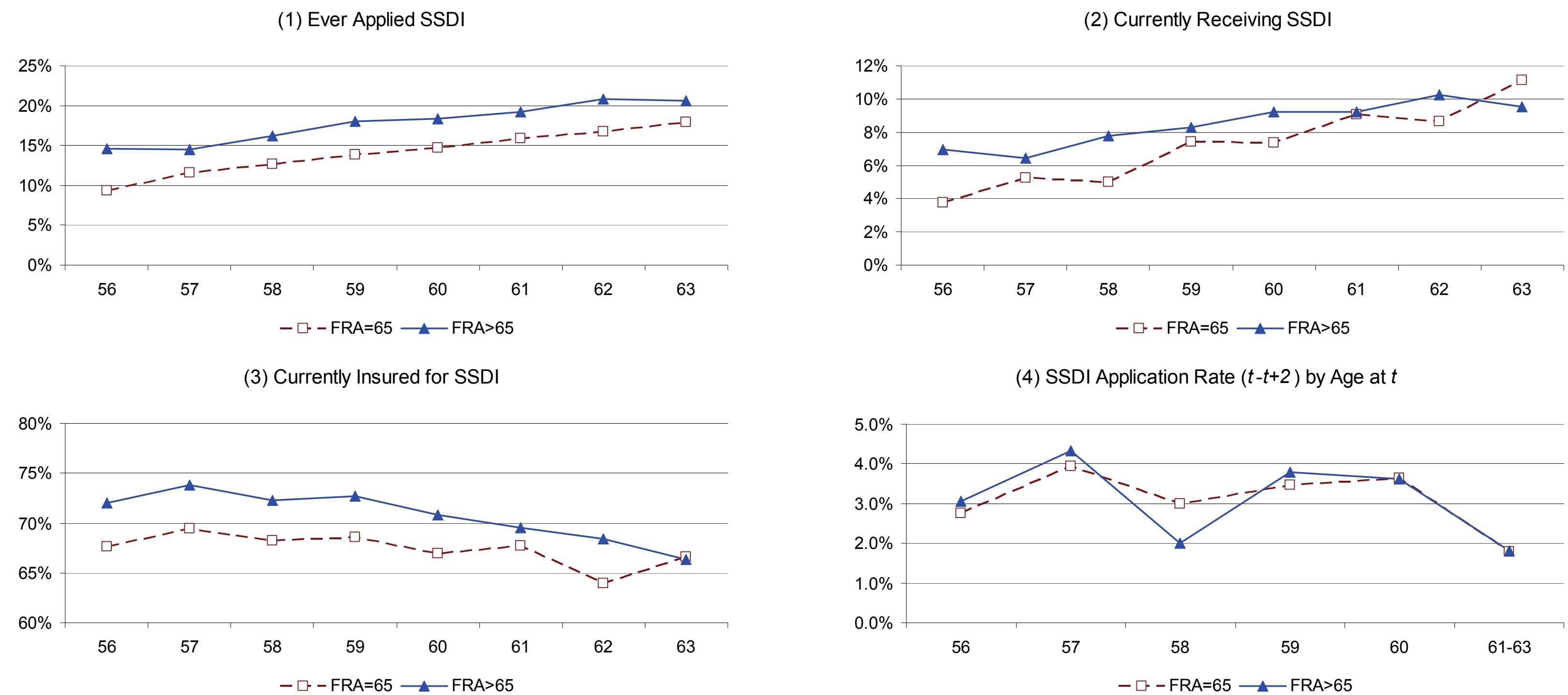
$a_{t_{OA}}(T_{FR})PIA(w)$: Annual SSR benefit amount, where $a_{t_{OA}}(T_{FR})$ is an actuarial adjustment factor at age t_{OA} for a given cohort-specific FRA T_{FR}

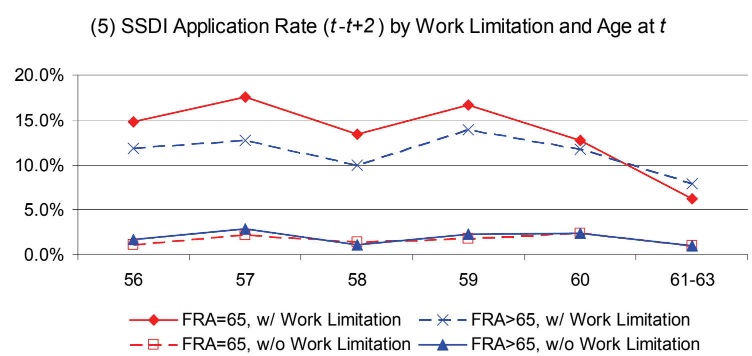
$c_{\min}$: A "consumption floor" representing basic needs consumption

$h_t(w)$: One-time hassle cost of SSDI application

$e(d_t)$: Annual utility cost of exerting effort when working

Figure 1.2 SSDI Insured Status, Application and Receipt Outcomes by Birth Cohort (FRA=65: b.1935-1937; FRA>65: b.1938-1940)





Notes: Sample includes HRS respondents from the original HRS cohort born in 1935-1940 who (1) reached their FRA by Wave 8, and (2) had matched SSA earnings records. Time *t* to time *t+2* SSDI application rate is conditional on being currently insured for SSDI and not applying/receiving SSDI at time *t*.

Table 1.1 Policy Variation across Birth Cohorts Selected for Comparison and Data Availability in HRS

Birth Cohorts in the Sample	Birth Year	FRA	SSR/SSDI Benefit Ratio at			Age at HRS Interview Waves and Corresponding Calendar Years							
						W1	W2	W3	W4	W5	W6	W7	W8
			Age 62	Age 63	Age 64	1992	1994	1996	1998	2000	2002	2004	2006
FRA "Control" Cohort	1935	65	80.0%	86.7%	93.3%	57	59	61	63	65	67	69	71
Total # in HRS: 2,050	1936	65	80.0%	86.7%	93.3%	56	58	60	62	64	66	68	70
# w/ SSA Match: 1,748	1937	65	80.0%	86.7%	93.3%	55	57	59	61	63	65	67	69
FRA "Treatment" Cohort	1938	65 and 2 months	79.2%	85.6%	92.2%	54	56	58	60	62	64	66	68
Total # in HRS: 1,976	1939	65 and 4 months	78.3%	84.4%	91.1%	53	55	57	59	61	63	65	67
# w/ SSA Match: 1,666	1940	65 and 6 months	77.5%	83.3%	90.0%	52	54	56	58	60	62	64	66

Note: Sample includes age-eligible respondents from the original HRS cohort who were born in 1935-1940 and reached their FRA by Wave 8.

HRS Waves between Age 56 and the FRA for Birth Cohort 1935-1937 (shaded)

HRS Waves between Age 56 and the FRA for Birth Cohort 1938-1940 (hatched)

Table 1.2 Cohort Comparison of Observables Related to SSDI Application

	FRA=65	FRA>65	
	b. 1935-1937	b. 1938-1940	T-Ratio
Generosity of SSR Benefits in Relative to SSDI Benefits			
SSR Benefit/SSDI Benefit at *t+1*	82.31%	80.53%	18.60
SSDI Benefit Level			
PIA (Monthly SSDI Benefit Amount) at *t*	$1,075	$1,194	-12.16
Health and Disability Status			
Work Limitation at *t*	12.5%	12.7%	-0.20
Sum of ADLs and Other Functional Limitations (0-13) at *t*	1.31	1.43	-2.72
Self-Reported Fair or Poor Health at *t*	13.8%	15.2%	-1.83
Sum of Major Health Conditions (0-8) at *t*	1.11	1.25	-6.13
Often Troubled with Pain at *t*	19.3%	21.2%	-2.20
Obese (Corrected BMI>=30) at *t*	31.2%	36.1%	-4.77
Subjective Probability of Living to 75+/Life Table Probability at *t*	94.8%	94.8%	-0.01
Ever Applied for and Received SSDI before *t*	1.3%	1.2%	0.68
Ever Applied for but Failed to Receive SSDI before *t*	2.2%	3.1%	-2.52
Demographics, SES and Labor Force Attachment			
Female	46.6%	48.0%	-1.28
Age at *t*	59.4	59.4	1.51
Years of Education	12.6	12.8	-4.28
Nonwhite	21.4%	23.3%	-2.11
Not Married at *t*	25.3%	26.0%	-0.73
Labor Income at *t*	$29,298	$33,484	-5.05
Household Non-Labor Income at *t*	$8,371	$7,814	0.04
Net Worth at *t*	$142,750	$151,100	-3.93
Covered by Health Insurance at *t*	80.1%	81.5%	-1.70
Lifetime Total Quarters of Coverage at *t*	128.5	131.5	-4.11
Person-Wave Observations	4,314	4,145	

Notes: Sample includes time *t* to time *t+2* transitions made by HRS respondents from the original HRS cohort born in 1935-1940 who (1) reached their FRA by Wave 8, (2) had matched SSA earnings records, and (3) were insured for SSDI at *t*, but not applying for or receiving SSDI at *t*, and between age 56 and age 63 at time *t*. All dollar amounts are expressed in 2006 dollars. For monetary variables (PIA, income and wealth amounts), sample medians and the z-statistic from the Wilcoxon rank-sum test are presented instead of sample means and the T-ratio.

Table 1.3 Probit Model of SSDI Application between *t* and *t+2*

	(1)		(2)	
	Coefficient	S.E.	Coefficient	S.E.
Generosity of SSR Benefits in Relative to SSDI Benefits				
SSR Benefit/SSDI Benefit at *t+1*	-3.553***	(1.185)	-2.211	(1.266)
(SSR/SSDI Benefit Ratio at *t+1*)*(Work Limitation at *t*)			-3.920**	(1.857)
SSDI Benefit Level				
PIA (Monthly SSDI Benefit Amount) at *t* (1,000)	-0.177	(0.157)	-0.171	(0.157)
Health and Disability Status				
Work Limitation at *t*	0.453***	(0.091)	3.609**	(1.497)
Sum of ADLs and Other Functional Limitations (0-13) at *t*	0.055***	(0.017)	0.056***	(0.017)
Self-Reported Fair or Poor Health at *t*	0.299***	(0.090)	0.298***	(0.090)
Sum of Major Health Conditions (0-8) at *t*	0.081***	(0.031)	0.083***	(0.031)
Often Troubled with Pain at *t*	0.156**	(0.079)	0.153	(0.080)
Obese (Corrected BMI>=30) at *t*	-0.092	(0.070)	-0.095	(0.070)
Subjective Probability of Living to 75+/Life Table Probability at *t*	-0.023	(0.087)	-0.019	(0.088)
Ever Applied for and Received SSDI before *t*	0.148	(0.195)	0.143	(0.195)
Ever Applied for but Failed to Receive SSDI before *t*	0.461***	(0.120)	0.442***	(0.120)
Demographics, SES and Labor Force Attachment				
Female	-0.148	(0.083)	-0.149	(0.083)
Age at *t* =56 (Reference Category)				
Age at *t* =57	0.190	(0.114)	0.192	(0.115)
Age at *t* =58	-0.043	(0.138)	-0.042	(0.139)
Age at *t* =59	0.201	(0.130)	0.202	(0.132)
Age at *t* =60	0.245	(0.146)	0.243	(0.148)
Age at *t* >=61	0.169	(0.154)	0.168	(0.155)
Years of Education	-0.034***	(0.012)	-0.034***	(0.012)
Nonwhite	-0.002	(0.086)	-0.002	(0.087)
Not Married at *t*	0.060	(0.075)	0.064	(0.075)
Labor Income at *t* (10,000)	0.001	(0.005)	0.001	(0.005)
Household Non-Labor Income at *t* (10,000)	0.001	(0.005)	0.001	(0.005)
Net Worth at *t* (100,000)	0.001	(0.003)	0.001	(0.003)
Covered by Health Insurance at *t*	0.018	(0.081)	0.021	(0.080)
Lifetime Total Quarters of Coverage at *t* (100)	0.001	(0.002)	0.001	(0.002)
Person-Wave Observations	8,312		8,312	
Log Likelihood	-863		-861	
Pseudo R-squared	0.1849		0.1866	

Notes: Sample includes time *t* to time *t+2* transitions made by HRS respondents from the original HRS cohort born in 1935-1940 who (1) reached their FRA by Wave 8, (2) had matched SSA earnings records, and (3) were insured for SSDI at *t* , but not applying for or receiving SSDI at *t* , and between age 56 and age 63 at time *t* . Both specifications include a constant, dummies for each interview wave, and a missing indicator for subjective survival probability. All dollar amounts are expressed in 2006 dollars. Standard errors in both specifications are clustered by respondent.
, *: Significant on a 0.05 and 0.01 level, respectively.

Table 1.4 Treatment Effect of the FRA Increase among People Born in 1938-1940

Policy Variables	Average Marginal Effect	Based on Which Model
SSR/SSDI Benefit Ratio	-0.189	Table 3, Specification (1)
(SSR/SSDI Benefit Ratio)*Work Limitation	-0.449	Table 3, Specification (2)

Increase in the FRA=0.33 Year	Change in SSR/SSDI Benefit Ratio	Treatment Effect (2-Year DI Application)	Treatment Effect (1-Year DI Application)
Whole Sample	-1.8%	0.34%	0.17%
Subsample with Work Limitation	-1.7%	0.77%	0.39%

Increase in the FRA=2 Years	Change in SSR/SSDI Benefit Ratio	Treatment Effect (2-Year DI Application)	Treatment Effect (1-Year DI Application)
Whole Sample	-5.4%	1.02%	0.51%
Subsample with Work Limitation	-5.4%	2.42%	1.22%

Notes: Sample includes time *t* to time *t+2* transitions made by HRS respondents from the original HRS cohort born in 1938-1940 who (1) reached their FRA by Wave 8, (2) had matched SSA earnings records, and (3) were insured by SSDI at *t*, but not applying for or receiving SSDI at *t*, and between age 56 and age 63 at time *t*.

Chapter 2. The Effect of the Full Retirement Age Increase on the Labor Supply of Older Men

Chapter Abstract

The Social Security Full Retirement Age (FRA) has been increased from age 65 for those born before 1937 to age 66 for those born between 1943 and 1954. This policy change creates an incentive for older workers to extend their working lives. Using the Basic Monthly Current Population Survey 1994-2009, this paper estimates that the labor force participation rate of men aged 62-65 increased by 3.5-4.5 percentage points in response to a one-year increase in the FRA. The estimate is more than 60 percent smaller than the most recent estimate of the effect by Mastrobuoni (2009). In comparison to Mastrobuoni (2009), this paper exploits a wider range of the variation in the FRA and uses an econometric specification which directly models the policy change with more extensive controls for cross-cohort trends.

2.1 Introduction

The full retirement age (FRA) is a key program parameter of the Social Security system in the United States. It is defined as the age at which a beneficiary can claim full Social Security retirement benefits. To improve the solvency of the Social Security system, the Congress scheduled an increase of the FRA from 65 years to 67 years in 1983.[42] As shown in Table 2.1, the FRA is set at age 65 for people born in 1937 and earlier, age 66 for people born between 1943 and 1954, and age 67 for people born in 1960 and later. For each birth year from 1938 through 1943 and from 1955 through 1960, the FRA is increased by two months. As the first cohort affected by the FRA increase, those born in 1938 reached age 62 (the earliest age at which one can claim Social Security retirement benefits) in the year 2000. Currently (in year 2010) the FRA is 66 years for those at age 62, at the midpoint of its scheduled rise to 67 years.

Table 2.1 also shows how the rise in the FRA affects the level of the Social Security retirement benefit. If the benefit is claimed at the FRA, the monthly amount would be equal to one's primary insurance amount (PIA, a function of a worker's lifetime earnings). If the benefit is claimed prior to the FRA, the monthly amount would be reduced from the PIA by 5/9th of one percent per month for the first thirty-six months before the FRA and 5/12th of one percent per month thereafter. In Table 2.1, the ratio of the benefit claimed at any age "X" below the FRA to the PIA (the full benefit) is denoted by "AX", the lower-than-one actuarial adjustment factor at the age. As the FRA rises from 65 to 66 and eventually to 67, the actuarial adjustment factor at age 62 (the benefit

[42] A summary of the 1983 Social Security Amendments can be found at http://www.ssa.gov/history/1983amend.html.

claimed at age 62 as a percentage of the full benefit) is reduced from 80 percent to 75 percent and finally to 70 percent. It follows that the actuarial adjustment factor at any age below the FRA is a decreasing function of the FRA. The increase in the FRA reduces the level of the Social Security retirement benefit and causes a loss in the lifetime Social Security income among affected beneficiaries, holding everything else constant.

The labor supply response to this policy change is easy to predict based on any standard economic model of retirement: because the inward shift of the budget constraint necessitates a reduction in consumption, which increases the marginal utility of consumption, an individual will reduce her leisure amount to equate the marginal utility of leisure to the marginal utility of consumption. This negative link between the Social Security benefit level and the labor supply level of older workers has also been extensively documented in the literature (see Lazear, 1986; Hurd, 1990; Lumsdaine and Mitchell, 1999; Feldstein and Liebman, 2002 for some reviews). Based on economic theory and empirical evidence in the literature, one can hypothesize that older workers would increase their labor force participation rates in response to the reduction in the Social Security retirement benefit caused by the FRA increase. The primary purpose of this paper is to test this hypothesis and quantify the magnitude of the effect. I focus on older men's labor force participation decisions in the analysis, because women's labor supply decisions are affected by both their own FRA and their husbands' FRA, which might be different.[43]

Because the FRA increase has not yet been fully implemented, the magnitude of the effect of the policy change on labor supply will significantly influence the future

[43] Many of them claim spousal benefits on the basis of their husbands' benefits amount.

financial status of Social Security. In projections officially presented in the Social Security Trustees Reports, it is unclear whether and how this effect has been taken into account. [44]

The importance of accurately estimating the impact of the FRA increase has become even greater in the context of the Social Security reform debate. Among the ten most up-to-date reform proposals listed at the website of the Social Security Office of the Chief Actuary, [45] nine of them include accelerating or extending the FRA increase as a prominent policy option.

In the following section (Section 2.2) of this paper, I begin by documenting the observed increase in men's labor force participation rates among birth cohorts affected by the FRA increase after the calendar year 2000. In Section 2.3, I present the econometric specification I use to estimate the effect of the FRA increase. I also highlight the advantages of my specification compared to that in the most recent literature (Mastrobuoni, 2009). Those advantages include: directly modeling the change in the Social Security incentive associated with the FRA increase, including a richer set of covariates and more extensive controls for unobserved trends over time and trends across cohorts. Using the male sample from the 1994-2009 Basic Monthly Current Population Survey (CPS) and exploiting the variation in the FRA from age 65 to age 66, I find that: as the FRA increases by one year from 65 years to 66 years, the labor force participation rate for men aged 62-65 rises by 3.5-4.5 percentage points. The estimates are reported in

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[44] The 2009 Trustees Report mentions the FRA increase as one of several trends that are "expected to encourage work at older ages" and says "some of these factors are modeled directly" (http://www.ssa.gov/OACT/TR/2009/V_economic.html#189335).
[45] http://www.ssa.gov/OACT/solvency/.

Section 2.4. In Section 2.5, I conclude with some discussion about next steps to further improve the estimate.

2.2 Trends in the Labor Force Participation Rates of Older Men

The official statistics for the labor force participation rates among individuals aged 55-69 from 1976 to 2009 are shown in Figure 2.1. Data for four separate age groups (55-59, 60-61, 62-64, and 65-69) are extracted from the Bureau of Labor Statistics website.

In Figure 2.1, the labor force participation rates for the two younger age groups (55-59 and 60-61) follow a similar trend – they decline before the mid-1990s and flatten afterwards; the rates for the two older age groups (62-64 and 65-69) follow a different trend – they decline before the mid-1980s, flatten between the mid-1980s and the mid-1990s, then increase afterwards.

After the first affected birth cohort (those born in 1938) entered the age group 62-64 in 2000, a change occurred in the slope of the trend for men aged 62-64: the rate of increase is as small as 0.3 percentage points per year between 1994 and 2000 (from 45.1 percent to 47.0 percent), but as large as 0.9 percentage points per year between 2000 and 2009 (from 47.0 percent to 55.1 percent). However, it would be misleading to directly attribute this increase to the effect of the FRA increase. After all, these trends are the result of a complex combination of birth cohort, time, and age effects.

There are two other policy changes to the Social Security system that are related to the trends shown in Figure 2.1, especially the trend for the age group 65-69 after 1990. One of the changes is the increase in the Delayed Retirement Credit (DRC), an incentive for older workers to postpone the receipt of retirement benefits. The DRC is the percentage increase in the retirement benefit for every year of delayed benefit claiming above the FRA. It is gradually increased by 0.5 percent every two birth years, from 3 percent for those born in 1917-1924 to 8 percent for those born in 1943 and later. The DRC increase became effective in 1990, when the first cohort with a DRC at 3.5 percent (b. 1925) reached age 65. The other change is the reduction in the benefit withholding rate of the Retirement Earnings Test (RET) between the FRA and age 70. The RET effectively defers retirement benefits for beneficiaries whose earnings are above a given threshold. The benefit withholding rate was reduced from 50 percent to 33 percent beginning in 1990 and then completely eliminated to 0 percent in April 2000, when the Senior Citizens' Freedom to Work Act of 2000 was signed.[46] This policy change weakens the labor supply disincentive of the retirement benefit. Studies evaluating these two policy changes have generally found positive effects on men's labor supply (see Pingle, 2006; Haider and Loughran, 2008; and Michaud and van Soest, 2008). These two policy changes apply at ages between the FRA and age 70, but they might also affect the labor supply decisions at younger ages for forward-looking individuals.

To better illustrate the association between the FRA (which varies by birth cohort) and labor force participation rates, I use the January and December surveys of the Basic Monthly Current Population Survey (CPS) to plot men's labor force participation rates from age 41 to 69 for birth cohorts with different FRAs in Figure 2.2.[47] The labor force

[46] Another policy change in the RET (which is not formally addressed in this paper) is the discontinuous jump over time in the threshold amount for the RET above the FRA since 1996 (Friedberg and Webb, 2009).
[47] I use January and December surveys to minimize the measurement error in the birth year (the CPS only collects age in years at the interview), following the "restricted"

participation rates for cohorts with different FRAs are close to each other over the life cycle with the exception of the age range 62-65. Within that age range, the labor force participation rates for those with higher FRAs are systematically higher than those among people with lower FRAs. Figure 2.2 suggests that the effect of the FRA increase on men's labor supply might be concentrated between age 62 and 65.

Figure 2.3 provides a different angle on the association between the FRA and men's labor force dynamics around retirement ages. For each cohort presented in the figure, I define the post-age-61 retirement rate at age *a* as the absolute value of the decline in the labor force participation rate between age *a* and age 61, divided by the labor force participation rate at age 61 of the cohort. The change in this retirement rate measure from *a* to *a+1* is equal to the fraction of people retired at age *a+1* among those who remained in the labor force at age 61. The most striking pattern in the figure is the shift of the retirement age distribution towards later ages as the FRA rises. The most affected cohorts (those born in 1943-1945) are least likely to retire at age 62 and most likely to retire at age 66. On the other hand, the cohorts with unaffected FRA (those born before 1938) have the highest fraction of people retiring at age 62 and the lowest fraction of people retiring at age 66.

Although the policy change was scheduled in 1983, men with higher FRAs do not seem to adjust their labor supply level until they reach the Social Security's earliest eligibility age. This seems like a puzzle but is likely explained by the inelasticity of labor

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method in Mastrobuoni (2009). The trends in the figures are weighted but not adjusted for the change in the CPS survey questions about labor force status in 1994. According to Polivka and Miller (1995), the 1994 change did not strongly affect labor statistics for people below age 65. The oldest birth cohort (b. 1935) included in Figure 2.2 was only age 59 in 1994. Therefore the comparison shown in the figures would not be invalidated by the 1994 design change of the CPS.

supply and the relative lack of knowledge about Social Security rules among younger workers. When taking into account the existence of labor market rigidities (in terms of fixed costs of working and tied wage-hour offers), the labor supply elasticity estimated from a dynamic structural life-cycle model significantly rises as one approaches age 62 (French, 2005). It might be an easier choice for older workers to simply postpone retirement for a few years to compensate for the Social Security benefit cuts, rather than to increase their work effort earlier in their careers (Song and Manchester, 2009). It is also likely that a considerable fraction of younger workers affected by the FRA increase did not know or understand the policy change. According to a nationally representative survey conducted in 2007 about retirement preparation, only 19 percent of workers aged 45 to 55 are able to give their correct FRA (Employee Benefit Research Institute, 2007).

2.3 Previous Literature and the Contribution of This Study

Besides the increase in labor supply, there are at least two other possible behavioral responses to the FRA increase: some older workers may delay claiming Social Security retirement benefits, while others may apply for Social Security Disability Insurance (SSDI) benefits.

The decision to claim Social Security retirement benefits is strongly correlated with the decision to stop working (Coile et al., 2002). Using Social Security administrative data, Song and Manchester (2009) and Benítez-Silva and Yin (2009) found that the FRA increase has encouraged older workers to postpone claiming of Social Security retirement benefits. An increase in the FRA of one year is estimated to decrease the probability of claiming benefits at age 62 by eight percentage points (Song and

Manchester, 2009). I do not examine Social Security retirement benefit claiming as the outcome variable in this paper, because a change in the timing of benefit claiming would not generate significant effects on the Social Security system's financial status, holding constant labor force participation – the adjustment of benefit amount with respect to claiming age is roughly actuarially fair.

As the FRA increases, the relative generosity of the Social Security retirement benefit drops relative to the Social Security disability benefit, creating an additional incentive for individuals to apply for disability benefits. Duggan, Singleton, and Song (2007) and Li (2010) have studied this effect. Application for disability benefits usually leads to early withdrawal from the labor force. Therefore, the FRA increase might actually reduce the labor force participation rate for a small fraction of workers with severe disabilities that could potentially qualify them for the SSDI program. Instead of directly addressing this effect and identifying those individuals, this paper tries to derive the net effect of the FRA increase on the population-average labor force participation rate of older men.

Two recent papers (Gustman and Steinmeier, 2009; Blau and Goodstein (forthcoming) have studied the joint effects of the FRA increase together with other policy changes in the Social Security system (the DRC increase and the changes in the RET). They find that these recent policy changes could explain a part (about 18 percent in Gustman and Steinmeier and 26-51 percent in Blau and Goodstein) of the observed increase in men's labor force participation rates since the mid-1990s.

Several studies have focused on the effect of the FRA increase on men's labor supply. Some predict the labor supply response to the FRA increase using structural models based on *pre-reform* data (data before the year 2000, when the first cohort affected by the policy change reached age 62): for example, Mitchell (1991), Coile and Gruber (2000), Panis, Hurd, Loughran, et al. (2002), and Bound, Stinebrickner, and Waidmann (2009). The estimates produced by these studies are consistently small. Mitchell (1991) estimates an increase of 1.9 months in the retirement age among men in response to the increase in the FRA from 65 to 67. Coile and Gruber (2000) estimate a 1.3-1.7 percentage point increase in the work participation rate of men aged 62-65 when the FRA is increased by one year. Panis et al. (2002) estimate a 0.1 percentage point decrease in the fraction of men completely retired between ages 62-65 in response to a one-year-increase in the FRA. Bound, Stinebrickner, and Waidmann (2009) predict that the average retirement hazard between age 55 and 65 would drop by 0.1 percentage point if the FRA rises from 65 to 67.

Mastrobuoni (2009), on the other hand, found a substantially larger estimate of the effect based on *post-reform* data using a “treatment effect” approach. The difference in the labor force participation rate between cohorts unaffected by the reform (“control” cohorts, those born before 1938) and cohorts affected by the reform (“treatment” cohorts, those born in 1938 or later) is interpreted as the effect of the FRA increase, after controlling for other observables across cohorts. Using observations at ages 61-65 for birth cohorts 1928-1941 from the Basic Monthly CPS 1989-2007, he finds that the average retirement age among men aged 62-66 in the affected cohorts increased by 0.5 months when the FRA is increased by one *month*. Following Equation 4 in his paper, the corresponding increase in the average labor force participation rate at age 62-65 is about 1 percentage point in response to a one-month-increase in the FRA[48].

Mastrobuoni has suggested two explanations for the inconsistency between his estimate and those in the previous structural literature. The first is that the pre-reform estimates might be biased because they rely on cross-sectional variation in the benefit level, which is a function of past earnings and might be endogenous, while his post-reform estimate is based on exogenous variation caused by a policy change. The second explanation is that his estimate might capture potential social "norms" associated with the FRA (for example, the FRA as a "focal point" retirement age) that does not operate through economic incentives.[49]

The econometric specification in Mastrobuoni (2009) can be summarized as the following:

$$Y_{icat} = \beta_0 + \beta_1 C_c \times A_a + \beta_2 P_{2cat} \times A_a + \beta_3 X_{icat} + \varepsilon_{icat} \qquad (2.1)$$

where subscripts i, c, a, and t respectively denote individual, birth cohort, age, and calendar year.[50] The dependent variable Y_{icat} is the labor force status of an individual at age a in calendar year t. Birth cohort dummies C_c are the primary policy variables in

[48] Equation 4 in Mastrobuoni (2009) shows that the summation of the increase in the labor force participation rates at ages 62-65 would be equal to the increase in the average retirement age (in year) between age 62-66. Dividing 0.5 months by 12*4 (12 for the number of months in a year, 4 for the number of ages between 62-65) leads to approximately 0.01.

[49] Research by Song and Manchester (2009) finds that the peak in the Social Security claiming hazard at the FRA does move at the same rate as the FRA increases, which might suggest the existence of signaling (non-economic) effect of the FRA (assuming that the Social Security's actuarial adjustment is fair enough so there is no additional economic incentive for workers to claim just at the FRA).

[50] Among the three variables—age, birth cohort and calendar year—any two of them can perfectly determine the third. It is redundant to use all three of these subscripts, which are kept in the specification just for the sake of clarity.

Mastrobuoni's specification. The dummy for the oldest "control" cohort (b.1937) is omitted, thus the coefficients β_1 for the "treatment" cohorts are interpreted as the effect of the FRA increase. P_{2cat} represents a group of control variables for the two other recent changes in the Social Security rules: the increase in the DRC, and the abolition of the RET between the FRA and age 70 since 2000. Both cohort dummies C_c and the DRC/RET policy variables P_{2cat} are fully interacted with a full set of age dummies A_a. The specification also controls for basic individual characteristics X_{icat} (race and ethnicity, marital status, household size, educational attainment, geographical region, local labor market conditions and macroeconomic indicators) and a random error term ε_{icat}.

The identifying assumption implied by this specification is a very strict one; that there is no other trend across birth cohorts or calendar years that might be correlated with the FRA increase. Because the change in the FRA is monotonic, any monotonically changing trend could be correlated with the FRA increase and potentially bias the estimate of the effect. Those potentially confounding trends include: the rise in average educational attainment, the cross-cohort trend among women towards higher labor force participation rate,[51] improvement in health status and life expectancy, the decline in traditional employer-sponsored defined benefit (DB) plans (and the rise in defined contribution (DC) plans), the decline in physically demanding jobs, and the reduction in employer-sponsored retiree health benefits (Maestas and Zissimopoulos, 2010). Some potentially confounding trends across cohorts might be difficult to observe, for example,

[51] Couples tend to retire together due to the complementarity in their leisure time. Having a working (and usually younger) wife could make the husband stay longer in the labor force (Schirle, 2008).

the rising preference for work, as noted by Maestas (2007). Among those trends, Mastrobuoni's model is only able to control for the change in educational composition.

Mastrobuoni includes dummies for each birth cohort in his model and interprets the difference in the coefficients between affected cohorts and unaffected cohorts as the effect of the FRA. His non-parametric method attributes all the cross-cohort differences in labor force participation rate that are not explained by his control variables to the effect of the FRA increase. Thus his estimate captures not only the effect of the policy change (operating through both economic channels and non-economic channels), but also the effect of other potentially confounding trends across cohorts that are not controlled for by X_{icat} and P_{2cat} .

In this paper, I use an alternative specification to directly model the variation in the Social Security incentive induced by the FRA increase and include more extensive controls for confounding trends through the addition of a set of calendar year fixed effects and a birth year trend function:[52]

$$Y_{icat} = \beta_0 + \beta_1 P_{1cat} \times A_a + \beta_2 P_{2cat} \times A_a + \beta_3 X_{icat} + \beta_4 A_a + \beta_5 T_t + \beta_6 F(C_c) + \varepsilon_{icat} \qquad (2.2)$$

where P_{1cat} represents the policy parameter characterizing the policy-induced change in the Social Security incentive, T_t is a full set of calendar year fixed effects, and $F(C_c)$ is a function to capture the effect of unobserved trends across birth cohorts (for example, a linear or quadratic birth year trend). Because P_{1cat} (as a function of the FRA) varies only across birth cohorts, it is infeasible to include unrestricted birth cohort dummies. Because

[52] Similar econometric specifications have also been used by Pingle (2006) for estimating the effect of the DRC increase using SIPP (Survey of Income and Program Participation) data; and Blau and Goodstein (forthcoming) for explaining the trends in labor force participation of older men using a synthetic panel of aggregate data based on CPS and SIPP.

P_{1cat} has a trend break between birth years 1937 and 1938, the effect of the FRA increase is still identifiable even with the inclusion of a smooth birth year trend function. If we assume that the differences in unobservables across birth cohorts are smooth, the birth year trend function should absorb most of those differences. The estimate β_1 from this specification would be more reliable because of more extensive controls for the impact of year-specific unobservables and the influence of unobserved trends across birth cohorts.

Unlike Mastrobuoni's non-parametric approach, my specification directly models the policy-induced change in the Social Security incentive. In this way, the effect of the FRA increase can be disentangled from the effects of other unobserved cross-cohort trends. The policy parameter P_{1cat} used in the paper is the actuarial adjustment factor at 62 ("A62" in Table 2.1). As a function of the FRA, it declines from 80% to 75% when the FRA is increased from 65 to 66. It is the most straightforward measure of the magnitude of the cut in Social Security retirement benefits for older workers, especially for those who need to decide whether to claim Social Security and retire at age 62 or delay their retirement for a few more years beyond age 62. In fact, age 62 is the most common age for retirement and retirement benefit claiming among older workers (Panis et al., 2002). Because the policy parameter "A62" is in fact a linear function of the FRA itself ("A62" decreases by 0.833 percent for every two-month increase in the FRA), my specification is also able to capture the change in retirement behavior related to the FRA through non-economic channels, assuming the size of the change is proportional to the magnitude of the FRA increase.

2.4 Empirical Model and Estimation Results

The data used in this study is the Basic Monthly Current Population Survey (CPS) 1994-2009. Following Mastrobuoni's "restricted sample" (January and December surveys in 1989-2007), pre-1994 surveys are dropped because the CPS redesign in 1994 made substantial changes to the labor force status questionnaire; January and December surveys in 2008-2009 are added to include more observations from the "treatment" cohorts. The final analysis sample in the study includes all male observations aged 60-69 years during the period from January 1994 to December 2009. As shown in Table 2.2, this sample covers more "treatment" cohorts in comparison to the sample in Mastrobuoni (2009). Mastrobuoni's sample covers four "treatment" cohorts (b.1938, b.1939, b.1940 and b.1941) with uncensored observations distributed over the age range 61-65. Three more "treatment" cohorts like those (b.1942, b.1943, and b.1944) are also covered by the analysis sample of this study. Mastrobuoni (2009) only exploits the variation of the FRA from 65 years to 65 years and 8 months, while this study exploits a 50 percent wider range of the variation, the increase in the FRA from 65 years and 66 years.

Table 2.3 shows the summary statistics of the analysis sample. I separate the person-month observations in the sample into three calendar year groups: 1994-1999, 2000-2005, and 2006-2009. Consistent with Figure 2.1, the average labor force participation rate among men aged 60-69 significantly rises over time, as more and more cohorts affected by the FRA increase enter the age range after 2000. Besides all the covariates included in Mastrobuoni's model, four sets of individual characteristics (immigration status, veteran status, spousal labor force status and family income) are also presented in the table. Comparing the variables across the three groups, I find that there have been substantial increases over the sixteen-year period in men's average educational attainment, family income level, and the fraction of married men with a spouse in the labor force. The fraction of men born outside the United States is higher in the post-year-2000 period than that in the pre-year-2000 period. On the other hand, the fraction of men ever in active military service is relatively lower in the post-year-2000 period.

A set of linear probability models is estimated based on the alternative specification described in Section 2.3, where the outcome variable is whether a man is participating in the labor force at time *t*.[53] The estimation results are reported in Table 2.4 (for the policy variables of interest only) and Table 2.5 (for the other control variables). The primary specification is specification (3) in Table 2.4, which includes control variables for the policy changes in the DRC and the RET, all of the covariates presented in Table 2.3,[54] a full set of age fixed effects, and a full set of calendar year fixed effects. On the basis of the primary specification, specifications (1) and (2) drop the calendar year fixed effects; while specification (4)/(5) respectively adds a linear/quadratic birth year trend function. Specification (1) also drops covariates that are not included in Mastrobuoni (2009): immigration status, veteran status, spousal labor force status and family income.

The effect of the FRA increase is assumed to operate through the increase in the penalty for early retirement at age 62 (characterized by the policy parameter "A62"). In each specification shown in Table 2.4, "A62" is interacted with each of the three age

[53] The employment rates are well-bounded between 20% and 70% in the sample. The linear probability models would not generate any predicted values out of the range [0, 1].
[54] One of those variables, whether the wife is in the labor force, is certainly not exogenous to the husband's labor force participation decision. The average labor force participation rate of the wife's birth cohort at age 54 (following Schirle (2008)'s instrumental variable approach) is an alternative more exogenous measure. The use of either measure will lead to about the same estimate for the FRA effect.

groups (60-61, 62-65, and 66-69) in the model to allow the effect of the FRA increase to vary by age. The coefficients for these interaction terms are the coefficients of interest in the models. Each of these coefficients can be interpreted as the effect of the FRA increase (through the reduction of the age 62 actuarial adjustment factor) for one specific age group.[55]

Similarly, the value of the DRC and a dummy for post-April-2000 observations are interacted with the age group dummies to capture the effects of the DRC increase and the change in the RET.[56] These interaction terms are included only to control for the potential effects of the other two policy changes. It would be inappropriate to interpret their coefficients as estimates of the effects of those policy changes.[57]

Among the three policy variables of interest in each specification shown in Table 2.4, only the interaction term between the policy parameter "A62" and age group (62-65) is statistically significant, suggesting that the increase in the FRA has non-zero effects on men's labor force participation rates only over this age range, consistent with what is shown in Figure 2.2. The coefficients for the interaction term across specifications (3)-(5) range from -0.703 to -0.925. Plugging in the change in "A62" (-5%) associated with the increase in the FRA from 65 to 66, the estimated increase in labor force participation rate

[55] There is no "reference" age group because I have fully interacted "A62" with each of the three age groups in the sample and omitted "A62" itself from the model.
[56] The policy change in the RET occurred in April 2000. When generating the calendar year dummies, I treat the observations in January 2000 as if they were collected in December 1999. The post-April-2000 dummy itself is perfectly collinear with the full set of year dummies. I can only include the interaction terms between the post-April-2000 dummy and two out of the three age groups.
[57] Because the gradual increase in the DRC (0.5 percent every two birth cohorts from b. 1925 to b. 1943) is strongly correlated with the birth year trend, the coefficients for the interaction terms between the DRC and age groups are quite sensitive to the addition of a linear or quadratic birth year trend to the model.

would be 3.5-4.5 percentage points at ages 62-65. Using the conversion process described in Footnote 48, the corresponding estimate of the policy-induced increase in the average retirement age between ages 62-66 would be 1.68-2.16 months (0.035*4*12-0.045*4*12) when the FRA is increased by 12 months. This estimate is more than 60 percent smaller than that (6 months increase in the average retirement age in response to a 12-month-increase in the FRA) in Mastrobuoni (2009).

This study and Mastrobuoni's study have different samples, different policy variables, different control variables, and different econometric specifications. It is difficult to attribute the discrepancy in the estimates from the two studies to any of those differences without further examination.

A comparison of the estimation results across specifications in Table 2.4 tells us that the difference in control variables and econometric specifications cannot explain why the estimate in this study is *smaller* than Mastrobuoni's estimate. In fact, the estimated effects would become slightly *larger* when calendar year dummies and additional covariates (spousal labor force status, family income, immigration status and veteran status) are added to the model, according to the difference in the coefficients of interest between specifications (1) and (3).

To explore whether the differences in samples and policy variables account for the difference between the two estimates, I estimate a simplified version of Mastrobuoni's specification (with cohort dummies, age dummies, and the same set of covariates as what he included in his model). The CPS sample used in this exercise (observations aged 62-65 for birth cohorts 1932-1941) is also similar to the "restricted sample" used in his study. The estimation results are presented in column (1) of Table

2.6. By dividing the coefficient for each "treatment" cohort (which is the estimated increase in labor force participation associated with the cohort in relation to those born in 1937) by the magnitude of the FRA increase (in terms of months) for the cohort and taking the average of those FRA-increase-normalized coefficients, I derive the estimated effect: a 1.10 percentage point increase in the labor force participation rate over the age range 62-65 in response to a one-month increase in the FRA, which is quantitatively very close to the estimate reported by Mastrobuoni (2009). In column (2) of Table 2.6, I add three more birth cohorts (b.1942-b.1944) to the data. As a component of the sample of this study, those three cohorts are not included in Mastrobuoni's sample. The inclusion of the three additional cohorts attenuates the estimated effect from 1.10 percentage points to 0.85 percentage points, suggesting that the effect of the policy change might be strongest at the beginning of its implementation and decrease afterwards. In columns (3) and (4) of the table, I replace the policy variables in the model and use policy parameter "A62" instead of cohort dummies. This experiment significantly decreases the estimated effects: from 1.10 to 0.64 when the birth cohorts included in the sample are 1932-1941, and from 0.85 to 0.46 when the birth cohorts included in the sample are 1932-1944. According to the comparison across alternative model specifications in Table 2.4 and Table 2.6, the inclusion of additional cohorts in the sample and the direct modeling of the policy change seem to be the primary explanations for the relatively smaller magnitude of the estimate from this study.

I have also tested the heterogeneity of the effect by socioeconomic status. In Table 2.7, the specification (3) in Table 2.4 is extended with additional interactions between the statistically significant policy variable of interest and two sets of control variables: education categories (column (1)), and family income categories (column (2)). The most robust results in this table across the two columns are the positive coefficients for the interaction terms between the policy variables and indicators for higher socioeconomic classes (in terms of education and income category), suggesting that the effects of the FRA increase are lower among men with higher socioeconomic status. In other words, those with relatively lower socioeconomic status are more likely to increase their labor force participation rates as the FRA increase, perhaps because they rely more on the Social Security as an income source. Mastrobuoni (2009) has reported similar results.

2.5 Discussion and Conclusion

This paper provides an alternative estimate of the labor supply effect of the FRA increase: the change in the FRA from 65 to 66 increased the labor force participation rates among male workers aged 62-65 by 3.5-4.5 percentage points. The paper also shows that the most recent reduced-form estimate of this effect (Mastrobuoni, 2009) would be reduced by more than 60 percent when using a more detailed econometric specification with direct modeling of the policy change to exploit a wider range of the variation in the FRA.

The estimate reported in the paper is still much larger compared to those in the pervious literature. To further reconcile the discrepancy between the reduced-form estimates and the structural estimates, a possible avenue of future research is to estimate a structural model of retirement using both pre-reform data and post-reform data. Ideally, the model would be able to fit the labor supply behaviors for both “control” cohorts and “treatment” cohorts.

The estimate reported in this paper might be subject to omitted variable bias. Among the empirically important cross cohort trends described in Section 2.3, this study is unable to control for trends in health status and job characteristics (pension type, physical demand, and availability of retiree health insurance) due to data limitations in the CPS. Recent literature suggests that those trends have positive effects on the labor force participation of older workers (Bound, Stinebrickner, and Waidmann, 2009; Friedberg and Webb, 2005; Johnson, Mermin and Resseger, 2007; Blau and Gilleskie, 2008), thus the omission of those variables in the model would cause an upward bias. In Table 2.8, a data set with richer information (but much smaller sample size) – the Health and Retirement Study (HRS) is used to compare the health status and job characteristics at pre-retirement ages (57-61) between birth cohorts with different FRAs. Those with FRA above 65 are less likely to have a work-limiting health problem (although the difference is not statistically significant), more likely to have DC pensions rather than DB pensions, and less likely to have a physically-demanding job or a job providing retiree health insurance. In a preliminary analysis (not shown) using the Survey of Income and Program Participation (SIPP) data, I find that an estimate of the effect of the FRA increase on men’s retirement hazard rates at ages 61-65 would be reduced by 6-16 percent (depending on the specification used) after controlling for those health and job characteristics variables. As an effort to further evaluate the robustness of the estimate from this study, it would be valuable to replicate the analysis presented in this paper using different survey data (for example, the HRS and the SIPP).

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Figure 2.1 Trends in Men's Labor Force Participation Rates by Age Groups
(Source: Bureau of Labor Statistics)

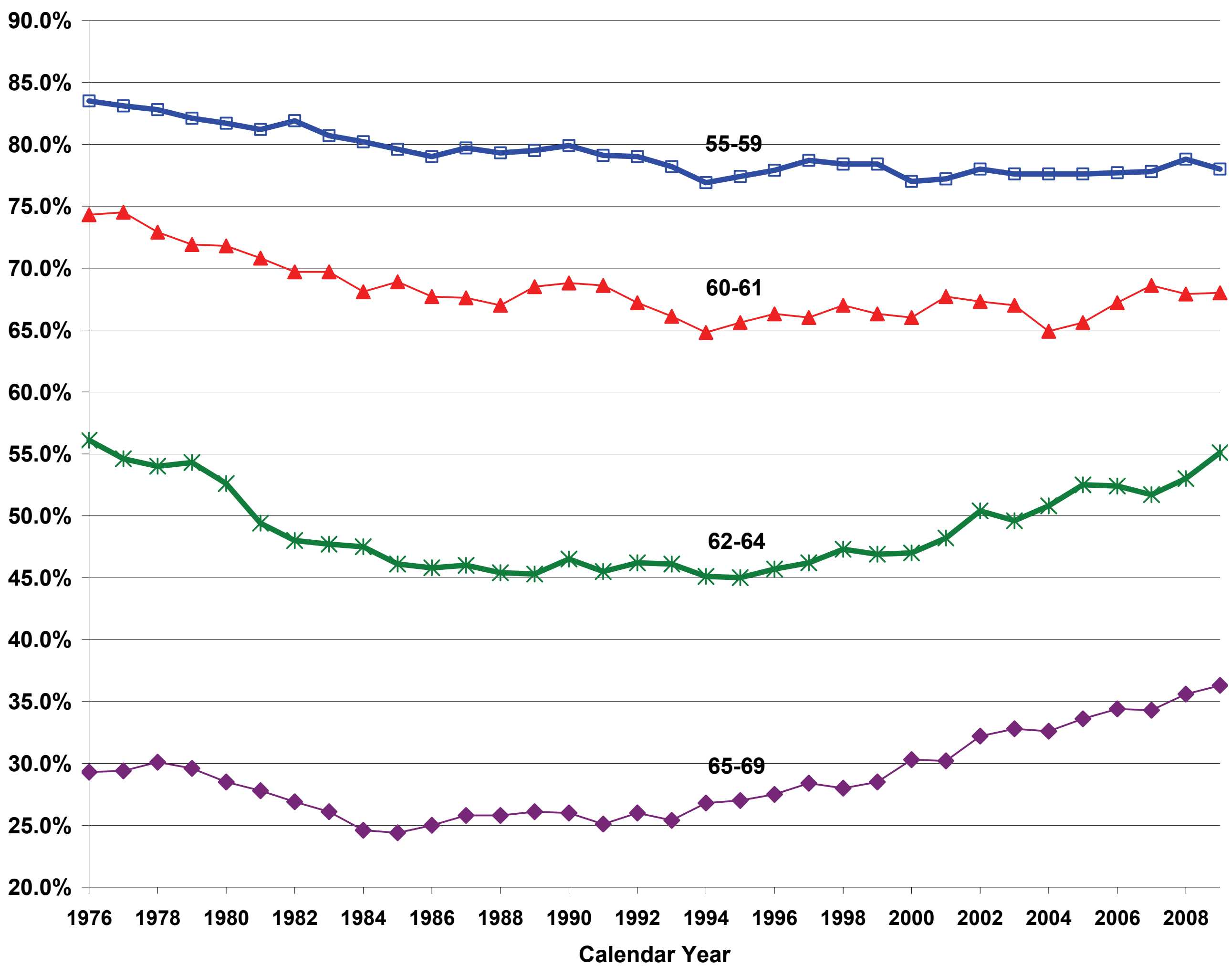

Figure 2.2 Men's Labor Force Participation Rates by Cohorts with Different FRAs
(Source: Basic Monthly CPS 1976-2009, January and December Surveys, Survey Weights Applied)

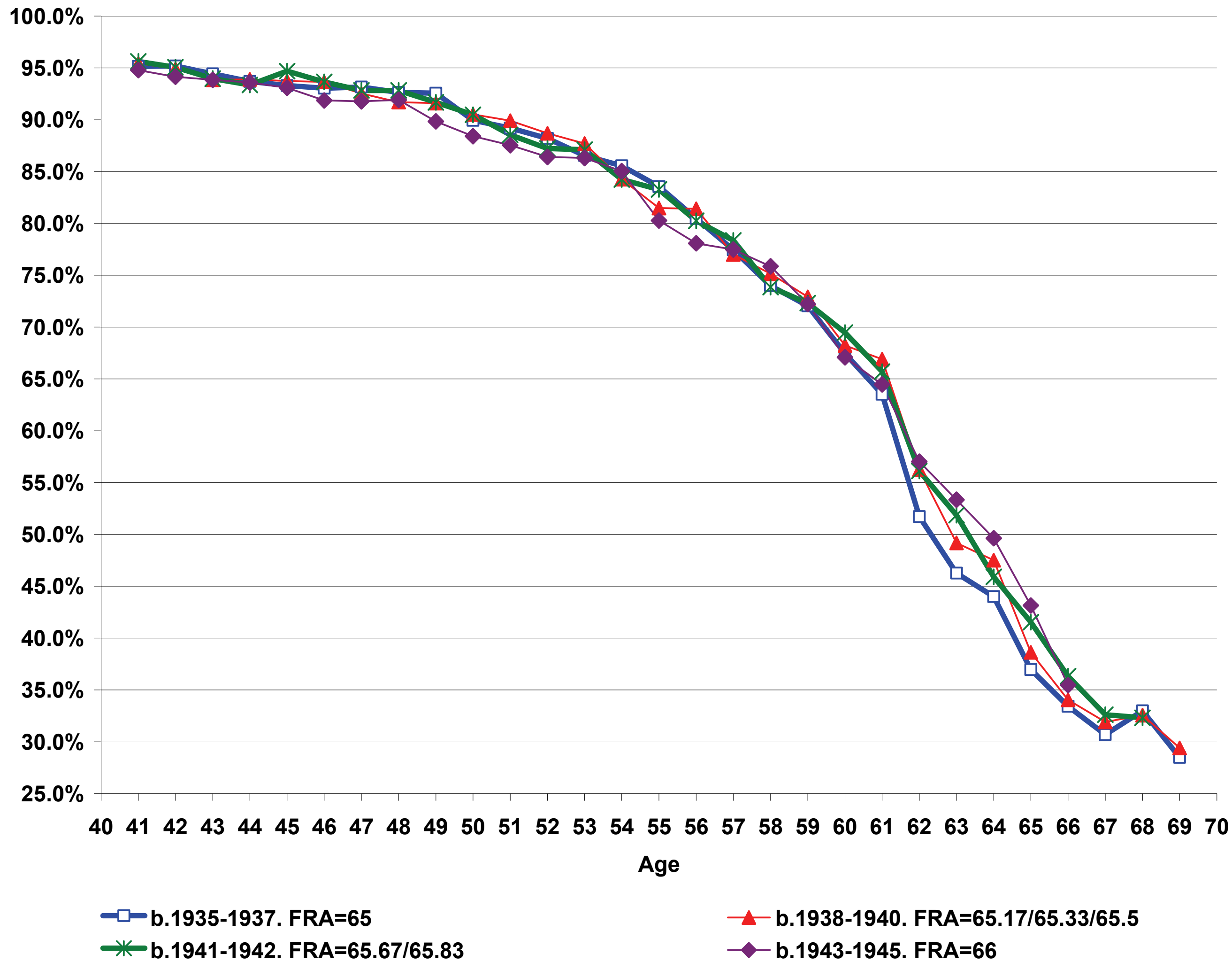

Figure 2.3 Post-Age-61 Retirement Rates by Cohorts with Different FRAs
(Source: Basic Monthly CPS 1994-2009, January and December Surveys, Survey Weights Applied)

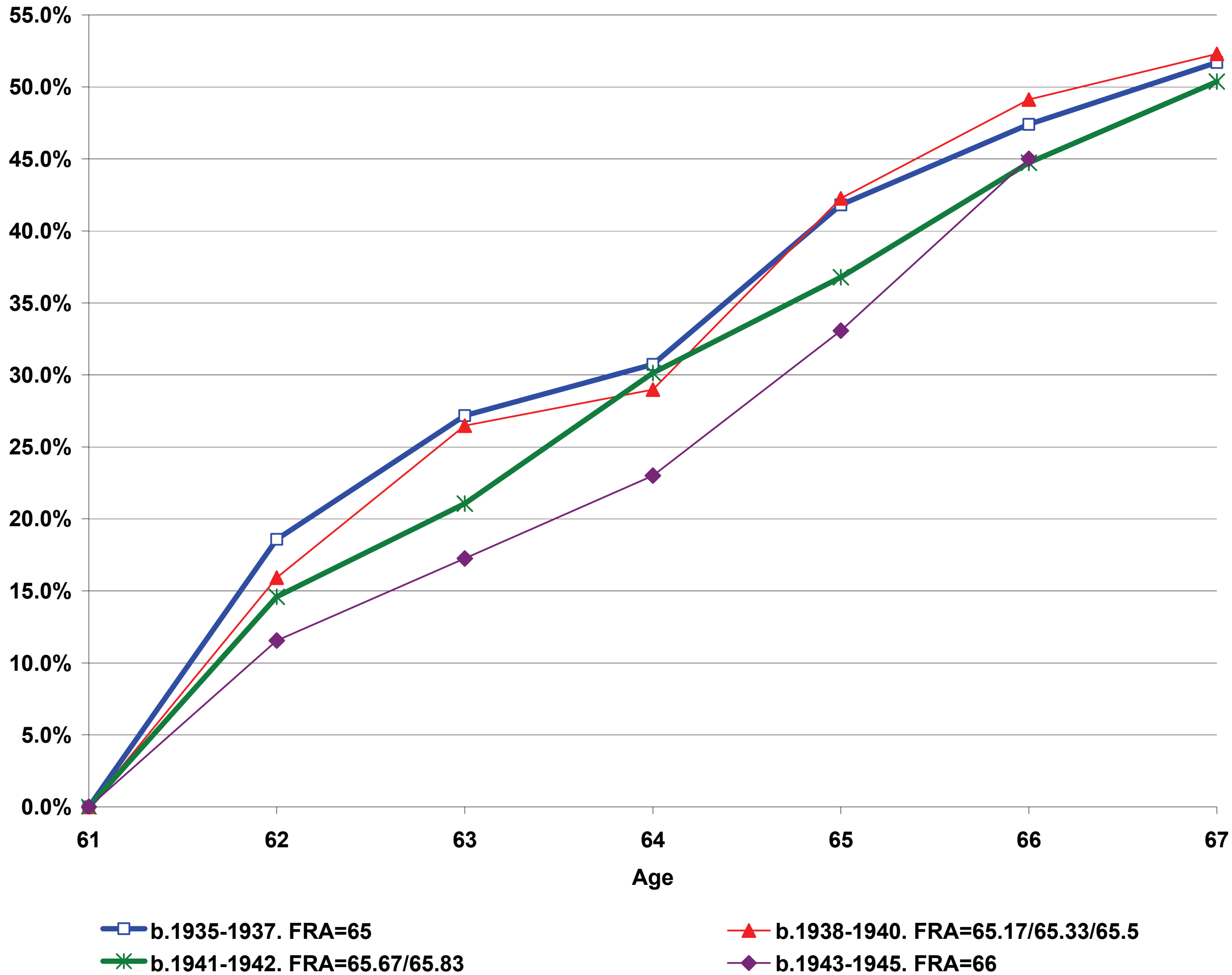

Table 2.1 Variation of the Full Retirement Age (FRA) across Birth Cohorts

Year of Birth	Calendar Year When the Cohort Reaches Age 62	FRA	Actuarial Adjustment Factor "AX" below or at the FRA (Benefit Claimed at Age X as a Percentage of the Full Benefit)					
			A62	A63	A64	A65	A66	A67
1937 and earlier	1999 and earlier	65 years	80.00%	86.67%	93.33%	100.00%		
1938	2000	65 years and 2 months	79.17%	85.56%	92.22%	98.89%		
1939	2001	65 years and 4 months	78.33%	84.44%	91.11%	97.78%		
1940	2002	65 years and 6 months	77.50%	83.33%	90.00%	96.67%		
1941	2003	65 years and 8 months	76.67%	82.22%	88.89%	95.56%		
1942	2004	65 years and 10 months	75.83%	81.11%	87.78%	94.44%		
1943-1954	2005-2016	66 years	75.00%	80.00%	86.67%	93.33%	100.00%	
1955	2017	66 years and 2 months	74.17%	79.17%	85.56%	92.22%	98.89%	
1956	2018	66 years and 4 months	73.33%	78.33%	84.44%	91.11%	97.78%	
1957	2019	66 years and 6 months	72.50%	77.50%	83.33%	90.00%	96.67%	
1958	2020	66 years and 8 months	71.67%	76.67%	82.22%	88.89%	95.56%	
1959	2021	66 years and 10 months	70.83%	75.83%	81.11%	87.78%	94.44%	
1960 and later	2022 and later	67 years	70.00%	75.00%	80.00%	86.67%	93.33%	100.00%

Source: Social Security Online - The Official Website of the U.S. Social Security Administration.
http://www.ssa.gov/OACT/ProgData/ar_drc.html; http://www.ssa.gov/OP_Home/handbook/handbook.07/handbook-0720.html.

Table 2.2 Comparison of Analysis Samples between Mastrobuoni (2009) and This Paper

Birth Cohorts	Age at CPS Monthly Interviews										
	Jan.1989	Dec.1989 Jan.1990	Dec.1990 Jan.1991	Dec.1991 Jan.1992	Dec.1992 Jan.1993	Dec.1993 Jan.1994	Dec.1994 Jan.1995	Dec.1995 Jan.1996	Dec.1996 Jan.1997	Dec.1997 Jan.1998	Dec.1998 Jan.1999
"Control" Cohorts											
b.1924	64	65	66	67	68	69	70	71	72	73	74
b.1925	63	64	65	66	67	68	69	70	71	72	73
b.1926	62	63	64	65	66	67	68	69	70	71	72
b.1927	61	62	63	64	65	66	67	68	69	70	71
b.1928	60	61	62	63	64	65	66	67	68	69	70
b.1929	59	60	61	62	63	64	65	66	67	68	69
b.1930	58	59	60	61	62	63	64	65	66	67	68
b.1931	57	58	59	60	61	62	63	64	65	66	67
b.1932	56	57	58	59	60	61	62	63	64	65	66
b.1933	55	56	57	58	59	60	61	62	63	64	65
b.1934	54	55	56	57	58	59	60	61	62	63	64
b.1935	53	54	55	56	57	58	59	60	61	62	63
b.1936	52	53	54	55	56	57	58	59	60	61	62
b.1937	51	52	53	54	55	56	57	58	59	60	61
"Treatment" Cohorts											
b.1938	50	51	52	53	54	55	56	57	58	59	60
b.1939	49	50	51	52	53	54	55	56	57	58	59
b.1940	48	49	50	51	52	53	54	55	56	57	58
b.1941	47	48	49	50	51	52	53	54	55	56	57
b.1942	46	47	48	49	50	51	52	53	54	55	56
b.1943	45	46	47	48	49	50	51	52	53	54	55
b.1944	44	45	46	47	48	49	50	51	52	53	54
b.1945	43	44	45	46	47	48	49	50	51	52	53
b.1946	42	43	44	45	46	47	48	49	50	51	52
b.1947	41	42	43	44	45	46	47	48	49	50	51
b.1948	40	41	42	43	44	45	46	47	48	49	50
b.1949	39	40	41	42	43	44	45	46	47	48	49

Birth Cohorts	Age at CPS Monthly Interviews										
	Dec.1999 Jan.2000	Dec.2000 Jan.2001	Dec.2001 Jan.2002	Dec.2002 Jan.2003	Dec.2003 Jan.2004	Dec.2004 Jan.2005	Dec.2005 Jan.2006	Dec.2006 Jan.2007	Dec.2007 Jan.2008	Dec.2008 Jan.2009	Dec.2009
"Control" Cohorts											
b.1924	75	76	77	78	79	80	81	82	83	84	85
b.1925	74	75	76	77	78	79	80	81	82	83	84
b.1926	73	74	75	76	77	78	79	80	81	82	83
b.1927	72	73	74	75	76	77	78	79	80	81	82
b.1928	71	72	73	74	75	76	77	78	79	80	81
b.1929	70	71	72	73	74	75	76	77	78	79	80
b.1930	69	70	71	72	73	74	75	76	77	78	79
b.1931	68	69	70	71	72	73	74	75	76	77	78
b.1932	67	68	69	70	71	72	73	74	75	76	77
b.1933	66	67	68	69	70	71	72	73	74	75	76
b.1934	65	66	67	68	69	70	71	72	73	74	75
b.1935	64	65	66	67	68	69	70	71	72	73	74
b.1936	63	64	65	66	67	68	69	70	71	72	73
b.1937	62	63	64	65	66	67	68	69	70	71	72
"Treatment" Cohorts											
b.1938	61	62	63	64	65	66	67	68	69	70	71
b.1939	60	61	62	63	64	65	66	67	68	69	70
b.1940	59	60	61	62	63	64	65	66	67	68	69
b.1941	58	59	60	61	62	63	64	65	66	67	68
b.1942	57	58	59	60	61	62	63	64	65	66	67
b.1943	56	57	58	59	60	61	62	63	64	65	66
b.1944	55	56	57	58	59	60	61	62	63	64	65
b.1945	54	55	56	57	58	59	60	61	62	63	64
b.1946	53	54	55	56	57	58	59	60	61	62	63
b.1947	52	53	54	55	56	57	58	59	60	61	62
b.1948	51	52	53	54	55	56	57	58	59	60	61
b.1949	50	51	52	53	54	55	56	57	58	59	60

Analysis Sample in Mastrobuoni (2009): Birth Cohorts: b.1928-b.1941; Ages: 61-65

Analysis Sample in This Paper: CPS Monthly Interviews: Jan.1994-Dec.2009; Ages: 60-69

Table 2.3 Summary Statistics of the Analysis Sample

	(1) Year 1994-1999		(2) Year 2000-2005		(3) Year 2006-2009	
	Mean	SD	Mean	SD	Mean	SD
Age	64.4	2.9	64.1	2.8	64.0	2.8
Year	1996.6	1.8	2002.8	1.6	2007.5	1.1
Dependent Variable						
Participating in the Labor Force	41.9%	49.3%	46.4%	49.9%	50.2%	50.0%
Social Security Program Parameters						
FRA	65.0	0.1	65.3	0.4	65.8	0.3
A62	79.9%	0.3%	78.3%	1.8%	76.1%	1.5%
DRC	5.1%	0.9%	6.7%	0.8%	7.6%	0.5%
Other Control Variables						
Race/Ethnicity: White	84.1%	36.6%	82.4%	38.1%	82.0%	38.5%
Race/Ethnicity: Black	7.6%	26.5%	7.9%	26.9%	7.3%	26.1%
Race/Ethnicity: Hispanic	4.6%	20.9%	5.5%	22.7%	5.5%	22.8%
Race/Ethnicity: Other	3.7%	18.9%	4.3%	20.2%	5.2%	22.2%
Not Married	19.9%	39.9%	21.2%	40.9%	23.2%	42.2%
Household Size: 1 Member	12.8%	33.4%	13.9%	34.6%	15.6%	36.3%
Household Size: 2 Members	63.3%	48.2%	64.4%	47.9%	62.7%	48.4%
Household Size: >2 Members	23.9%	42.6%	21.6%	41.2%	21.7%	41.3%
Education: Less Than High School	24.8%	43.2%	19.0%	39.3%	13.8%	34.5%
Education: High School Graduates or GED	32.6%	46.9%	33.2%	47.1%	30.6%	46.1%
Education: Some College	18.5%	38.8%	20.9%	40.7%	23.8%	42.6%
Education: College Graduates	13.1%	33.7%	14.5%	35.2%	16.9%	37.5%
Education: Above College	11.0%	31.3%	12.4%	33.0%	14.8%	35.5%
Census Region: Northeast	23.7%	42.5%	21.9%	41.3%	20.8%	40.6%
Census Region: Midwest	23.2%	42.2%	23.9%	42.6%	22.9%	42.0%
Census Region: South	31.7%	46.5%	31.0%	46.3%	32.3%	46.8%
Census Region: West	21.4%	41.0%	23.2%	42.2%	24.0%	42.7%
Local Unemployment Rate	3.6%	2.3%	3.7%	1.9%	4.5%	2.9%
Local Average Weekly Working Hours	34.0	5.9	33.4	5.5	34.1	5.7
Age 60-62 COLA	0.94	0.02	0.95	0.01	0.94	0.01
Log Monthly Dow Jones Index	8.8	0.4	9.2	0.1	9.3	0.2
Foreign Born	8.3%	27.6%	9.1%	28.8%	8.9%	28.5%
Veteran	59.2%	49.1%	46.5%	49.9%	43.4%	49.6%
Spouse Is in the Labor Force	39.9%	49.0%	45.8%	49.8%	49.2%	50.0%
Family Income<$30,000	46.4%	49.9%	33.1%	47.1%	25.3%	43.5%
Family Income>=$30,000 and <$60,000	33.6%	47.2%	34.7%	47.6%	33.6%	47.2%
Family Income>=$60,000	20.0%	40.0%	32.2%	46.7%	41.1%	49.2%
Number of Person-Month Observations	58,457		56,179		47,423	

Notes: Sample includes male observations aged 60-69 in January and December Surveys of Basic Montly CPS 1994-2009. "A62" is the cohort-specific actuarial adjustment factor at age 62. As a function of the FRA, it declines from 80% to 75% when the FRA is increased from 65 to 66. Local labor market conditions (unemployment rate and average weekly working hours) for each individual are computed using data for men aged 50-55 who are in the same educational category and geographical region as the individual. Age 60-62 COLA measures the cost of living adjustment between age 60 and 62, which affects the level of the Social Security retirement benefit.

Table 2.4 Linear Probability Models of Labor Force Participation for Men Aged 60-69

Dependent Variable: Respondent is Participating in the Labor Force	(1)	(2)	(3)	(4)	(5)
Policy Variables of Interest					
A62*(Age 60-61)	0.138	-0.029	-0.229	-0.081	-0.323
	(0.565)	(0.426)	(0.544)	(0.550)	(0.555)
A62*(Age 62-65)	-0.659**	-0.635***	-0.707***	-0.703***	-0.925***
	(0.280)	(0.246)	(0.270)	(0.270)	(0.280)
A62*(Age 66-69)	0.254	0.418	0.418	0.394	0.043
	(0.312)	(0.275)	(0.299)	(0.300)	(0.323)
Control Variables for:					
Other Policy Changes	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Race/Ethnicity	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Marital Status and Household Size	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Educational Attainment	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Geographical Region	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Local Labor Market Conditions	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Macroeconomic Indicators	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Immigration Status and Veteran Status	***No***	*Yes*	*Yes*	*Yes*	*Yes*
Spousal Labor Force Status	***No***	*Yes*	*Yes*	*Yes*	*Yes*
Family Income	***No***	*Yes*	*Yes*	*Yes*	*Yes*
Age Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Calendar Year Fixed Effects	***No***	***No***	*Yes*	*Yes*	*Yes*
Birth Year Trend				0.006**	0.009
				(0.003)	(0.005)
Birth Year Trend Squared					-0.000
					(0.000)
Number of Person-Month Observations	162,014	162,014	162,014	162,014	162,014
R-Squared	0.1281	0.1903	0.1903	0.1903	0.1904

Notes: Sample includes male observations aged 60-69 in January and December Surveys of Basic Montly CPS 1994-2009. All specifications include a constant. Specifications (2)-(5) also include a missing indicator for whether one's spouse is in the labor force and a missing indicator for family income category. Standard errors are clustered by individuals. "A62" is the cohort-specific actuarial adjustment factor at age 62. As a function of the FRA, it declines from 80% to 75% when the FRA is increased from 65 to 66. See Table 5 for a detailed list of the control variables.

, *: Significant at a 0.05 and 0.01 level, respectively.

Table 2.5 Detailed Estimated Results for Control Variables in the Primary Specification

Primary Specification: Specification (3) in Table 4	Coeffient	Standard Error
Control Variables for Other Policy Changes		
DRC*(Age 60-61)	-0.627	(1.150)
DRC*(Age 62-65)	-0.105	(0.803)
DRC*(Age 66-69)	1.448**	(0.687)
(Post Year 2000 RET Change)*(Age 62-65)	0.018	(0.015)
(Post Year 2000 RET Change)*(Age 66-69)	0.001	(0.015)
Other Control Variables		
Race/Ethnicity: Black	-0.059***	(0.004)
Race/Ethnicity: Hispanic	0.037***	(0.006)
Race/Ethnicity: Other	-0.042***	(0.006)
Not Married	-0.076***	(0.011)
Household Size: 1 Member	0.021***	(0.005)
Household Size: >2 Members	0.015***	(0.003)
Education: Less Than High School	-0.029***	(0.006)
Education: Some College	0.016***	(0.004)
Education: College Graduates	0.034***	(0.006)
Education: Above College	0.072***	(0.007)
Census Region: Midwest	0.021***	(0.003)
Census Region: South	-0.004	(0.003)
Census Region: West	-0.011***	(0.003)
Local Unemployment Rate	-0.136	(0.075)
Local Average Weekly Working Hours	0.002***	(0.001)
Age 60-62 COLA	0.030	(0.102)
Log Monthly Dow Jones Index	-0.019	(0.012)
Foreign Born	0.067***	(0.005)
Veteran	-0.025***	(0.002)
Spouse Is in the Labor Force	0.209***	(0.003)
Family Income<$30,000	-0.109***	(0.003)
Family Income>=$60,000	0.126***	(0.003)
Number of Person-Month Observations	162,014	
R-Squared	0.1903	

Notes: See Table 4 for additional notes about this specification. "Year 2000 RET Change" refers to the policy change occurred in April 2000 which removed the retirement earnings test (RET) for individuals who have attained their FRA. The omitted education category is "high school graduates or GED". The omitted family income category is ">=$30,000 and <$60,000". Local labor market conditions (unemployment rate and average weekly working hours) for each individual are computed using data for men aged 50-55 who are in the same educational category and geographical region as the individual. Age 60-62 COLA measures the cost of living adjustment between age 60 and 62, which affects the level of the Social Security retirement benefit.

, *: Significant at a 0.05 and 0.01 level, respectively.

Table 2.6 Estimated Effects Based on Specifications Similar to Mastrobuoni's Specification

Dependent Variable: Respondent is Participating in the Labor Force	(1)	(2)	(3)	(4)
Birth Cohorts Included in the Sample	***b.1932-b.1941***	***b.1932-b.1944***	***b.1932-b.1941***	***b.1932-b.1944***
Ages Included in the Sample	*62-65*	*62-65*	*62-65*	*62-65*
Policy Variables of Interest				
Born in 1937 (Reference Category)				
Born in 1938	0.042***	0.042***		
	(0.011)	(0.011)		
Born in 1939	0.039***	0.039***		
	(0.011)	(0.011)		
Born in 1940	0.044***	0.044***		
	(0.011)	(0.011)		
Born in 1941	0.048***	0.050***		
	(0.011)	(0.011)		
Born in 1942		0.052***		
		(0.011)		
Born in 1943		0.062***		
		(0.010)		
Born in 1944		0.058***		
		(0.011)		
A62			-1.545***	-1.098**
			(0.238)	(0.135)
Other Cohort Dummies				
Born in 1932	-0.015	-0.023		
	(0.016)	(0.014)		
Born in 1933	-0.029**	-0.033***		
	(0.013)	(0.013)		
Born in 1934	-0.010	-0.012		
	(0.012)	(0.012)		
Born in 1935	0.012	0.011		
	(0.011)	(0.011)		
Born in 1936	-0.003	-0.003		
	(0.011)	(0.011)		
Number of Person-Month Observations	38,865	52,974	38,865	52,974
R-Squared	0.0586	0.0620	0.0580	0.0614
Estimated Percentage Points Increase in Labor Force Participation Rates at Ages 62-65 as the FRA Is Increased by One Month	1.10	0.85	0.64	0.46

Notes: Samples are drawn from January and December Surveys of Basic Montly CPS 1994-2009. All specifications include controls for race/ethnicity, marital status and household size, educational attainment, geographical region, local labor market conditions, macroeconomic indicators, age dummies, and a constant. Standard errors are clustered by individuals. "A62" is the cohort-specific actuarial adjustment factor at age 62. As a function of the FRA, it declines from 80% to 75% when the FRA is increased from 65 to 66.

, *: Significant at a 0.05 and 0.01 level, respectively.

Table 2.7 Heterogeneity of the Effect of the FRA Increase by Socioeconomic Status

Dependent Variable:	(1)		(2)	
Respondent is Participating in the Labor Force	Coeff.	S.E.	Coeff.	S.E.
A62*(Age 62-65)	-0.671**	(0.270)	-0.704***	(0.270)
A62*(Age 62-65)*(Less Than High School)	0.003	(0.008)		
A62*(Age 62-65)*(Some College)	0.035***	(0.008)		
A62*(Age 62-65)*(College Graduate)	0.064***	(0.009)		
A62*(Age 62-65)*(Above College)	0.075***	(0.010)		
A62*(Age 62-65)*(Family Income<$30,000)			-0.015**	(0.007)
A62*(Age 62-65)*(Family Income>=$60,000)			0.047***	(0.007)
Number of Person-Month Observations	162,014		162,014	
R-Squared	0.1908		0.1906	

Notes: Sample includes male observations aged 60-69 in January and December Surveys of Basic Montly CPS 1994-2009. All specifications are based on specification (3) in Table 4 (the primary specification of the paper), with additional interaction terms. Standard errors are clustered by individuals. "A62" is the cohort-specific actuarial adjustment factor at age 62. As a function of the FRA, it declines from 80% to 75% when the FRA is increased from 65 to 66. The omitted education category is "high school graduates or GED". The omitted family income category is ">=$30,000 and <$60,000".

, *: Significant at a 0.05 and 0.01 level, respectively.

Table 2.8 Cohort Comparison on Health Status and Job Characteristics based on Age 57-61 Observations from HRS Male Respondents

	(1) b. 1935-1937 FRA=65		(2) b. 1938-1941 65.17<=FRA<=65.67		(3) b. 1942-1944 65.83<=FRA<=66		T-Ratio (1)-(2)	T-Ratio (2)-(3)
	Mean	SD	Mean	SD	Mean	SD		
Health Status								
Work-Limiting Health Problem	24.1%	42.8%	22.7%	41.9%	22.4%	41.7%	1.32	0.23
Self-Reported Fair or Poor Health	22.0%	41.5%	21.4%	41.0%	22.0%	41.5%	0.61	-0.49
Job Characteristics								
Current Job Requires Lots of Physical Effort	28.7%	45.3%	25.3%	43.5%	25.0%	43.3%	3.13	0.15
Current Job Does **Not** Require Lots of Physical Effort	44.1%	49.7%	46.1%	49.9%	44.5%	49.7%	-1.61	1.03
Primary Pension from Current Job is **DB**	20.4%	40.3%	18.2%	38.6%	18.5%	38.9%	2.18	-0.26
Primary Pension from Current Job is **DC**	18.8%	39.1%	22.9%	42.0%	21.0%	40.7%	-4.02	1.44
Health Plan from Current Job Covers Retirees	41.6%	49.3%	39.3%	48.8%	39.9%	49.0%	1.81	-0.37
Health Plan from Current Job Does **Not** Cover Retirees	14.6%	35.4%	17.2%	37.7%	17.4%	37.9%	-2.69	-0.20
Person-Wave Observations	2,884		3,722		1,409			

Source: Health and Retirement Study, Wave 1-Wave 8.
Note: All values are weighted. For each of the job characteristics variables, the fraction of people with certain job characteristics among the whole population (not just people having a job) is shown. Statistically significant T-Ratios (with absolute values>2) are highlighted with grey shading.

Chapter 3. Job Search Outcomes of Older Workers in the United States

(This chapter is coauthored with Nicole Maestas.)

Chapter Abstract

Many have suggested we adopt policies that explicitly encourage the elderly to work. Behind this suggestion is the assumption that if an older person desires a job, one will be found; however, little is known about the extent to which this is true, and in the Health and Retirement Study, many more respondents say they expect to work after retirement than actually undertake work. This raises an important question: To what extent can the elderly readily find suitable jobs? In the context of a theoretical job search model, we examine the probability of transitioning to employment using a sample of older unemployed workers from the Health and Retirement Study. The effects of both supply-side factors (individual characteristics) and demand-side factors (local labor market conditions) are estimated with a set of reduced form econometric models. We find employment transition rates are relatively low for older searchers: only half of older searchers successfully attain jobs. A negative age gradient in job attainment is estimated from the reduced-form models, which although not conclusive, corroborates other evidence in the literature of statistical age discrimination in the labor market for older workers.

3.1 Introduction

Much recent discourse has centered on the idea that older workers are an underutilized economic resource, one which could be used to alleviate the economic and fiscal effects of population aging. For example, the additional payroll taxes paid by older workers could help ease financial pressures on the Social Security and Medicare systems (Diamond and Orszag, 2002), and the retention of older workers in the labor force could perhaps alleviate anticipated labor shortages. In addition to potential macroeconomic benefits, there could be microeconomic benefits accruing to older workers themselves. Many apparently desire to maintain productive activity during retirement (Roper ASW, 2002), and still others, while they may not necessarily wish to work, may find themselves in unexpected financial circumstances requiring them to do so. Indeed, individuals may count on their labor supply as a way to offset financial risk or recover from bad financial realizations. For those not working, this means finding a job. But how readily can an older person find a job should he or she want or need one?

Recent evidence points to potential difficulties. In a study of the age structure of hires into different occupations, Hirsch et al. (2000) conclude that employment opportunities for older workers are restricted. Older workers are least likely to be hired into occupations requiring substantial computer use or where the return to job tenure is high, and most likely to be hired into lower-wage occupations. Lahey (2008) documents evidence of statistical age discrimination against older female job applicants in an experimental study of employer hiring practices. Based on establishment data in the UK and Germany, Heywood and his colleagues find that the strategic, delayed compensation scheme in the lifetime incentive structures provided by employers is the major explanation for the limited hiring opportunities faced by older job searchers (who are considered by employers to be less well motivated by delayed compensation due to their shorter employment horizon) (Daniel and Heywood, 2007; Heywood, Jirjahn, and Tsertsvardze, 2010). Studies of displaced older workers have noted relatively severe displacement effects (Chan and Stevens, 2001; Elder, 2004). For example, Chan and Stevens report that a worker who is laid off at age 55 has a 61 percent chance of being back at work two years later if male and a 55 percent chance if female. According to the BLS data, among displaced workers aged 55-64 who lost their jobs from January 2005 through December 2007, only 61 percent were reemployed when surveyed in January 2008; among displaced workers aged 65 years and over, the reemployment rate was only 18 percent (Bureau of Labor Statistics, 2008). Furthermore, more individuals say they intend to work after retirement than actually do work (Maestas, 2010).

In this paper, we study the job search outcomes of older workers. We begin by documenting the presence of frictional unemployment among older workers which follows the business cycle. We then examine two-year employment transition rates, and show that only half of older job seekers successfully transition to employment. To interpret these stylized facts, we use a theoretical model of the optimal search decision that illustrates how the employment transition probability is determined by both the offer arrival rate, which depends on search effort, and the probability of receiving a wage offer yielding utility in excess of reservation utility. Using our model for guidance, we examine self-reported reservation wages, finding they appear consistent with theoretical predictions and that older job-seekers have reservation wages below prevailing wages.

We then turn to several reduced form econometric specifications of the probability of transitioning to employment by time *t+2* conditional upon searching at time *t*. We analyze the effects of both labor supply and labor demand variables, the latter achieved by merging the HRS with county labor market data. Among our more striking results is the steeply declining age gradient in job attainment, holding constant search effort and a rich set of covariates measuring demographics and socioeconomic status, health and cognition, employment history, local labor market conditions, as well as *changes* in health and cognition variables between *t* and *t+2*. Although not conclusive, this pattern is consistent with the existence of a modest degree of statistical age discrimination. We also compare older unemployed workers' self-reported probabilities of job attainment with their actual job attainment outcomes, and identify subgroups of older job-seekers who tend to be overly-optimistic about their job prospects. We conclude with a discussion and interpretation of our findings in light of some additional data and recent findings about age discrimination and skill mismatches.

3.2 Unemployment

We begin by considering whether there exists notable unemployment among older workers. Using the HRS, we compute age group-specific unemployment rates for different birth cohorts at three points in time. In order to match the introduction and passage of cohorts through the HRS panel over time, we choose age bands of 51-56, 57-61, 62-67, and 68-72 and calendar years 1992, 1998 and 2004. The unemployment rate for age group *a* in each period *t* is the number of respondents in *a* who are not working and searching for work at time *t* divided by the number in *a* who are either employed or not working and searching at time *t*. All estimates are constructed using the HRS population weights. In Table 3.1, each row shows the time pattern in unemployment rates for a given age group. For comparison, the last row shows the unemployment rate for the civilian population aged 16 and over from the Bureau of Labor Statistics (Bureau of Labor Statistics, 2006). Like the BLS estimates, the unemployment rates for older workers show clear evidence of cyclicality. In all age groups, unemployment rates were highest during the recessionary period of 1992, lowest during the expansion in 1998, and higher during 2004 than in 1998. Although the unemployment rates for older workers are always lower than that of the general population, they are non-trivial in size—ranging between 46 and 87 percent of the general unemployment rate. Comparing rates within a column gives the cross-sectional age profile in unemployment holding time trends constant (but not cohort). Not surprisingly, the age profile is fairly flat, implying that the numerator and denominator of the unemployment rate are declining at the same rate with age, consistent with the presence of a high labor force exit rate (i.e., retirement). An exception is age group 51-56 in 2004, which has a relatively high unemployment rate (87 percent of the general unemployment rate). This group consists of the Early Baby Boomers (b. 1948-1953), who appear to have stronger labor force attachment than earlier cohorts (Maestas, 2007). The longitudinal age profile in unemployment can be seen by following the diagonals of the table. With the exception of the early Baby Boomers, the cohorts experience similar levels and cyclical changes in unemployment over time.

In sum, while frictional unemployment rates of older workers are lower than those of the general population, they are nontrivial in size, and appear to be responsive to general economic conditions. The relatively high unemployment rate of the Early Baby

Boomers compared to earlier cohorts at the same age suggests that job search by older workers is an issue of growing salience.

3.3 Employment Transition Rates

We next examine employment transition rates of non-workers aged 51 and above in the HRS. We exclude the AHEAD cohort (b. 1890- 1923) from our sample because non-workers in this cohort were not asked about job search in the 1993 survey wave and most were also not asked in later waves for various reasons. In addition, many other key variables that are relevant for the somewhat younger non-workers in our sample are either missing or are simply not relevant for AHEAD respondents. The loss of generality implied by this sample restriction is small since by 2002 those who are still alive are in their 80s and 90s, and hence highly unlikely to seek labor force re-entry. We further exclude non-workers who reported "temporarily laid off, on sick or other leave" from the sample because their non-working status is temporary.

We begin by constructing a panel dataset of person-wave records in which we observe respondents in at least two consecutive waves and select a subset of 31,311 records where a respondent reports not working for pay in year *t*, where $t \in \{1992, 1994, 1996, 1998, 2000, 2002\}$. We then observe whether the respondent has transitioned to employment (either full-time or part-time, wage/salary job or self-employment) by the following survey wave in year *t+2*.

In Figure 3.1 we present employment transition rates of non-workers in the HRS based on four definitions of successful "employment transition" or "job attainment". The first definition is whether the respondent is working when interviewed at *t+2*. The second definition is whether the respondent has ever worked within the time period from *t* to *t+2*, taking into account the attainment of short-spell jobs that are ended by *t+2*. The third and the fourth definitions apply stricter criteria based on the "quality" of the jobs in terms of earnings and duration. The third definition is whether the respondent has ever worked by *t+2* and has annual earnings of more than $1,000 in the calendar year preceding the *t+2* interview. The fourth definition is whether the respondent has ever worked by *t+2* on a job that has lasted for more than 3 months. We disaggregate the sample according to whether or not the respondents say they were searching for work at *t*.[58] Not surprisingly, those searching for work ("searchers") have much higher employment transition rates compared to those not searching for work ("non-searchers"). The fraction of searchers who get a job between *t* and *t+2* is 65 percent (according to the second definition). However, many of these jobs are either temporary or associated with very low earnings. Re-classifying successful job attainers as those who are working at *t* (the first definition) reduces the fraction to 47 percent; restricting successful job attainers to those with *t+1* annual earnings above $1,000 (the third definition) reduces it to 50 percent; restricting to those with employment durations above 3 months by *t+2* (the fourth definition) leads to a success rate of 58 percent. The third definition will be used as our definition of successful employment transition (job attainment) in the analyses thereafter.

In the HRS, follow-up questions were asked to searchers about their job search targets - if the respondent preferred a full-time or part-time job, whether the respondent looked for the same kind of job as they had before the current non-work spell or something different. HRS also asked all searchers to list their recent job search methods.

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[58] Non-working respondents were asked, "Have you been doing anything to find work during the last four weeks?"

Responses to the question could be classified into four sets of strategies (which are not mutually exclusive): reading/placing/answering ads or contacting employers ("direct employer contact"); checking public or private agencies ("employment agency"); asking friends or relatives ("social network"); and attending school or receiving training ("school/training"). Simple summation of the total number of the above strategies used gives a 0-4 search intensity score for each older searcher.[59]

Table 3.2 shows the computed employment transition rates for all searchers and subgroups of searchers according to their search targets, search strategies and search intensity. Interestingly, transition rates were much higher (59 percent versus 39 percent) for those searching for full-time work than for those searching for part-time work. Given that a considerable fraction of searchers said they favored part-time work, this could be evidence of a mismatch between the desired hours of older job-seekers and the needs of employers, although it could also be that those seeking full-time work are more motivated or effective searchers on account of the higher expected return to work. The fact that those searching for either full-time or part-time employment have a higher transition rate than those searching for only part-time suggests that mismatch may play a role. Not surprisingly, those looking for a job similar to what they had before have higher transition rates in comparison to those who attempted to change industries or occupations, where they may have been less competitive candidates owing to a potential lack of industry- or occupation-specific knowledge or experience. The low job attainment rates

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[59] Another candidate measure of search intensity available in the HRS is the number of employers contacted. However, it is only available for searchers who use the "contacting employers" method and does not appear to be strongly correlated with the job attainment rate. The average job attainment rate is 55 percent among those who contacted 1-5 employers and 56 percent among those who contacted 6+ employers.

among those looking for part-time jobs or jobs different from what they previously held are consistent with other findings about the difficulties faced by older workers in following through with their plans of gradual retirement: many HRS respondents reported "working fewer hours" or "changing the kind of work" when asked about their retirement plans, but only 20-30 percent of those plans are successfully realized (Abraham and Houseman, 2005).

Although the average transition rate associated with each search strategy is quite similar, there is a clear association between search intensity and job attainment. The employment transition rate is positively correlated with the total number of strategies used.

In Table 3.3, we break the searchers sample into five age groups (51-54, 55-59, 60-64, 65-69, and age 70 and above) according to their time *t* age. Then we compare the average job attainment rates, fraction of searchers with different search targets and strategies, and search intensity across those age groups. The job attainment rate is negatively correlated with the age of the searcher. After an older job-seeker reaches age 60, the chance that he or she obtains a job significantly declines (from 55 percent for age group 55-59 to 43 percent for age group 60-64 and finally to 26 percent for those older than 70). Accompanying the drop in the job attainment rate, search intensity also declines with age, consistent with the findings of Brzozowski and Crossley (2010) that older job searchers search less intensely (in terms of hours of search and out-of-pocket expenditure on search) compared to mid-career job searchers. On the other hand, the desire for part-time work among searchers rises sharply with age.

An important question raised by the patterns in Figure 3.1, Table 3.2, and Table 3.3 is why are success rates of older searchers so low (only half of them succeed in obtaining jobs)? Two-year success rates for younger searchers (aged 20-65) are much higher—89.6 percent in the PSID and 96.8 percent in the NLSY (inferred from Table 3.2 in DellaVigna and Paserman (2005)). We explore this question in detail in the following sections. First we turn to theory.

3.4 A Model of the Job Search Decision

Studies of older workers typically focus on labor force exit, not re-entry. However, Maestas (2010) finds that labor force re-entry rates by retired workers are substantial. Benítez-Silva (2006) argues that the job search decision is salient throughout the lifecycle, and offers a dynamic lifecycle model in which individuals choose consumption, leisure, and whether to search in every period. Rather than specify the unified dynamic decision program, we follow the tradition of the labor market search literature and begin with a simple model of the individual's search decision. Of course, a successful employment transition is an equilibrium outcome. A more realistic formulation of the search problem would be two-sided, accounting for the search problem of employers as well; however, since we lack detailed employer data, and our motivations are primarily empirical, we abstract from this consideration.

Our starting point is a model of endogenous search effort in the spirit of DellaVigna and Paserman (2005) and with foundations in Lippman and McCall (1976) and Mortensen (1986). The stationary decision problem of a non-worker is to choose search effort s to maximize the current value function V^U:

$$\max_{s} \; V^U = b - c(s) + \delta\left\{p(s)E_{F(w)}\left[V^E(w) \mid V^E(w) > V^U\right] + (1 - p(s))V^U\right\}, \quad (3.1)$$

where b is the value of any benefits received while not working (e.g., unemployment or retirement benefits) and $c(s)$ is the cost of search such that $c'(s) > 0$, $c''(s) > 0$. With probability $p(s)$, the non-worker will transition to employment, in which case he receives the expected payoff from employment, $E_{F(w)}\left[V^E(w) \mid V^E(w) > V^U\right]$ (where the expectation is taken with respect to the distribution of wage offers *F(w)*), and with probability $(1 - p(s))$ he continues to be unemployed and receives payoff V^U. The employment transition probability $p(s)$ depends on search effort such that $p'(s) > 0$. The payoffs are discounted by an exponential discount factor $\delta = \frac{1}{1+r}$, where r is the discount rate. The value of employment at wage w is:

$$V^E(w) = \delta\left[w + qV^U + (1-q)V^E(w)\right], \quad (3.2)$$

where q is the per-period job exit probability. Thus the value of employment is the wage plus the expected value of future utility, which depends on the likelihood that the employment relationship will end. Given that older workers have a necessarily shorter horizon of labor force participation, q could be quite high, and will consequently reduce the payoff from employment.

The employment transition probability $p(s)$ is a function of the offer arrival rate $a(s)$ (where $a'(s) > 0$, $a''(s) < 0$) and the probability that the wage offer will be such that the employment payoff exceeds the unemployment payoff:

$$p(s) = a(s)\Pr(V^E(w) > V^U) \quad (3.3)$$

This expression implies that an empirical model of the probability of job attainment should include factors that affect the job offer arrival rate, such as search effort, search effectiveness, interview skills, experience, qualifications, and local labor market conditions. Local labor market conditions will also affect $\Pr(V^E(w) > V^U)$ through their impact on the distribution of wage offers, $F(w)$.

The reservation wage $w*$ can be found by solving for the value of w that equates V^U and V^E:

$$w* = rV^U . \tag{3.4}$$

The reservation wage is the "return" to unemployment, and thus is increasing in the payoff associated with unemployment. In other words, the reservation wage will be increasing in current benefit receipt b and the wage offer distribution $F(w)$. As Blau (1991) notes, individuals have preferences over a set of job-specific characteristics, not just wages, and thus the reservation wage property of job search models may be too restrictive. Indeed, for many older workers, hours will be an important additional consideration. The model is easily generalizable to a reservation utility setting.

Finally, solving for the first order condition with respect to s yields the following equation for the optimal search decision:

$$c'(s*) = \delta p'(s*) \int_{V^U}^{\infty} (V^E(w) - V^U) dF(w), \tag{3.5}$$

where $p'(s*) = a'(s*) \Pr(V^E(w) > V^U)$. Hence, the optimal level of search effort equates the marginal cost of search with its discounted expected marginal return. Equation 3.5 implies that an increase in the reservation wage will reduce the optimal level of search effort, whereas an upward shift in the wage distribution will increase search effort.

The theoretical model described above reveals several important aspects related to the search outcome of an older job seeker and especially highlights the critical role of the reservation wage. In the following sections, we examine the empirical distribution of the reservation wage data in the HRS, and then estimate reduced form models of job attainment including all of those aspects: reservation wage, job search intensity, searcher's skill and qualification, local labor market conditions, etc.

3.5 Reservation Wages

One potential explanation for the relatively low success rate of job searchers is that while they report searching for work, they might have reservation wages sufficiently high that the probability of receiving a wage offer that exceeds their reservation wage is low. In the extreme, the existence of searchers with near-zero probabilities of receiving an acceptable offer can artificially inflate unemployment estimates since although they may be engaged in search, they are not willing to work at the prevailing wage. Although both criteria must be met for an individual to be correctly classified as unemployed, survey respondents are not typically asked about the second criterion. This is not the case in the HRS. All respondents who reported searching were asked to state their reservation wage, as were non-searching respondents who said they wanted a job.[60] In this section

[60] Searchers were first asked, "Are you looking for the same kind of work you did before, or something different?", followed by "If someone offered you work like that, how high would the wage or salary have to be for you to take it? Is that per hour, week, month, or year?" When the reported time unit was not the hour, we computed the hourly reservation wage by dividing the reported amount by the time unit, assuming 8 hours per day, 5 days per week, 4.33 weeks per month, and 52 weeks per year. In cases where the respondent said "minimum wage" or "social security limit" instead of giving an amount, we used the federal minimum wage or the social security earnings test threshold in effect during that interview year.

we analyze reservation wage responses to assess whether older non-workers appear willing to work at prevailing wages.

Several authors have cautioned against the use of self-reported reservation wages on the grounds that they are often inconsistent with structurally estimated reservation wages (e.g., Mohanty 2005; Hofler and Murphy 1994). Since we do not undertake structural estimation in this paper, we cannot evaluate the self-reported reservation wage data on this basis; however, as an alternative, we first examine whether they appear consistent with theoretical predictions.

Table 3.4 shows reported reservation wages among older searchers. The wage rate associated with one's most recent employment duration ("last-job wage" or "previously-accepted wage") is also presented and compared to the reservation wage. Although the last-job wage distribution is not the same as the distribution of offered wages, which theory tells us is the relevant comparison, last-job wages nevertheless offer a useful benchmark comparison. Among all searchers, the median last-job wage rate ($10.64 per hour) exceeds the median reservation wage rate ($8.98 per hour). This pattern is consistent with the reservation wage property of job search theory: because an accepted wage is observed only if it exceeds the reservation wage, the median of the previously-accepted wage distribution will be greater than or equal to the median of the reservation wage distribution. Reservation wages for full-time jobs are higher than those for part-time jobs, accurately reflecting the lower prevailing wages of part-time jobs. For searchers looking for jobs similar to last jobs, the median of the ratio between the reservation wage rate to the last-job wage rate is close to 1. For searchers looking for part-time jobs or jobs different from last jobs, the ratio between the reservation wage rate to the last-job wage rate is relatively lower, suggesting that those people appear to internalize the wage penalties associated with part-time jobs and changing job categories.

In further descriptive analyses (not shown), we found that self-reported reservation wages were positively correlated with variables indicative of a higher value of leisure, such as education, household income, workforce tenure, cognition, the wage earned on one's longest tenured job, and having worked one's longest tenured job in a managerial or professional occupation. Self-reported reservation wages are also higher in counties with higher average wage rates, appropriately reflecting geographic variation in local labor market conditions, and positively correlated with the subsequent accepted wage of successful searchers.[61]

In sum, the self-reported reservation wage data in the HRS are not inconsistent with search theory; rather we find descriptive evidence supporting a variety of theoretical predictions. Second, we find no evidence that older job seekers hold reservation wages that are so high as to render the probability of attaining an acceptable job near zero. Indeed, we find median reservation wages of job seekers are lower than median previously-accepted wages. Somewhat reassuringly, Elder (2004) found a similar pattern using *structurally estimated* reservation wages instead of subjective reservation wages in the HRS.

[61] The opposite finding would not necessarily be inconsistent with search theory given the two-year time difference between reservation wage measurement and attained wage measurement. In a model where the prevailing wage distribution is not assumed to be known, Bayesian updating of the prior distribution as the search process evolves could account for a subsequent downward revision in the initially reported reservation wage. Alternatively, negative duration dependence could explain a declining reservation wage over time, whether on account of stigma (Vishwanath, 1989) or simply because the reservation wage is a function of the probability of transitioning to employment, which by definition of negative duration dependence is falling over time.

3.6 Econometric Model of the Transition to Employment

3.6.1 Econometric Framework

We next turn to reduced form econometric models of the probability of job attainment conditional on searching.

For individual *i,* job attainment measured at time $t+2$ ($y_{i,t+2}$), depends on search effort at time *t* (S_{it}), the reservation wage at *t* (R_{it}), individual characteristics (X_{it}) that plausibly affect the job offer arrival rate, and local labor market characteristics (Z_{it}) that plausibly affect the expected wage distribution and the job offer arrival rate. We let ε_{it}^{y} be a stochastic error term. We also let *changes* in X between *t* and *t+2* affect job attainment by including $\Delta X_{i,t+2} = X_{i,t+2} - X_{i,t}$:

$$y_{i,t+2} = \alpha^{y} + \phi^{y} R_{it} + \beta_1^{y} X_{it} + \beta_2^{y} \Delta X_{i,t+2} + \beta_3^{y} Z_{it} + \varepsilon_{it}^{y} \tag{3.6}$$

$$y_{i,t+2} = \alpha^{y} + \gamma^{y} S_{it} + \phi^{y} R_{it} + \beta_1^{y} X_{it} + \beta_2^{y} \Delta X_{i,t+2} + \beta_3^{y} Z_{it} + \varepsilon_{it}^{y} \tag{3.7}$$

The difference between the two equations lies in whether to include the endogenous regressors S_{it} or not. The equation without the search targets and intensity variables (Equation 3.6) is our primary econometric specification shown in Table 3.6. The one with those variables included (Equation 3.7) is separately estimated as an alternative specification in Appendix Table 3.1. Defining $y_{i,t+2}$ as a dichotomous variable calls for probit estimation.

3.6.2 Data and Estimation Sample

We use information from the first seven survey waves of the longitudinal HRS, which occurred every two years during the period 1992 to 2004. As noted earlier, we omit AHEAD cohort respondents because most of them were not asked about job search in various waves. The unit of observation in our sample is the person-wave. Respondents contribute one person-wave record to our sample for every wave in which they report not working. We add to each record at time *t* the respondent's employment status at *t+2*. The final "searchers" sample we use includes respondents aged 51 and above at *t* who are not working or temporarily laid-off, and report they have been looking for work during the past four weeks.

In order to measure the effect of local labor market conditions on job attainment, we merged the HRS with Bureau of Labor Statistics and Census Bureau measures of county-year unemployment, the distribution of establishment size, industry composition, average wages, and the age distribution, using the HRS restricted geographic identifiers. We also used the 2006 NCHS Urban-Rural Classification Scheme to create a variable identifying large metropolitan counties.

Table 3.5 presents sample means for the two subsamples of our "searchers" sample – those who successfully obtain a job ("attainers") and those who do not ("non-attainers") . As we might expect, the samples are quite different on many dimensions. "Attainers" are more likely to be younger (57.8 v. 59.5), White (68.3 v. 60.6), and better educated (12.4 v. 11.4 years of schooling). Interestingly, they also have higher reservation wages compared to "non-attainers". Not surprisingly, attainers are healthier on a variety of time *t* measures. They also scored slightly higher on cognition measures.[62] They are less likely to have sources of subsidized health insurance other than from an employer. [63]

The employment histories of "attainers" also differ. They worked more years in the labor force (32.0 v. 29.8 years), their last job ended more recently (1.5 v. 3.1 years), and the longest job they held was most likely in a managerial/professional occupation or in the services industry. There are few notable differences in the local labor market conditions faced by the two groups. Compared to "attainers", "non-attainers" are more likely to experience a negative health shock between *t* and *t+2*.

3.6.3 Estimation Results for Job Attainment Model

In Table 3.6, we show the estimation results of the job attainment equation (Equation 3.6) using a probit model.

The log reservation wage is insignificantly different from zero; this is not surprising since we control for many of the determinants of the reservation wage.[64] An age spline with a knot at age 60 reveals a pronounced age gradient in job attainment consistent with the observed patterns in Table 3.3. They suggest that even after controlling for the rich set of covariates dictated by Equation 3.3, which include

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[62] The Cognition Summary Score is a summation of scores from three cognition tests (word recall, serial 7, and backwards counts). The summation score is divided by 27 (the maximum possible total score) to get a value scaled between 0-1. A difficulty with the cognition variables in the HRS is that the set of tests administered and in some cases their content changed between Waves 1, 2, and the later waves. Using these three tests, we were able to construct a consistent measure for 80 percent of person-wave observations. We impute the remaining 20 percent by using the summary score from the following wave. The missing scores were mostly for respondents in Wave 1 and 2. We include an imputation indicator in all estimation models.

[63] Those sources include: (1) governmental health insurance program (such as Medicare or Medicaid), (2) health insurance provided by the employer of one's spouse, or (3) retiree health insurance provided by one's previous employer.

[64] The reservation wage is of course an endogenous variable; still the estimation results do not change much if we drop the reservation wage from the models.

demographics, socioeconomic status, health and cognition, employment history, and labor market conditions, as well as *changes* in health and cognition, the probability of successfully obtaining a job nevertheless decreases with age. According to the marginal effect estimates, the job attainment probability decreases by 1.2 percentage points per age at ages before 60 and 2.1 percentage points per age at ages after 60. While not conclusive, this pattern is consistent with an interpretation of age discrimination by employers.

The other time invariant variables in the model include gender, race, socioeconomic status, employment history, and local labor market conditions. With respect to employment history and qualifications, job attainment is decreasing in time out of the labor force, and rising in labor force attachment as measured by total years of tenure in the labor force. One additional year of tenure in the labor force increases the job attainment rate by 0.3 percentage points; while one additional year out of work as of time *t* decreases the job attainment rate by 1.7 percentage points. Holding age constant, access to health insurance other than employer-provided health insurance is strongly negatively correlated with job attainment. One interpretation is that those with health insurance are more likely to give up searching because the value of a new job is lower for them.[65] Turning next to the time-varying variables in the model, having a work-limiting health problem at time *t* sharply reduces the probability of job attainment as does self-reported fair or poor health, by 18 (work limitation) and 12 (fair or poor health) percentage points, respectively. In addition, an *onset* of a work-limiting health problem and a drop in

[65] This result is not driven by the effect of Medicare eligibility. After we add a dummy for observations with age at and above 65, the coefficient is still negative and statistically significant.

cognition between *t* and *t+2* also significantly reduce the probability of job attainment. Individuals whose work capacity becomes limited between *t* and *t+2* are 20 percentage points less likely to find a job. Those who suffer from a 1 percent decline in the cognition score are 0.3 percentage points less likely to successfully attain a job. Thus, a partial explanation for the lower job attainment rates of older workers lies in shocks to health and cognition, which may render some unable to complete a search.

Interesingly, the variation in local labor market conditions, on the scale that took place during our sample period, did not explain the variation in search outcomes.

In Appendix Table 3.1, we show results for Equation 3.7 using the same set of covariates plus the inclusion of search targets and search intensity variables. The coefficient for the post-age-60 segment of the age spline drops but is still statistically significant, suggesting that the variation in search effort across age (shown in Table 3.3) explain part, but not all of the negative age gradient in job attainment.

It is possible that age itself could proxy for the inefficiency of one's search effort, holding constant search targets, strategies, and intensity. Job seekers at older ages might not be able to process job information as efficiently as their younger counterparts. The quality of their social network might also deteriorate with age. This possibility suggests that some caution is warranted in making the statistical age discrimination interpretation of the negative age gradient estimated from the reduced-form models.

3.7 Older Searcher's Job Attainment Expectations

If older searchers have unrealistic expectations about their chances of success, the level of search effort they choose might be inefficient. Searchers are asked about their perceived probability of job attainment in the expectation section of the HRS. The question is: “You told us earlier that you were looking for a new job. On this 0 to 100 scale, what are the chances that you will find a job like the one you're looking for within the next few months?” Because the time frame of the question is “next few months”, the self-reported job attainment probability is not exactly comparable to our job attainment outcome measure, which is based on the transition over a two-year period. However, the difference between the perceived job attainment probability and the actual job attainment rate can still be used as a measure of the optimism of expectations. We create an index ranging from -1 to 1, where 1 is extremely optimistic (when one self-reported a 100 percent chance but failed to get a job) and -1 is extremely pessimistic (when one self-reported a 0 percent change but did find a job).

In Table 3.7, self-reported job attainment probabilities are compared to actual job attainment outcomes for all searchers and subgroups of interest among the searchers sample. Surprisingly, the subjective probability of finding a job “within next few months” is higher than the actual job attainment rate over a two-year period (55.7 percent versus 49.9 percent), which is suggestive of the overall upward bias in expectations. Many subgroups of searchers tend to be overly-optimistic, with their perceived job attainment probability substantially greater than their actual job attainment rate. The overly-optimistic subgroups include: those aged 65 or older, those with self-reported fair or poor health at *t* and those who experience an onset of a work limitation between *t* and *t+2*, those who have not worked for more than 3 years, those searching for part-time jobs, and those searching with low intensity. For those with a non-employment spell longer than 3 years, the perceived probability (50.5 percent) is larger than the actual rate (30.1 percent) by more than 20 percentage points, suggesting that some searchers do not effectively internalize the depreciation of their skills during the lengthy period since their last jobs ended. Those looking for part-time jobs are much more optimistic than those looking for full-time jobs. The gap between the subjective job attainment probability and actual job attainment rate is as large as 16 percentage points for the former and only 1.1 percentage points for the latter. This finding suggests that older job searchers appear not to have internalized the fact that opportunities for part-time jobs are limited. The existence of these overly-optimistic groups has important policy implications. To the extent older non-workers regard their ability to work as a form of self-insurance against undesirable economic outcomes, incorrect expectations about their prospects of finding work should the need arise might lead to suboptimal life-cycle decisions regarding savings and labor supply.

Another interesting finding in Table 3.7 is the relatively weak correlation between the subjective job attainment probability and job search intensity. It appears that older searchers who report higher chances of finding a job do not adjust upward the intensity of their search efforts. The existence of a gradient in the subjective job attainment probability with respect to age and the lack of such a gradient with respect to job search intensity are suggestive of a negative age gradient in search *efficiency*.

Table 3.8 presents estimation results from a regression model of the index with the same set of covariates in the specification shown in Table 3.6. Appendix Table 3.2 shows results from a similar specification with the addition of the search targets and intensity variables as covariates. Putting the results in the two tables together, the most prominent finding is the strong positive linkage between over-optimism and the length of the non-employment spell as of *t*. Not surprisingly, the onset of a work limitation after *t* is statistically significant in both tables, because this shock cannot be fully anticipated at *t* – the job attainment expectation at *t* can only be formed based on information available as of *t*. Having fair or poor self-reported health is significantly associated with being overly-optimistic (in Table 3.8 only). According to the results in Appendix Table 3.2, searchers who look for part-time jobs or search with low intensity tend to have overly optimistic expectations about their job attainment probabilities as well.

Besides the survey question about self-perceived probability of job attainment within a few months, the HRS also asks each non-worker about the chances that they "will be working for pay at some time in the future" in Wave 2 and forward. As expected, the subjective probability of working in the future is strongly correlated with the subjective probability of finding a desired job within a few months (the correlation between the two variables is 0.60), and the mean of the former is higher than the mean of the latter (69 percent versus 58 percent) among the older searchers sample of this paper (excluding the Wave 1 observations). Compared to the job attainment expectation variable, the future work expectation variable has a stronger correlation with job search intensity: the average probability among searchers using 0/1/2/3+ search strategies are 61/67/72/78 percent, respectively. Search intensity is strongest among those who think they have the highest chances of being employed in the future.

3.8 Discussion and Conclusion

Although unemployment is a classical theme in the labor economics literature, job search behavior and transitions to employment by non-working older people have not been fully explored, probably owing to the conventional understanding of retirement as an absorbing state and older individuals as generally inactive in pursuing jobs. However, as we document, these phenomena are empirically important, and likely to become more important in the future. Using nationally representative panel data (HRS), we find that a non-trivial number of older Americans are actively looking for a job, yet half of them fail to find a job within 2 years. The question of why many of older non-workers had undesirable job search outcomes is also policy relevant, in the context of the increasing fiscal burden of the Social Security system.

Based on a theoretical model including job search effort as an endogenous choice variable, we illustrate how the reservation wage, individual characteristics, and local labor market conditions affect the decision to search and the probability of job attainment. Using our model for guidance, we estimate several reduced form econometric specifications of the probability of job attainment. Among our more striking results is the steeply declining age gradient in job attainment, holding constant search effort and a rich set of covariates measuring demographics and socioeconomic status, health and cognition, employment history, local labor market conditions, as well as *changes* in health and cognition variables between t and $t+2$.

Finally, we find that older searchers are somewhat overly optimistic about their chances of success in the job market. In particular, those who had been out of work for a lengthy period of time are more likely to have overly-optimistic expectations. Health shocks also impede the search plans of older job seekers. From a policy perspective, this is worrisome in that it suggests that some who may be counting on their ability to find a job to supplement their retirement or other income may not be able to do so. It suggests the possibility that consumption and other behaviors may be guided by incorrect expectations about one's ability to use labor supply as an adjustment margin to compensate for unfavorable outcomes or risk. In addition to economic well-being, subjective well-being may be at stake. Using a 0-5 index comprised of five items from the CES-D depression scale,[66] searchers at *t* have lower subjective well-being (3.88 versus 4.11) compared to non-workers who are not searching at *t*. Subjective well-being increases by 0.31 (from 3.97 to 4.28) between *t* and *t+2* among searchers with a successful search outcome, in fact surpassing the subjective well-being of non-searchers at *t*. However, among unsuccessful searchers, subjective well-being rises by only half that (0.16, from 3.78 to 3.94).

A phenomenon often mentioned in the context of older workers and employment is age discrimination. Although not conclusive, our evidence is consistent with the presence of statistical age discrimination, skills mismatch or other unfavorable constraints in the labor market for older workers. Support for this interpretation comes from experimental evidence. In a recent labor market experiment to assess hiring conditions for older women, Lahey (2008) sent fictitious resumes to randomly selected employers posting entry-level job openings in Boston, MA and St. Petersburg, FL. All else equal, she found that a younger worker was 40 percent more likely to be offered an interview than an older worker. She interprets her findings as evidence of statistical discrimination largely on the basis of obsolete computer skills. Thus age discrimination may directly affect the job offer arrival rate.

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[66] Those items include: not feeling depressed, not feeling lonely, not feeling sad, being happy and enjoying life. The subjective well-being index is the summation of the five items. The change in the HRS questionnaire between Wave 1 and later waves prevents us from constructing this index using Wave 1 data.

The findings of Lahey (2008) point to a mismatch, whether perceived or real, between the skills of older jobseekers and the skill needs of employers. In addition, the high prevalence of work limiting health conditions among older workers in general suggests that the set of feasible jobs is restricted for many older workers. Employers, recognizing this, may statistically discriminate on this basis as well. To assess the merit of this speculation, more empirical evidence is needed, especially that which focuses on the demand side of the labor market for older workers.

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Figure 3.1 Employment Transition Rates of Older Non-Workers
(Sample: Non-Workers Aged 51+ in the Health and Retirement Study)

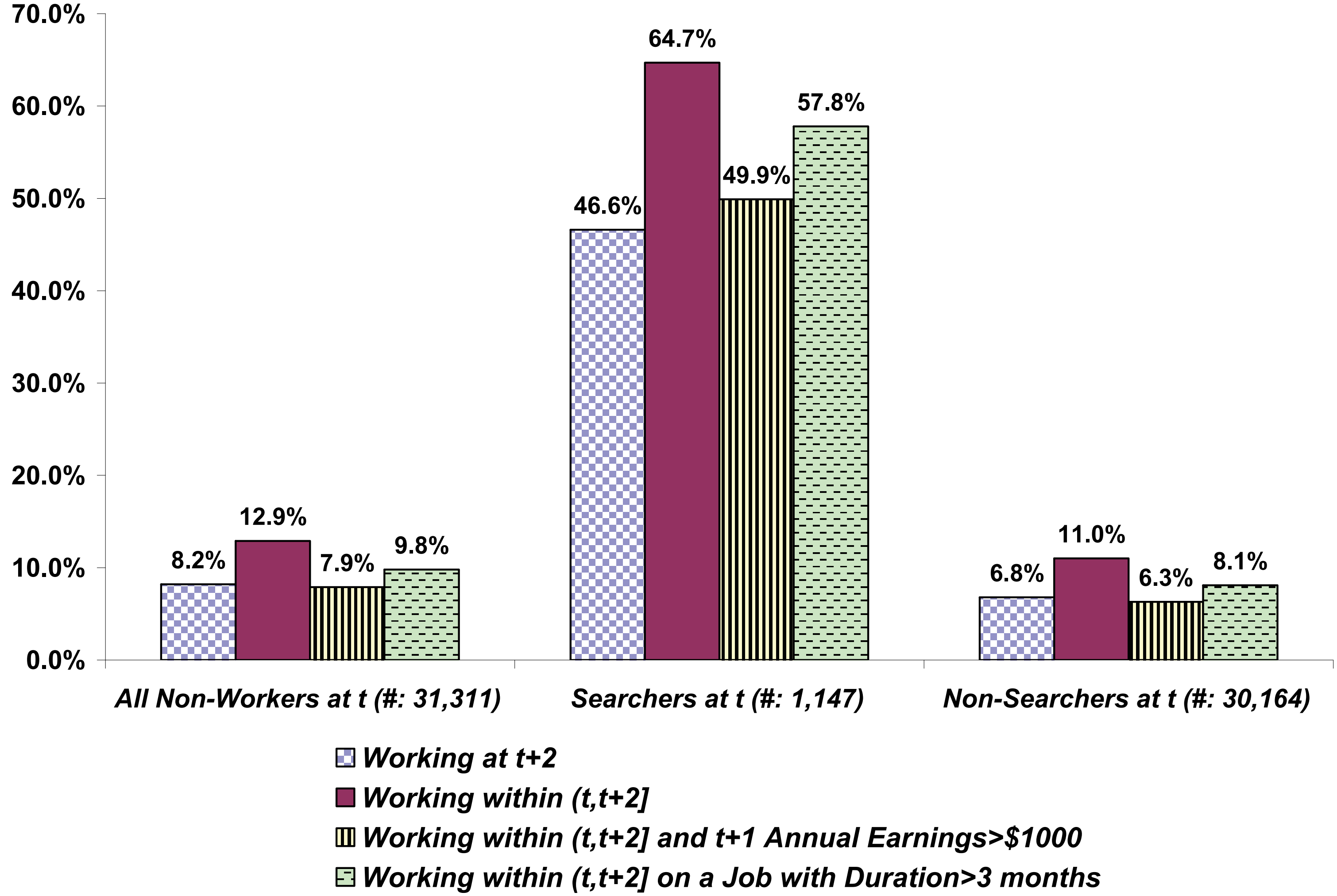

Table 3.1 Unemployment Rates of Older Workers

Age Group	1992	1998	2004
51-56	3.9	2.6	4.8
57-61	4.1	2.2	2.6
62-67		2.3	2.8
68-72		3.0	3.2
16+	7.5	4.5	5.5

Source: Unemployment rates for Age 16+ come from Bureau of Labor Statistics (2006). All other rates are authors' tabulations of HRS data.

Table 3.2 Job Attainment Rates of Older Job-Seekers

Searchers at *t*	N	Fraction	Percent Working within (t, t+2] and *t+1* Annual Earnings>$1000
All Searchers	1,147	100.0	49.9
Searching for FT Job	488	42.5	58.8
Searching for PT Job	405	35.3	38.8
Searching for Either FT or PT Job	254	22.1	50.4
Searching for Same Job	429	37.4	53.1
Searching for Different Job	342	29.8	47.4
Searching for Either Same or Different Job	375	32.7	48.5
Strategy Used: Direct Employer Contact	929	81.0	51.9
Strategy Used: Employment Agency	361	31.5	55.4
Strategy Used: Social Network	347	30.3	52.4
Strategy Used: School/Training	36	3.1	52.8
Total Number of Above Strategies Used=0	79	6.9	36.7
Total Number of Above Strategies Used=1	578	50.4	45.8
Total Number of Above Strategies Used=2	359	31.3	55.2
Total Number of Above Strategies Used=3 or 4	124	10.8	58.9
Search Strategy is Missing	7	0.6	--

Notes: The "searchers" sample includes HRS respondents aged 51+ who are not working or temporarily laid-off, and report they have been looking for work during the past four weeks when interviewed. Searchers are further asked by the HRS about the type of job which they are looking for: full-time or part-time, same kind of work as one did before or something different.

Table 3.3 Job Attainment Rates and Job Search Targets, Strategies, and Intensity by Age Group

	Age [51, 54]	Age [55, 59]	Age [60, 64]	Age [65, 69]	Age>=70
Job Attainment Rate	56.3%	55.3%	43.2%	38.2%	25.6%
Fraction of Searchers by Search Targets and Strategies					
Searching for FT Job	52.9%	52.4%	35.2%	7.8%	7.0%
Searching for PT Job	20.2%	26.9%	43.2%	72.5%	76.7%
Searching for Either FT or PT Job	26.8%	20.8%	21.6%	19.6%	16.3%
Searching for Same Job	30.1%	39.5%	39.7%	38.2%	44.2%
Searching for Different Job	31.3%	27.5%	32.1%	31.4%	25.6%
Searching for Either Same or Different Job	38.6%	33.0%	28.2%	29.4%	30.2%
Strategy Used: Direct Employer Contact	84.1%	83.0%	81.4%	71.6%	73.8%
Strategy Used: Employment Agency	40.2%	33.0%	29.1%	20.6%	7.1%
Strategy Used: Social Network	29.5%	34.1%	29.5%	25.5%	16.7%
Strategy Used: School/Training	2.2%	3.6%	3.5%	3.9%	0.0%
Average Number of Above Strategies Used	1.56	1.54	1.44	1.22	0.98
N	272	443	287	102	43

Notes: The "searchers" sample includes HRS respondents aged 51+ who are not working or temporarily laid-off, and report they have been looking for work during the past four weeks when interviewed. Searchers are further asked by the HRS about the type of job which they are looking for: full-time or part-time, same kind of work as one did before or something different. Job attainment is defined as working within (t , $t+2$] and having annual earnings at $t+1$ above $1,000 conditional on searching at t .

Table 3.4 Reservation Wages of Older Job-Seekers

	Reservation Wage (Hourly Rate, Median)	Last-Job Wage (Hourly Rate, Median)	Reservation Wage/Last-Job Wage (Median)
All Searchers	8.98	10.64	0.94
Searching for FT Job	10.26	11.46	0.96
Searching for PT Job	7.92	9.81	0.93
Searching for Either FT or PT Job	8.33	10.09	0.92
Searching for Same Job	11.20	11.79	0.98
Searching for Different Job	8.36	10.17	0.90
Searching for Either Same or Different Job	8.03	10.21	0.88

Notes: The "searchers" sample includes HRS respondents aged 51+ who are not working or temporarily laid-off, and report they have been looking for work during the past four weeks when interviewed. Searchers are further asked by the HRS about the type of job which they are looking for: full-time or part-time, same kind of work as one did before or something different. All dollar amounts are expressed in 2002 dollars.

Table 3.5 Summary Statistics of Time *t* Searchers Sample

	Attainers	Non-Attainers	T-Test P-Value
Covariates Measured at Time t			
Reservation Wage (Hourly)	13.4	11.6	0.040
Demographics			
Female	50.2	53.0	0.332
Age	57.8	59.5	0.000
White Non-Hispanic	68.3	60.6	0.007
Black Non-Hispanic	17.0	18.1	0.615
Hispanic	10.7	17.9	0.000
Asian/Other	4.0	3.3	0.519
Married	66.9	63.7	0.249
Socioeconomic Status			
Years of Education	12.4	11.4	0.000
Total Household Non-Labor Income (10,000)	$15,222	$14,970	0.883
Total Net Non-Pension Wealth (10,000)	$211,933	$166,577	0.052
Health and Cognition			
Sum of Major Health Conditions (0-8)	1.20	1.42	0.002
Self-Reported Fair or Poor Health	16.3	31.8	0.000
Work Limiting Health Problem	22.2	33.6	0.000
Cognition Summary Score (0-1)	0.63	0.59	0.000
Health Insurance Coverage			
Access to Other Sources of Subsidized Health Insurance	51.9	59.8	0.007
Employment History			
Years of Tenure at Longest Job	14.2	14.0	0.757
Years of Tenure in Labor Force	32.0	29.8	0.005
Years Since Last Job Ended	1.5	3.1	0.000
Hourly Wage Rate on Last Job	19.0	14.2	0.258
Longest Job Occupation: Managerial/Professional	31.8	21.8	0.000
Longest Job Occupation: Sales/Administrative	23.5	26.3	0.286
Longest Job Occupation: Services	13.1	14.1	0.618
Longest Job Occupation: Precision Production/Craft	14.8	16.2	0.517
Longest Job Occupation: Operators/Laborers	16.9	21.6	0.053
Longest Job Industry: Agriculture/Mining/Construction	12.5	12.1	0.868
Longest Job Industry: Manufacturing	27.6	29.5	0.501
Longest Job Industry: Wholesale/Retail	14.2	19.1	0.033
Longest Job Industry: Services	45.7	39.3	0.035
County Labor Market Conditions			
Large Metropolitan County	51.2	53.8	0.379
Proportion of Population 60+ Years Old	17.2	17.1	0.805
County Unemployment Rate (Percent)	6.3	6.6	0.118
County Average Annual Wage (10,000)	$32,733	$32,702	0.945
Proportion of Services Establishments	79.6	79.8	0.616
Difference in Health and Cognition between Time t+2 and t			
Increase of Major Health Conditions	0.18	0.26	0.003
Onset of Work Limiting Health Problem	-3.0	9.5	0.000
Decrease of Cognition Summary Score (0-1)	0.00	0.01	0.118
Person-Wave Observations	572	575	

(See notes for the table on the next page)

Table 3.5 Notes:

The "searchers" sample includes HRS respondents aged 51+ who are not working or temporarily laid-off, and report they have been looking for work during the past four weeks when interviewed. "Attainers" are those searchers who attained a job within t and t+2 with t+1 annual earnings above $1,000. "Non-attainers" are those searchers who failed to attain such a job within t and t+2. All dollar amounts are expressed in 2002 dollars. Major health conditions include: hypertension, diabetes, cancer, lung disease, heart problems, stroke, psychiatric problems, and arthritis. Cognition summary score is a [0-1] measure of respondents' cognitive abilities based on their responses to three cognitive tests (word recall, serial 7's and backward counts. "Other sources of subsidized health insurance" include (1) governmental health insurance program (such as Medicare or Medicaid), (2) health insurance provided by the employer of one's spouse, or (3) retiree health insurance provided by one's previous employer. County-year labor market data from the Bureau of Labor Statistics and the Census Bureau was merged to the HRS using restricted geographic identifiers. We used the 2006 NCHS Urban-Rural Classification Scheme to identify large metropolitan counties. The negative mean for the covariate "onset of work limitation health problem" for the job-attainers column means that the fraction of people with work limitation among the group drops between the two years.

Table 3.6 Probit Model of Job Attainment (Sample: Time *t* Searchers)

	Coefficient	Standard Error	Marginal Effect
Covariates Measured at Time t			
Log Reservation Wage (Hourly)	0.017	(0.085)	*0.006*
Demographics			
Female	0.037	(0.104)	*0.013*
MIN(Age, 60)	-0.036**	(0.016)	*-0.012*
MAX(Age-60, 0)	-0.062***	(0.018)	*-0.021*
Black Non-Hispanic	0.028	(0.127)	*0.009*
Hispanic	-0.129	(0.152)	*-0.044*
Asian/Other	0.264	(0.267)	*0.089*
Married	0.007	(0.093)	*0.002*
Socioeconomic Status			
Years of Education	0.022	(0.018)	*0.008*
Total Household Non-Labor Income (10,000)	0.003	(0.015)	*0.001*
Total Net Non-Pension Wealth (10,000)	-0.001	(0.001)	*-0.000*
Health and Cognition			
Sum of Major Health Conditions	0.037	(0.041)	*0.013*
Self-Reported Fair or Poor Health	-0.348***	(0.111)	*-0.121*
Work Limiting Health Problem	-0.531***	(0.124)	*-0.181*
Cognition Summary Score (0-1)	0.604	(0.349)	*0.206*
Health Insurance Coverage			
Access to Other Sources of Subsidized Health Insurance	-0.201**	(0.092)	*-0.069*
Employment History			
Years of Tenure at Longest Job	-0.006	(0.005)	*-0.002*
Years of Tenure in Labor Force	0.010**	(0.004)	*0.003*
Years Since Last Job Ended	-0.049***	(0.014)	*-0.017*
Log Wage on Last Job (Hourly)	0.033	(0.061)	*0.011*
Longest Job Occupation: Sales/Administrative	-0.147	(0.124)	*-0.050*
Longest Job Occupation: Services	-0.057	(0.171)	*-0.020*
Longest Job Occupation: Precision Production/Craft	-0.013	(0.161)	*-0.004*
Longest Job Occupation: Operators/Laborers	-0.076	(0.156)	*-0.026*
Longest Job Industry: Agriculture/Mining/Construction	0.068	(0.165)	*0.023*
Longest Job Industry: Wholesale/Retail	-0.208	(0.138)	*-0.071*
Longest Job Industry: Services	0.037	(0.121)	*0.013*
County Labor Market Conditions			
Large Metropolitan County	-0.090	(0.106)	*-0.031*
Proportion of Population 60+ Years Old	-0.365	(0.869)	*-0.124*
County Unemployment Rate (Percent)	-0.202	(1.650)	*-0.069*
County Average Annual Wage (10,000)	0.016	(0.080)	*0.006*
Proportion of Services Establishments	0.169	(0.821)	*0.058*
Difference in Health and Cognition between Time t+2 and t			
Increase of Major Health Conditions	-0.097	(0.086)	*-0.033*
Onset of Work Limiting Health Problem	-0.627***	(0.106)	*-0.204*
Decrease of Cognition Summary Score (0-1)	-0.964**	(0.450)	*-0.329*
Person-Wave Observations		1,130	
Log Likelihood		-676	
Pseudo R-Squared		0.1375	

(See notes for the table on the next page)

Table 3.6 Notes:

The "searchers" sample includes HRS respondents aged 51+ who are not working or temporarily laid-off, and report they have been looking for work during the past four weeks when interviewed. Job attainment is defined as working within (t, t+2] and having annual earnings at t+1 above $1,000. Standard errors are clustered with respect to individuals. Average marginal effect is reported in italics for each covariate. The model also includes a constant, dummies for interview wave, and missing value dummies for covariates with considerable proportions of missing values. We don't include such dummies for covariates with relatively small proportions of missing values, so the number of observations in the estimation sample is slightly lower than the sample size for the "searchers" sample reported in Table 3.5. All dollar amounts are expressed in 2002 dollars. For longest job occupation, the reference group is managerial/professional. For longest job industry, the reference group is manufacturing. See Table 3.5 for additional notes about the covariates.

,*: significant on a 5, and 1 percent level, respectively.

Table 3.7 Subjective Job Attainment Probabilities of Older Job-Seekers

	Self-Reported Job Attainment Probability	Actual Job Attainment Rate	Difference
All Searchers	55.7	49.9	5.8
Age Range [51, 54]	57.0	56.3	0.8
Age Range [55, 59]	58.5	55.3	3.2
Age Range [60, 64]	53.5	43.2	10.3
Age Range [65, 69]	52.5	38.2	14.3
Age>=70	40.0	25.6	14.4
Self-Reported Health at *t* is Fair or Poor	49.7	33.7	16.0
Self-Reported Health at *t* is Excellent, Very Good, or Good	57.5	55.0	2.5
Having Work Limiting Health Problem at *t*	48.4	39.7	8.7
Not Having Work Limiting Health Problem at *t*	58.4	53.8	4.6
Having Onset of Work Limiting Health Problem within (t, $t+2$]	50.3	32.6	17.7
Not Having Onset of Work Limiting Health Problem within (t, $t+2$]	56.5	52.5	4.0
Years Since Last Job Ended<1	61.5	62.2	-0.7
Years Since Last Job Ended>=1 and <3	48.4	42.9	5.5
Years Since Last Job Ended>=3	50.5	30.1	20.4
Searching for FT Job	59.9	58.8	1.1
Searching for PT Job	55.1	38.8	16.4
Searching for Either FT or PT Job	48.5	50.4	-1.9
Searching for Same Job	59.1	53.1	5.9
Searching for Different Job	51.2	47.4	3.8
Searching for Either Same or Different Job	55.8	48.5	7.3
Strategy Used: Direct Employer Contact	55.5	51.9	3.7
Strategy Used: Employment Agency	54.6	55.4	-0.8
Strategy Used: Social Network	55.8	52.4	3.4
Strategy Used: School/Training	61.3	52.8	8.5
Total Number of Above Strategies Used=0	53.3	36.7	16.6
Total Number of Above Strategies Used=1	56.0	45.8	10.2
Total Number of Above Strategies Used=2	55.2	55.2	0.1
Total Number of Above Strategies Used=3 or 4	55.6	58.9	-3.3

(See notes for the table on the next page)

Table 3.7 Notes:

The "searchers" sample includes HRS respondents aged 51+ who are not working or temporarily laid-off, and report they have been looking for work during the past four weeks when interviewed. Searchers are further asked by the HRS about the type of job which they are looking for: full-time or part-time, same kind of work as one did before or something different. Searchers are also asked about their perceived probability of finding a job within the next few months. Actual job attainment is defined as working within (t, t+2] and having annual earnings at t+1 above $1,000.

Table 3.8 Regression Model of the Index of the Optimism of Job Attainment Expectations

Perceived Job Attainment Probability-Actual Job Search Outcome	Coefficient	Standard Error
Covariates Measured at Time t		
Log Reservation Wage (Hourly)	0.019	(0.029)
Demographics		
Female	-0.033	(0.043)
MIN(Age, 60)	0.008	(0.007)
MAX(Age-60, 0)	0.005	(0.006)
Black Non-Hispanic	0.006	(0.053)
Hispanic	0.086	(0.066)
Asian/Other	-0.033	(0.098)
Married	-0.041	(0.039)
Socioeconomic Status		
Years of Education	-0.001	(0.007)
Total Household Non-Labor Income (10,000)	0.001	(0.006)
Total Net Non-Pension Wealth (10,000)	0.000	(0.000)
Health and Cognition		
Sum of Major Health Conditions (0-8)	-0.019	(0.017)
Self-Reported Fair or Poor Health	0.109**	(0.045)
Work Limiting Health Problem	0.077	(0.049)
Cognition Summary Score (0-1)	-0.119	(0.144)
Health Insurance Coverage		
Access to Other Sources of Subsidized Health Insurance	0.068	(0.038)
Employment History		
Years of Tenure at Longest Job	-0.000	(0.002)
Years of Tenure in Labor Force	-0.001	(0.002)
Years Since Last Job Ended	0.014***	(0.004)
Log Wage on Last Job (Hourly)	0.011	(0.026)
Longest Job Occupation: Sales/Administrative	0.075	(0.049)
Longest Job Occupation: Services	0.092	(0.067)
Longest Job Occupation: Precision Production/Craft	0.011	(0.068)
Longest Job Occupation: Operators/Laborers	0.041	(0.062)
Longest Job Industry: Agriculture/Mining/Construction	-0.017	(0.063)
Longest Job Industry: Wholesale/Retail	0.087	(0.057)
Longest Job Industry: Services	0.024	(0.050)
County Labor Market Conditions		
Large Metropolitan County	0.026	(0.043)
Proportion of Population 60+ Years Old	-0.162	(0.334)
County Unemployment Rate (Percent)	-0.349	(0.686)
County Average Annual Wage (10,000)	-0.031	(0.032)
Proportion of Services Establishments	0.159	(0.310)
Difference in Health and Cognition between Time t+2 and t		
Increase of Major Health Conditions	0.021	(0.035)
Onset of Work Limiting Health Problem	0.178***	(0.043)
Decrease of Cognition Summary Score (0-1)	0.326	(0.188)
Person-Wave Observations	1,060	
R-Squared	0.0846	

(See notes for the table on the next page)

Table 3.8 Notes:

The "searchers" sample includes HRS respondents aged 51+ who are not working or temporarily laid-off, and report they have been looking for work during the past four weeks when interviewed. Searchers are further asked by the HRS about the type of job which they are looking for: full-time or part-time, same kind of work as one did before or something different. Searchers are also asked about their perceived probability of finding a job within the next few months. Actual job attainment is defined as working within (t, t+2] and having annual earnings at t+1 above $1,000. The index of the optimism of job attainment expectations equals to self-reported job attainment probability minus the actual outcome. It ranges from -1 to 1, where 1 is extremely optimistic and -1 is extremely pessimistic. Standard errors are clustered with respect to individuals. The model also includes a constant, dummies for interview wave, and missing value dummies for covariates with considerable proportions of missing values. See Table 3.5 and Table 3.6 for additional notes about the covariates.

,*: significant on a 5, and 1 percent level, respectively.

Appendix Table 3.1 Probit Model of Job Attainment (Alternative Specification)

	Coefficient	Standard Error	Marginal Effect
Covariates Measured at Time t			
Log Reservation Wage (Hourly)	-0.022	(0.089)	*-0.007*
Searching for FT Job	0.118	(0.109)	*0.040*
Searching for PT Job	-0.124	(0.119)	*-0.042*
Searching for Same Job	0.005	(0.101)	*0.002*
Searching for Different Job	-0.098	(0.105)	*-0.033*
Total Number of Search Strategies Used	0.099	(0.053)	*0.033*
Demographics			
Female	0.072	(0.105)	*0.024*
MIN(Age, 60)	-0.030	(0.017)	*-0.010*
MAX(Age-60, 0)	-0.055***	(0.018)	*-0.018*
Black Non-Hispanic	0.003	(0.127)	*0.001*
Hispanic	-0.178	(0.154)	*-0.060*
Asian/Other	0.270	(0.274)	*0.090*
Married	0.031	(0.094)	*0.010*
Socioeconomic Status			
Years of Education	0.023	(0.018)	*0.008*
Total Household Non-Labor Income (10,000)	0.008	(0.016)	*0.003*
Total Net Non-Pension Wealth (10,000)	-0.001	(0.001)	*-0.000*
Health and Cognition			
Sum of Major Health Conditions	0.040	(0.041)	*0.014*
Self-Reported Fair or Poor Health	-0.340***	(0.113)	*-0.117*
Work Limiting Health Problem	-0.493***	(0.126)	*-0.167*
Cognition Summary Score (0-1)	0.601	(0.355)	*0.203*
Health Insurance Coverage			
Access to Other Sources of Subsidized Health Insurance	-0.180	(0.093)	*-0.061*
Employment History			
Years of Tenure at Longest Job	-0.005	(0.005)	*-0.002*
Years of Tenure in Labor Force	0.010**	(0.004)	*0.003*
Years Since Last Job Ended	-0.044***	(0.014)	*-0.015*
Log Wage on Last Job (Hourly)	0.019	(0.062)	*0.006*
Longest Job Occupation: Sales/Administrative	-0.143	(0.124)	*-0.048*
Longest Job Occupation: Services	-0.036	(0.174)	*-0.012*
Longest Job Occupation: Precision Production/Craft	-0.045	(0.164)	*-0.015*
Longest Job Occupation: Operators/Laborers	-0.064	(0.158)	*-0.022*
Longest Job Industry: Agriculture/Mining/Construction	0.090	(0.166)	*0.030*
Longest Job Industry: Wholesale/Retail	-0.204	(0.140)	*-0.069*
Longest Job Industry: Services	0.020	(0.123)	*0.007*
County Labor Market Conditions			
Large Metropolitan County	-0.097	(0.107)	*-0.033*
Proportion of Population 60+ Years Old	-0.302	(0.866)	*-0.102*
County Unemployment Rate (Percent)	-0.045	(1.668)	*-0.015*
County Average Annual Wage (10,000)	0.030	(0.081)	*0.010*
Proportion of Services Establishments	0.280	(0.823)	*0.095*
Difference in Health and Cognition between Time t+2 and t			
Increase of Major Health Conditions	-0.105	(0.086)	*-0.035*
Onset of Work Limiting Health Problem	-0.619***	(0.107)	*-0.200*
Decrease of Cognition Summary Score (0-1)	-1.021**	(0.456)	*-0.345*
Person-Wave Observations		1,123	
Log Likelihood		-666	
Pseudo R-Squared		0.1448	

(See notes for the table on the next page)

Appendix Table 3.1 Notes:

The "searchers" sample includes HRS respondents aged 51+ who are not working or temporarily laid-off, and report they have been looking for work during the past four weeks when interviewed. Searchers are further asked by the HRS about the type of job which they are looking for: full-time or part-time, same kind of work as one did before or something different. Job attainment is defined as working within (t, t+2] and having annual earnings at t+1 above $1,000. Standard errors are clustered with respect to individuals. Average marginal effect is reported in italics for each covariate. The model also includes a constant, dummies for interview wave, and missing value dummies for covariates with considerable proportions of missing values. "Searching for Either FT or PT job" and "Searching for Either Same or Different Job" are omitted as reference categories. Search strategies asked in the HRS include: 1) direct employer contact, 2) employment agency, 3) social network, and 4) school/training. See Table 3.5 and Table 3.6 for additional notes about the covariates.

,*: significant on a 5, and 1 percent level, respectively.

Appendix Table 3.2 Regression Model of the Index of the Optimism of Job Attainment Expectations (Alternative Specification)

Perceived Job Attainment Probability-Actual Job Search Outcome	Coefficient	Standard Error
Covariates Measured at Time t		
Log Reservation Wage (Hourly)	0.023	(0.030)
Searching for FT Job	0.058	(0.044)
Searching for PT Job	0.140***	(0.049)
Searching for Same Job	0.012	(0.041)
Searching for Different Job	-0.021	(0.044)
Total Number of Search Strategies Used	-0.052**	(0.022)
Demographics		
Female	-0.051	(0.043)
MIN(Age, 60)	0.003	(0.007)
MAX(Age-60, 0)	0.001	(0.006)
Black Non-Hispanic	0.027	(0.053)
Hispanic	0.105	(0.066)
Asian/Other	-0.020	(0.097)
Married	-0.058	(0.039)
Socioeconomic Status		
Years of Education	-0.002	(0.008)
Total Household Non-Labor Income (10,000)	0.000	(0.006)
Total Net Non-Pension Wealth (10,000)	0.000	(0.001)
Health and Cognition		
Sum of Major Health Conditions (0-8)	-0.018	(0.017)
Self-Reported Fair or Poor Health	0.088	(0.046)
Work Limiting Health Problem	0.069	(0.050)
Cognition Summary Score (0-1)	-0.123	(0.145)
Health Insurance Coverage		
Access to Other Sources of Subsidized Health Insurance	0.051	(0.038)
Employment History		
Years of Tenure at Longest Job	-0.001	(0.002)
Years of Tenure in Labor Force	-0.001	(0.002)
Years Since Last Job Ended	0.013***	(0.005)
Log Wage on Last Job (Hourly)	0.015	(0.026)
Longest Job Occupation: Sales/Administrative	0.073	(0.049)
Longest Job Occupation: Services	0.078	(0.067)
Longest Job Occupation: Precision Production/Craft	0.031	(0.067)
Longest Job Occupation: Operators/Laborers	0.028	(0.061)
Longest Job Industry: Agriculture/Mining/Construction	-0.043	(0.063)
Longest Job Industry: Wholesale/Retail	0.075	(0.057)
Longest Job Industry: Services	0.018	(0.051)
County Labor Market Conditions		
Large Metropolitan County	0.025	(0.043)
Proportion of Population 60+ Years Old	-0.158	(0.337)
County Unemployment Rate (Percent)	-0.256	(0.684)
County Average Annual Wage (10,000)	-0.034	(0.031)
Proportion of Services Establishments	0.105	(0.311)
Difference in Health and Cognition between Time t+2 and t		
Increase of Major Health Conditions	0.024	(0.035)
Onset of Work Limiting Health Problem	0.175***	(0.043)
Decrease of Cognition Summary Score (0-1)	0.312	(0.189)
Person-Wave Observations	1,055	
R-Squared	0.0998	

(See notes for the table on the next page)

Appendix Table 3.2 Notes:

The "searchers" sample includes HRS respondents aged 51+ who are not working or temporarily laid-off, and report they have been looking for work during the past four weeks when interviewed. Searchers are further asked by the HRS about the type of job which they are looking for: full-time or part-time, same kind of work as one did before or something different. Searchers are also asked about their perceived probability of finding a job within the next few months. Actual job attainment is defined as working within (t, t+2] and having annual earnings at t+1 above $1,000. The index of the optimism of job attainment expectations equals to self-reported job attainment probability minus the actual outcome. It ranges from -1 to 1, where 1 is extremely optimistic and -1 is extremely pessimistic. Standard errors are clustered with respect to individuals. The model also includes a constant, dummies for interview wave, and missing value dummies for covariates with considerable proportions of missing values. "Searching for Either FT or PT job" and "Searching for Either Same or Different Job" are omitted as reference categories. Search strategies asked in the HRS include: 1) direct employer contact, 2) employment agency, 3) social network, and 4) school/training. See Table 3.5 and Table 3.6 for additional notes about the covariates.

,*: significant on a 5, and 1 percent level, respectively.