

TRENDS IN RETIREMENT TIMING: HOW MUCH CAN THE OCCUPATIONAL COMPOSITION EXPLAIN?

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ABSTRACT: This paper seeks to account for the increasing labor force participation rate among older males in the U.S., which follows a long trend of declining participation. Here I show the extent to which these higher participation rates reflect a change in the composition of job types held towards more cognitive and less physically demanding tasks. In the Health and Retirement Study survey data, we see that those in physically demanding occupations retire sooner and, before exiting, switch to less physically intense jobs. I find that the difference in timing across occupations is primarily driven by disparate earnings processes; decline in physical ability as one ages affects productivity more adversely in physically intense jobs. Changing occupational type composition explains part of the trend of higher participation rates at older ages, helping also to inform the labor supply behavior we might expect to see in the future as well as changes we might see in Social Security benefit claiming ages. Connecting occupation-effort relationships in the HRS responses with historical occupational data from the Current Population Survey (CPS), a decomposition of participation decisions suggests that over one-third of the recent increase in participation of men over age 65 to changes in occupational composition. Counterfactuals using results from estimation of the dynamic decision model are compared with the decomposition and suggest that higher participation is due in part to changes in composition, though it cannot account for as much of the change in participation.

1. INTRODUCTION

Understanding the labor force decisions of older individuals has become increasingly important both as this population is expected to grow substantially over the coming decades and as the viability of the U.S. Social Security system—which influences retirement decisions greatly for some—is uncertain. One shift in the economic behavior in later life has been the increase in labor force participation over the last two decades in the U.S., reversing

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a long trend in declining participation rates that spanned all but the last two decades of the twentieth century.¹ Determining what might be driving this trend is worthwhile inasmuch as this can tell us more about what sort of participation behavior we can expect to see in the future for a population that is expected to double over the next forty years.² In this study I aim to add another dimension to our understanding of retirement behavior and health by forming and estimating a structural, life-cycle model that relates the physical demands of jobs, physical ability, and work decisions at older ages. This model allows us to predict later-life labor force decisions under counterfactual policy settings.

I seek to show here the extent to which changes in the composition of occupations held by men in the U.S. labor force can explain why the labor force participation of older males has increased and why it may continue to do so—despite the ever-higher earnings that might have caused participation rates to ever have declined in the first place.³ As we shall see, this rests on observations made from the Health and Retirement Study (HRS), which indicate that those in relatively more physically intense occupations have lower participation rates at older ages than otherwise similar men. The proportion of men working in such physically demanding jobs, however, has been falling over the years and, inversely, the proportion in less physically intense jobs has been rising. Correspondingly, since those men in less physical occupations are more likely to remain in the labor force at later ages, we find that the overall participation rates of older males are rising.

The fact that those in more physically demanding jobs tend to retire earlier—and, before exiting, often switch to less physically intense jobs—motivates the following questions, which I seek to answer in this paper: What is the mechanism through which this earlier exit from the labor force occurs? Can we model this mechanism to match labor supply behaviors observed in the data? How has the proportional decrease in physically demanding jobs contributed to the increasing labor force participation rates among older males? What are the welfare effects of and implications for Social Security design when we consider the effect of the physical demands of jobs? By estimating a dynamic programming model that relates the physical requirements of jobs, health transitions occurring with age, and labor supply decisions, the model will help us make sense of differences in retirement behavior, and welfare implications resulting from counterfactual policy experiments for individuals with dissimilar job types.

Several studies have focused in the role of occupational characteristics in the labor force

¹U.S. participation rates for males by age group, as reported through the Current Population Survey (CPS), are given in Figure 1, found in Appendix A, page 4.

²According to the U.S. Administration on Aging, the population age 60 and over is projected to grow from 56,986,401 in 2010 to 112,037,396 in 2050. The population over age 64 is expected to grow from 40,228,712 in 2010 to 88,546,973 in 2050. Source aoa.gov/AoARoot/AgingStatistics.

³? attributes the declining participation rates observed for most of the twentieth century and prior to a rise in total lifetime income; higher earnings are associated with a higher demand for lifetime leisure, with this leisure presumably occurring at a the time in life when the opportunity cost for it—wage—is lowest for most individuals.

decisions at older ages. Though employing different data and methods, most conclude that the physical demands of work have an effect on retirement decisions. Filer and Petri (1988) focus on the effect of pensions on retirement behavior, which were assumed to have a direct causal effect in much of the retirement literature at the time. They suggest that what's behind the effect of pensions on retirement behavior is job characteristics: Indeed, pensions anticipate retirement timing, including the earlier retirement of those in physically demanding or stressful jobs. They test the effects of job characteristics on retirement and pension structure. They present a model in which jobs with different characteristics have different levels of disutility and productivity associated with them and change with age; what matters for retirement is the rate at which disutility increases relative to the rate at which productivity decreases. They conclude that those in more physically demanding work will retire earlier and have such accommodating pensions, testing their proposition by regressing (1) age at retirement and (2) pension replacement (relative to lifetime earnings) on job characteristics using cross-sectional CPS data and job characteristics using the *Dictionary of Occupational Titles* (DOT). They conclude that public policy programs aimed at affecting retirement ages will be ineffective to that end, but will affect private pensions and savings.

Hayward and Grady (1986) also use occupational characteristics from the DOT and the March CPS to study labor force transitions. Focusing on the recruitment and retention of older workers, using logit estimates on transitions they find that exit from the labor force is lower for those workers in occupations that, among other things, involve lower physical demands. Using a discrete-time hazard modeling approach, Hayward et al. (1989) also find such effects with data from the National Longitudinal Survey of Older men.

The relatively recent trend of increasing participation rates among older males has been explored in several studies. Bloom et al. (2007) attribute the increase in participation rates to greater longevity; the “income effect” of longer lifespans dominate the substitution effect of higher wages, which increases the *proportion* of one's life spent in retirement, but the absolute years spent work also increases as well. In Jacobs (2013), I attribute, in addition to increased longevity, some of this rise in participation rates to the higher proportion working in jobs that are not physically demanding, which allows for the absolute number of years spent working to be higher. Blau and Goodstein (2010) attribute the increase in the labor force participation of older men to both changes in Social Security rules and higher educational attainment, while Schirle (2008) argues that the rise in participation among older men in the U.K, Canada, and the U.S. can be attributed to the rise of working spouses.

Blekesaune and Solem (2005) study the effect of working conditions on disability and

Figure 1: *CPS Labor Force Participation Rates for Males by Age Group over Time*

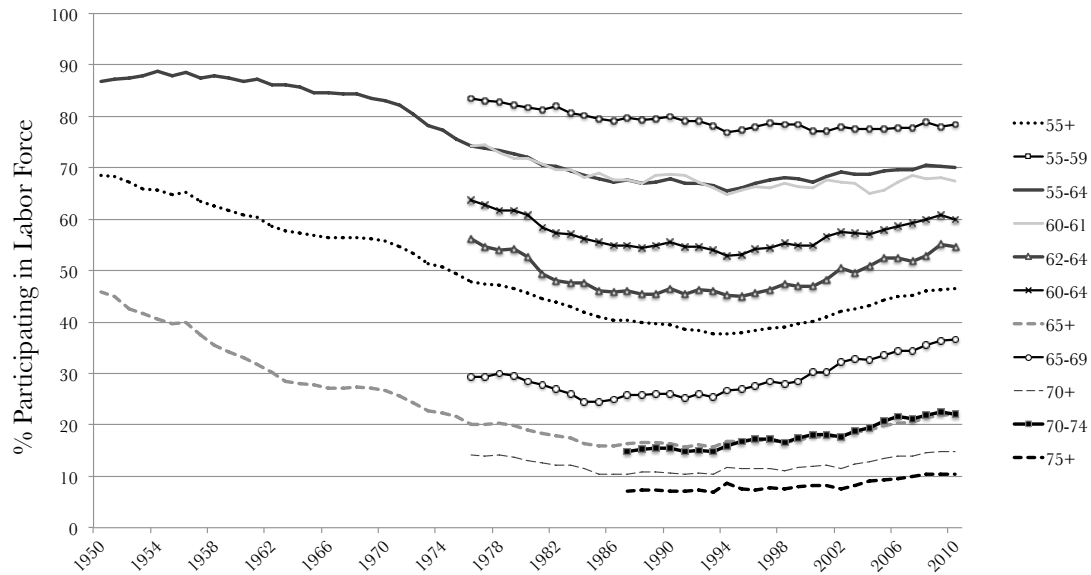
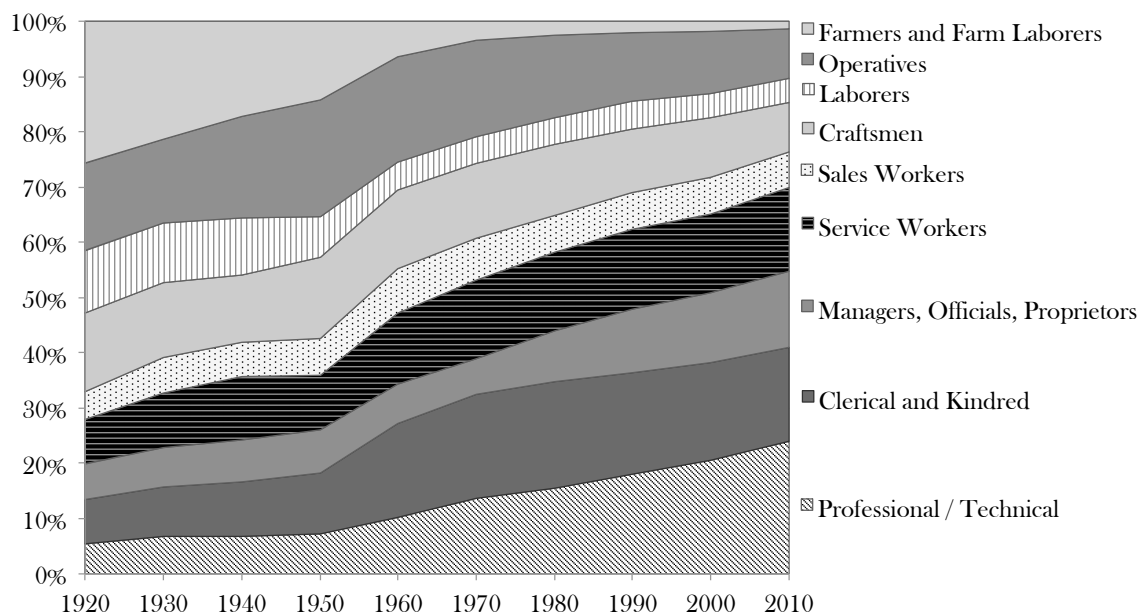


Figure 2: *Changes in Occupational Composition over Time, U.S. Census and CPS*



non-disability retirement in Norway. Their duration model finds that disability-induced retirement is connected with physical strain in work, and non-disability retirement is associated with higher job stress. They connect this, as I do here, with the disparate effects of changes to mandatory savings schemes (Social Security in the U.S.; Norwegian National Social Security in Norway). Logistic regressions on early retirement—which is taken up by about 60 percent of the labor force in Norway—and disability retirement confirm their hypothesis that job strains lead to earlier voluntary and involuntary (i.e., disability) retirement. Like Blekesaune and Solem (2005), Chirikos and Nestel (1991) also found a connection between working in physically demanding occupations and increased chances of disability retirement. They do not, however, generally find there to be a difference in labor force exit in between those with strenuous and sedentary jobs in a competing-hazard model of retirement, disability, and death. While I do not model formal disability retirement (or Social Security Disability Insurance claims) explicitly in this paper, the primary channel through which labor force exit occurs is declining productivity resulting in declining—though not detrimental declines in—functional ability.

In this paper, I estimate a discrete choice dynamic programming model, in which I can explicitly model health transitions and interactions with productivity in different types of jobs. This model can account for not only differences in patterns of labor force participation at older ages, but also incorporates the decision to switch job types to account for the tendency towards working in less physically demanding jobs with age. The basis of my model is French (2005), who models labor force participation and savings when future health and wages are not known with certainty. As my focus is on the interactions between the physical demands of work, health, and labor force decisions, I extend the model to allow for the wage process to differ by job type and for individuals to switch job types in the model.

Estimating a structural model in which occupational characteristics play a role in participation decisions will be useful not only in identifying the mechanism through which labor force participation patterns differ, but also in allowing us to predict behavior under counterfactual policy scenarios.

In the first counterfactual scenario, I look at changes in labor force behavior arising from Social Security benefit structure changes. The Social Security incentives that respondents face—which differ depending on birth year and past earnings—are consequential not only as they affect labor supply decisions but, as currently structured, do *not* differ depending on job type. A counterfactual experiment in which the “full retirement” claiming age increases—as is being gradually implemented—induces early transitions to less physically demanding jobs and, even with these transitions affects those initially in physically demanding jobs more adversely, highlighting one inefficient aspect of the Social Security structure. A second counterfactual will be helpful in understanding changes we have seen

and might continue to see in overall participation trends for the large and growing population of older individuals: The increasing labor force participation rates in later life for males over the last two decades in the U.S., which reverses a long trend in declining participation rates that spanned all but the last two decades of the twentieth century. By changing the initial composition of jobs to be less physically demanding, as has been occurring in the last century, we can see what the effect is on participation; indeed, under this counterfactual, aggregate participation increases as we see in the data.

In summary, this study aims to contribute to the broader literature on the labor supply decisions of older individuals by incorporating the effects of occupational requirements and health on productivity into the modeling of these decisions. Considering what job requirements mean for productivity and hence participation at older ages decisions will enable us to better measure and evaluate policy effects and anticipate overall participation trends for this growing, significant population.

The remainder of this paper is organized as follows. Section 3 describes the life-cycle model to be estimated. In Section 2, I present descriptive statistics from the HRS data. Section 4 describes the method of simulated moments estimation procedures, with results and counterfactual experiments in Section 5. Section 6 concludes the paper with a discussion of these results and future work.

2. DATA AND DESCRIPTIVE STATISTICS

In this section I present descriptive statistics from the Health and Retirement Study as well as some reduced-form results on work type, health, and participation as background and motivation for the model estimated in this paper.

2.1. HRS SAMPLE SELECTION AND SUMMARY

I use data from the Health and Retirement Study (HRS), a large, panel survey of men and women ages 50 and older. This biennial survey began in 1992 and provides responses on work and finances, physical and mental well being, and numerous other demographic variables. For this study, I will be modeling the behavior of male respondents only. One reason for this is the desirability of modeling the behavior of a relatively more homogeneous group. Another is that men are much more likely to be working in physically demanding occupations, the effects of which are of primary interest here.

Of the 13,313 males the HRS by the 10th survey Wave in 2010, for the descriptive statistics and the model, I include those born 1938-1953. I keep only those born after 1938 because they were at least 62 years old in year 2000, and thus did not face the Social Security earnings test; older birth year cohort faced a Social Security regime struc-

ture in which benefits were taxed away highly when income beyond a modest threshold was earned through work. These birth years include some of original “HRS” cohort (born 1931-1941) observed Waves 1-10, “War Babies” (1942-1947) observed Waves 4-10, and “Early Boomers” (1948-1953) observed Waves 7-10. In these birth years $13,313 - 8,457 = 4,856$ remain. I also drop those observed only once (since I need to see transitions for many of the statistics and estimation), leaving $4,856 - 314 = 4,542$. This gives a total of 27,677 person-year observations, with at least half responding in six or more of the ten Waves available (biennially, 1992-2010). Missing variables for some person years decreases the number of person-year observations used to produce the model estimation results presented in Section 5.

Table 1 highlights some basic characteristics of the sample. The youngest a respondent can be observed in this sample is 50; the oldest is 72. Nearly 18 percent report not having completed high school (with the majority having 9-12 years of education), 30 percent completed high school or GED, 24 percent report having some college, and 26 report having at least a bachelor’s degree. A substantial portion—over 40 percent—have veteran status.

In the second panel are the average annual earnings of those working full-time and part-time given by age group, where we can see that average earnings in the 55–59 age group are highest for both full-time and part-time workers, then falling at older ages. This is reflected in the wage estimates described in Section 4. Total asset levels, including home equity, are also given. There is a great deal of variation in total household assets, though on average assets increase and are the highest at ages 65-69, then fall for ages 70–72 as many have left the labor force, stopped accumulation assets further, and have begun to draw on these assets for consumption. Assets are negative in seven percent of person-years observations, and the model will allow for this (though no additional borrowing).

Labor force participation rates for respondents in the youngest age category, including full-time and part-time work, is 83 percent, with that proportion falling to 29 percent for the oldest age group.⁴ The percent whose spouses are working goes from 71 percent for respondents ages 50–54 to 28 percent for ages 70–72 (their wives are not necessarily in the same age category). Those in later birth years are somewhat more likely to have spouses who report working.

In the fourth panel of Table 1 are responses regarding pensions. Of those who report having a pension when age 55, the proportion that are defined benefit (DB) and defined contribution (DC) are roughly equal.⁵ Just over a quarter of those who have any pension

⁴This comes from RAND HRS variable `rWwork`, in which the respondent reports that he is “currently working for pay” (for my purposes, participating) or not. This measure is fairly consistent with similar HRS variables, such as `rWlbf`.

⁵By looking at responses for age 55 only, we get a better measure of the proportion of all respondent with pensions as the response to this question changes for some respondents from one interview to the next

Table 1: *Some Characteristics of the HRS Sample Respondents*

Ages Observed	50–72		
Educational Category (4,534)			
<i>Less than HS</i>	18.0%		
<i>GED</i>	4.9%		
<i>High School</i>	26.6%		
<i>Some College</i>	24.3%		
<i>College and Above</i>	26.2%		
Percent Veteran (4,533)	41.1%		

<i>Age</i>	Annual Earnings		<i>Total HH Assets* (s.d.) (obs)</i>
	FT (s.d.) (obs)	PT (s.d.) (obs)	
50-54	\$67,292 (73,816) (4,379)	\$40,574 (62,128) (207)	\$351,814 (802,388) (6,310)
55-59	69,812 (135,771) (5,554)	41,726 (56,938) (406)	443,494 (1,669,201) (9,614)
60-64	62,858 (63,083) (2,494)	30,158 (36,801) (462)	560,957 (2,390,652) (6,538)
65-69	55,921 (53,087) (655)	29,322 (50,187) (369)	638,087 (2,053,675) (3,885)
70-72	52,436 (71,691) (78)	20,526 (25,225) (73)	470,066 (885,242) (916)

<i>Age</i>	Labor Force Participation	
	Respondent (obs)	Spouse (obs)
50-54	.834 (6,301)	.713 (5,047)
55-59	.758 (9,601)	.673 (7,686)
60-64	.589 (6,533)	.553 (5,293)
65-69	.401 (3,880)	.377 (3,100)
70-72	.294 (914)	.281 (705)

Percent of FT Workers with Pension, Age 55: 67.3% (1,460)

<i>Pension Type</i>	Pension 1 (957)	Pension 2 (268)
DB	47.0	30.0
DC	46.4	67.1
DB and DC	6.6	3.0

Social Security Claiming Age (2,161)

Age Claimed	Percent
<62	25.0
62	41.1
63	7.8
64	5.8
65	15.5
>65	4.9

Note: Number of responses in parenthesis above.

All monetary figures are given in 2010 dollars.

*Around 7 percent held negative assets.

also report having a second pension, with about two-thirds of those being DC pensions. Finally, in the last panel we see that by far the most common age to begin claiming Social Security benefits is 62, followed by age 65. A surprisingly high number—25 percent—report

and the number of Waves observed differs among respondents.

having claimed benefits before age 62; this includes SSDI benefits.

2.2. PHYSICAL INTENSITY OF WORK

To capture the physical intensity (PI) of one’s work, I use a broad self-reported measure from the HRS that asks respondents, “How often does your [current] job require physical effort?” with the possible responses being “Always”, “Often”, “Sometimes”, or “Never”.⁶ Table 2 shows the proportion for each category, including the 15 percent who cannot be categorized. Because this question is only asked when the respondent is working, most of those who have no response were not working during any of the interviews. Their longest reported occupation and education categories are more similar to those who report on average that their jobs “Always” or “Often” require physical effort, though because categorizing them would require imputation, which is less desirable on this rather important variable, they will simply not be included in estimation.⁷ Given that the respondents whom are taken out of the estimation sample have such low participation, if they are indeed more likely to have had physically intense jobs, then the results will unfortunately understate the effect of this job characteristic on labor force exit. Of those whom we do have responses for, in the model to be presented, I’ll refer to the nearly 40 percent with jobs “Always” or “Often” requiring physical effort as being in *High PI* occupation; those whose jobs “Never” or “Sometimes” require a lot of physical effort will be referred to as *Low PI* workers.

Using this measure, we also see in Table 2 that transition to less physically intense jobs over time is fairly common, even over the relatively short observation time occurring towards the end of these respondents’ work lives. Of those who work in jobs that require a lot of physical effort “Always”, nearly half later report that their jobs are less physically intense in later interviews. Though not indicated in the table, these lower-PI jobs are often with the same employer. Movement from *Low PI* jobs to *High PI* jobs is much less common. Both possibilities, however, will be allowed for in the model of behavior.

Table 3 shows the results of a probit regression on whether one is working in a High-PI job. Consistent with the transitions seen in Table 2, higher education level decreases the probability of being in a more physically intense job, as does age. Out of concern of the apparent relationship between education and the physical requirements of one’s job, in estimating the parameters of the structural model, I will include only the largest education category, *High School*. We will see that even controlling for education category, there is a difference in the labor force exit behavior between those initially in Low- and High-PI jobs.

⁶The is RAND HRS variable `rwjphys`. Another candidate for measuring the physical requirements of one’s work in this survey is through variables that ask respondents how often they need to stoop/kneel/crouch or lift heavy objects in their current work. I use `rwjphys` as it may capture other activities such as standing on one’s feet for long periods of time, repetitive motions, etc.

⁷This can be seen in Table 11 of Appendix A.

Table 2: *Physical Intensity of Work and Transitions with Age*

<i>How Often Job Requires Physical Effort (on Average)</i> ¹				
<i>High-PI:</i>	Always	17.90%		
	Often	15.13		
<i>Low-PI:</i>	Sometimes	24.37		
	Never	27.41		
Excluded:	Not Observed	15.19		
<i>Job-Type Transitions</i> ²				
<i>First Observed Working:</i>	<i>Last Observed Working:</i>			
	Always (19.0%)	Often (15.1%)	Sometimes (32.8%)	Never (32.8%)
Always (22.4%)	51.1	18.9	20.8	9.2
Often (17.2%)	19.4	37.2	33.8	9.6
Sometimes (28.5%)	9.5	11.9	51.7	26.9
Never (31.9%)	4.7	3.3	23.9	68.0

¹: 4,542 observations.²: 2,908 observations. This includes those observed working in at least three waves.Table 3: *Probit on Whether in High PI Job*

	Coeff.	Std. Error	Marginal Effect at Means
<i>Education Category</i>			
Less than HS	-	-	.636
GED	-.477	.055	.449
High School	-.347	.033	.500
Some College	-.763	.034	.339
College and Above	-1.469	.035	.131
<i>Age Category</i>			
50-54	-	-	.364
55-59	-.039	.025	.349
60-64	-.085	.029	.332
65-69	-.163	.041	.305
70-74	-.274	.092	.267
Constant		.282	.061

Note: Includes Census Division dummies and race dummies. 17,166 observations.

2.3. FUNCTIONAL LIMITATIONS AND HEALTH

In the model presented in this study, declining physical ability correspondingly decreases productivity in the labor force, prompting labor force exit. Furthermore, the decline in productivity that results from a decline in ability is, as we will see, greater in physically intense jobs. There are a number of ways to capture physical ability in the HRS data. Here I discuss the measure of *functional limitation* that will be proxy for physical ability

Table 4: *Functional Limitations, Health, and Age*

<i>Average Number of Functional Limitations</i>			
<i>Age Category</i>	<i>Self-Reported Health</i>		<i>Total</i>
	<i>Fair/Poor</i>	<i>E/VG/Good</i>	
50-54	4.24 (895)	.78 (3,676)	1.46 (4,571)
55-59	4.52 (2,164)	.935 (7,432)	1.74 (9,596)
60-64	4.62 (1,629)	1.174 (4,899)	2.03 (6,528)
65-69	4.43 (1,048)	1.33 (2,833)	2.17 (3,881)
70-72	5.33 (256)	1.71 (660)	2.72 (916)

<i>Proportion with</i>		
<i>Age</i>	<i>At Least One</i>	<i>In Fair or Poor</i>
	<i>Functional</i>	<i>Self-Reported</i>
	<i>Limitation</i>	<i>Health</i>
50-54	42.9	19.0
55-59	48.2	22.5
60-64	55.1	25.0
65-69	59.8	27.0
70-72	65.1	28.0

Note: 25,504 person-years for functional limitation; 27,250 person-years for health.

and compare this to the *self-reported health* measure, which is a popular choice in many studies using HRS data and will be useful here as well, though in the context of mortality expectations.

The functional limitation measure I use here is the total number of of limitations out of a possible fourteen. This was formed by totaling the number of physical limitations under three of the six RAND HRS Functional Limitation indices: Mobility (`rWmobila`), Large Muscle (`rWlgmusa`), and Gross Motor Skills (`rWgrossa`).⁸

There is a relationship between functional limitations total and self-reported health. The difference between the number of functional limitations of those with Fair/Poor self-reported health and those in Good/Very Good/Excellent health is fairly similar across age categories. In Table 4, we have the average number of functional limitations by self-reported health. Though the average number of functional limitations increases with age for both

⁸The other three categories are Activities of Daily Living (`rWadlwa`, `rWadla`), Fine Motor Skills (`rWfinea`), and Instrumental Activities of Daily Living (`rWiadle`, `rWlmcoga`, `rWiadlza`). These are explained in the RAND Version L documentation page 15. I chose to not make use of these measures because (1) the relationship with physical work is somewhat less direct as difficulty in these areas may limit any work and (2) there is not as much variation with age for these measures.

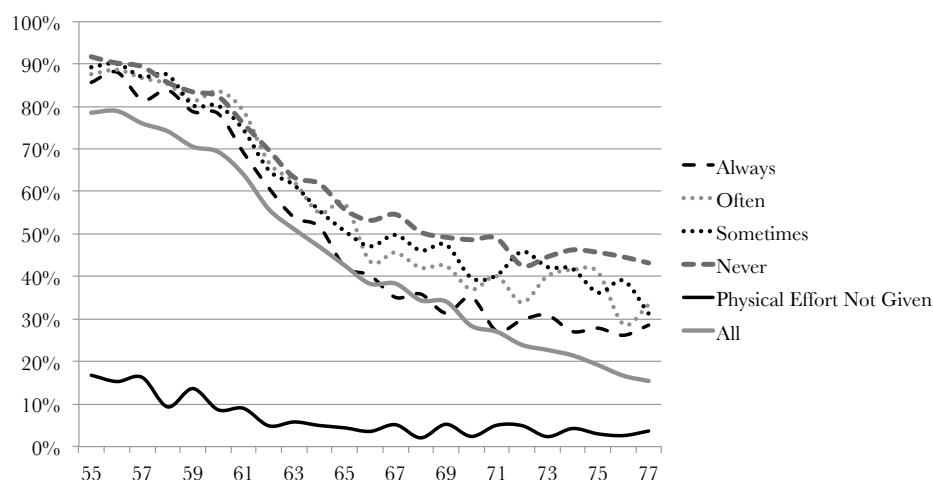
health categories is increasing with age, for all age categories, those in the Fair/Poor health category have approximately 3 to 3.5 more functional limitations on average than do those with Excellent/Very Good/Good self-reported health.

The proportion of individuals having at least one functional limitation by age category is shown in Table 4.⁹ Both the proportion with at least one functional limitation and those reporting Fair or Poor health increase with age. Nearly 43 percent have at least one functional limitation at ages 50–54, and 65 percent do by ages 70–72; those with self-reported Fair or Poor increase from 19 percent at ages 50–54 to 28 percent at ages 70–72. While the more general self-reported health measure is certainly related to productivity and thus labor force participation, the functional limitations measure more palpably corresponds to physical efforts required in work.

2.4. PI AND PARTICIPATION

In the next section, we model the mechanism through which those in more physically intense jobs have lower labor force participation rates at older ages to match the behavior we observe in the data. Figure 3 shows the participation rates for high school graduates working in, across all interviews, Low- and High-PI jobs. We can see that while participation rates are nearly identical for these groups at ages 50–54, by ages 70–72, the participation rate differs greatly for those in the Low- and High-PI groups, which is the outcome of

Figure 3: *HRS Respondents' Labor Force Participation by Age and How Often Physical Input is Required in Work*



Note: 50,912 person-year observations.

⁹In all age categories, a substantial proportion of those having at least one functional limitation have no more than two out of the possible fourteen measured by the sum of the three Functional Limitation indices used here.

chief interest in this paper. This difference is even greater when education category is not accounted for.

Before turning to the structural model, further motivation for the components of the model that will be estimated is given in Table 5 on page 14, which presents results from a probit regression of the effects of functional limitations on labor force participation in the next period. Controlling for education and age, we see that the effects of having at least one functional limitation is much more likely to be followed by exit from the labor force for those in High-PI jobs compared to those in Low-PI jobs. The lower panel of Table 5 gives the predicted probability of work in the next period for high school graduates by age for those with no functional limitations, those with at least one limitation who work in a Low-PI job, and those with at least one functional limitation who work in High-PI jobs. Those with no functional limitations have a higher probability of continuing work in the following period for all ages. Those with at least one functional limitation who worked in Low-PI jobs have a probability of continuing work that is about five percentage points lower than those with no limitations, while those in the High-PI jobs had a probability of continued work that was about 10 percentage points lower at all ages.

3. THE MODEL

This section presents a discrete choice dynamic programming model in which agents make choices about labor force participation, the type of job, and whether to apply for Social Security benefits, as well as savings, consumption, and bequests. The goal is to find the parameters of the model that generate the behavior seen in the data. This structural model allows us to (1) determine the mechanisms driving the differences in participation and transitions to less physically intense jobs and (2) perform counterfactual “out-of-sample” experiments and measure ensuing changes in behavior as well as measure welfare changes.

The dynamic programming model presented here is an extension of French (2005); in my model the wage process differs by job type and I allow for and measure costs of switching job type. Because we see in the HRS data that some respondents switch to less physically intense jobs over time, sometimes working continuously with the same employer, the ability (or inability) to switch to less physically intense work is part of the life cycle model the model in this paper.

The behavior modeled is of a household head maximizing future expected lifetime utility, who in each period t —here one year—chooses whether and how much to work (P_t), whether to work in a *high*- or *low*-PI job (PI_t) how much to consume (C_t) and save, whether to apply for and draw his Social Security benefits at certain ages (SSB_t). We will refer to these as the decision variables and define $\mathbf{D}_t = \{P_t, C_t, PI_t, SSB_t\}$. At the beginning of period t , when making these decisions, he knows the values of current assets (A_t), current

Table 5: *Effects of Age, Education, and the Interaction Between Functional Limitations and Job on Participation*

<i>Outcome Variable: Labor Force Participation</i>			
	Coeff.	Std. Error	Probability at Means
Function Limitation with			
<i>High-PI Job</i>	-.315	.077	*
<i>Low-PI Job</i>	-.164	.064	**
Education Category			
<i>Less than HS</i>	-	-	.740
<i>GED</i>	-.015	.165	.735
<i>High School</i>	.017	.085	.745
<i>Some College</i>	-.012	.091	.736
<i>College and Above</i>	.279	.088	.822
Age	-.024	.013	-
Constant	2.267	.852	-
<i>Marginal Effects</i>			
	Pred. Prob. of Working***		
<i>Age</i>	No Functional Limitations	At Least One Functional Limitation <i>Low PI</i>	<i>High PI</i>
62	.813	.766	.718
63	.807	.759	.710
64	.800	.752	.702
65	.794	.744	.694
66	.787	.737	.685
67	.780	.729	.677
68	.773	.721	.668
69	.766	.713	.660
70	.759	.705	.651

Note: Outcome variable is whether working in the next period. 2,466 observations, over age 61.

functional limitations status (F_t) and age (a_t), earnings (w_t), as well as last period's participation (P_t) and occupation type (PI_t), and whether Social Security benefits were applied for last period. These are state variables $\mathbf{S}_t = \{A_t, F_t, a_t, w_t, P_{t-1}, PI_{t-1}, SSB_{t-1}\}$. While state variables are known with certainty, for other variables affecting future utility only a stochastic process is known. These variables include next period's survival probability (s_{t+1}), functional limitations (F_{t+1}), and earnings (w_{t+1}).

3.1. PREFERENCES

In every period in which the agent survives, which occurs with probability s_t , the agent obtains utility from consumption C_t and leisure time L_t and has CES/CRRA preferences

over these variables, along with a participation preference shock $\epsilon(P_t)$:

$$u(C_t, L_t, P_t, \epsilon_t) = \frac{1}{1-\eta} (C_t^{\alpha_c} L_t^{1-\alpha_c})^{1-\eta} + \alpha_P \epsilon_t(P_t). \quad (1)$$

The parameters have the following interpretations: η captures the curvature of the utility function over consumption and leisure, $\eta \geq 0$, where higher η implies greater curvature and less willing to substitute utility across time; α_c represents the utility weight of consumption, $\alpha_c \in (0, 1)$. Parameter α_P scales the effect of work preference shock $\epsilon_t(P_t)$. Leisure L_t is defined by

$$L_t = L - N_t - \phi_P \mathbb{1}_{\{P_t=1\}} - \phi_{H^{Bad}} \mathbb{1}_{\{H_t=Bad\}} - \phi_{RE} \mathbb{1}_{\{P_t \neq P_{t-1}\}} - \phi_{OCC} \mathbb{1}_{\{OCC_t \neq OCC_{t-1}\}}. \quad (2)$$

The total number of hours available for leisure is fixed to L . N_t is the number of hours the individual works and parameter ϕ_P is the fixed cost of work; $\phi_{H^{Bad}}$ is the leisure cost of bad health; ϕ_{RE} captures the cost of reentering the labor force; ϕ_{OCC} is the cost of switching occupation type.

With probability $1 - s_t$, the agent does not survive and utility in that period comes in the form of a bequest equal to his assets A_t . The bequest component of utility is of the form

$$b(A_{t+1}) = \frac{\alpha_B (A_{t+1} + K_0)^{1-\eta}}{1-\eta}.$$

where parameter α_B scales the bequest and K_0 is the bequest shifter.

3.2. VALUE FUNCTION

The forward-looking individual's choice problem at time t can be expressed recursively as follows:

$$V(\mathbf{S}_t) = \max_{\mathbf{D}_t} \left\{ u(C_t, L_t, \epsilon_t) + \beta \left[(1 - s_{t+1}) b(A_{t+1}) + s_{t+1} \int V_{t+1}(\mathbf{S}_{t+1}, \epsilon_{t+1}) dF(\mathbf{S}_{t+1} | \mathbf{S}_t, \epsilon_t) \right] \right\}. \quad (3)$$

At the beginning of period t , given state variables $\mathbf{S}_t = \{A_t, H_t, a_t, w_t, P_{t-1}, PI_{t-1}, SSB_{t-1}\}$, the agent chooses $\mathbf{D}_t = \{P_t, C_t, PI_t, SSB_t\}$ to maximize equation (3) subject to the following budget constraint:

$$A_{t+1} = A_t + Y_t^R - C_t, \quad (4)$$

where Y_t^R is after-tax income $Y_t^R = Y(rA_t + w_t + g_t + SSB_t^R, \tau)$. Here, r is the interest earned on assets, before taxes, SSB_t^R is Social Security earnings, and τ describes the tax structure.

Agents are not allowed to borrow,¹⁰ but are able to hold negative assets; indeed some enter the data with negative assets. Consumption is thus restricted as follows:

$$C_t \leq \begin{cases} A_t + Y_t^R + SS_t^R & \text{if } A_t \geq 0 \\ Y_t^R + SS_t^R & \text{if } A_t < 0 \end{cases} . \quad (5)$$

Following French and Jones (2011), who follow Hubbard et al. (1994), outside transfers g_t (sources could be government, children, charity, etc.) provide a consumption floor so that $C_t \geq \underline{C} > 0$:

$$g_t = \max \{0, \underline{C} - (A_t + Y_t + SS_t^R)\} . \quad (6)$$

Table 6 summarizes the variables included in the model. In the next section we will describe the procedure for estimating this model.

4. ESTIMATION

Through the method of simulated moments (MSM), we find the preference parameters that generate simulated life-cycle decision profiles that best match the decision profiles found in our data. I estimate the model presented in the previous section using a two-stage approach similar to Gourinchas and Parker (2002), French (2005), French and Jones (2011) and others to emply the problem computationally. In the first stage, we estimate parameters that can be determined outside the model, which include the state transition probabilities (for wages, functional limitations, and mortality). In the second stage, the preference parameters of the model are estimated jointly with the type prediction parameters using the first-stage transition estimates.

First, the “inner” maximization problem is solved: Optimal savings (and equivalently consumption) is computed conditional on each participation P_t and Social Security benefit claiming choice SS_t (which can be to claim at age 62, 63, 64, or 65). Next, the optimal claiming age is found. Lastly, the optimal participation choice in any period is the one that yields the greatest value given the optimal savings, S.S. claiming, and the realization of the preference shock $\epsilon_t(P_t)$. Next the “outer” maximization problem of finding the parameters that best match the data is solved using the two-stage approach.

The parameters estimated in the first stage are represented by $\hat{\chi}$. Further, let θ denote the vector of parameters estimated in the second stage, which includes parameters of utility

¹⁰One reason I impose this restriction is the relative challenge of securing approval for a loan in old age with no income; a second related reason is that one can’t legally borrow against future Social Security earnings.

Table 6: Summary of Variables

<i>Description</i>	
<i>Choice Variables, $\mathbf{D}_t$</i>	
P_t	labor force participation (none, PT, or FT)
C_t	consumption
PI_t	physical intensity of job (low or high)
SSB_t	apply for Social Security benefits (yes, no)
<i>State Variables, $\mathbf{S}_t$</i>	
A_t	total assets
F_t	functional limitations
a_t	age
w_t	wage (annual earnings)
g_t	government transfers
P_{t-1}	last period labor force participation
PI_{t-1}	last period physical intensity
SSB_{t-1}	applies last period for SS benefits
<i>Preference Parameters (to be estimated)</i>	
η	substitution between consumption and leisure
θ	consumption weight
α_P	scales the effect of work preference shock $\epsilon_t(P_t)$
ϕ_P	fixed cost of work
$\phi_{H^{Bad}}$	leisure cost of bad health
ϕ_{RE}	cost of reentry
ϕ_{OCC}	cost of switching occupation type
α_B	scales the bequest
K_0	bequest shifter
<i>Fixed Parameters</i>	
τ	tax structure
L	Total leisure hours available
r	interest earned on assets, before taxes
—	
H_t	hours worked
SS_t^R	Social Security earnings
s_t	survival probability

function, fixed costs of work, and type prediction. The estimator $\hat{\theta}$ is given by

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \hat{\varphi}(\theta, \hat{\chi})' \Omega \hat{\varphi}(\theta, \hat{\chi}) \quad (7)$$

where $\hat{\varphi}$ denotes the vector of moment conditions described below, and Ω is a symmetric weighting matrix. The weighting matrix contains the inverse of the estimated variance-covariance matrix of the estimates of the sample moments along and off the diagonal.

The solution to (7) is obtained by the following procedure

1. Compute sample moments and weighting matrix Ω from the sample data.
2. From the same data, generate an initial distribution for wages, functional limitations, AIME, assets, job type, and preference type assigned using our type prediction equation (described below). Many of the first-stage parameters contained in χ are also estimated from these data.
3. Using $\hat{\chi}$, we generate matrices of random health, wage, mortality, and preference shocks. The matrices hold shocks for 10,000 simulated individuals.
4. Each simulated individual receives a draw of assets, health, wages, job type, AIME, as well as preference type from the initial distribution, and is assigned one of the simulated sequences of shocks.
5. Given $\hat{\chi}$ and an initial guess of θ , I compute the decision rules and simulate profiles for the decision variables.
6. Compute moment conditions by finding the distance between the simulated and true moments, which we seek to minimize as shown in (7).
7. Pick a new value of θ , update the simulated distribution of preference types, and repeat steps 4-7 until the $\hat{\theta}$ that minimizes (7) is found.

Identification of the models parameters comes from observable variation in participation, job type transitions, and savings levels.

4.1. FIRST-STAGE ESTIMATES: TRANSITION PROCESSES

4.1.1. Health Transitions

Health transitions are measured through an ordered probit, in which expectations on future health status depend on current self-reported health status and age. The statuses are divided into “*Good, Very Good, or Excellent*”, “*Fair*”, and “*Poor*”. While, at most ages, the majority of respondents report that they are in the “*Good, Very Good, or Excellent*”

category, we choose these groupings because movements among them may have significant consequences for labor force participation. In other words, a change from “*Good*” health to “*Poor*” health is more significant than movements from “*Good*” to “*Excellent*”. Conditional health transition probabilities for ages 55, 65, and 72 are shown in Table 7.

Table 7: *Sample Health Transition Probabilities*

		Next Period Health		
	Current Health	G/VG/E	Fair	Poor
Age=55	G/VG/E	.87	.12	.01
	Fair	.46	.37	.17
	Poor	.15	.36	.49
Age=65	G/VG/E	.84	.14	.02
	Fair	.42	.39	.20
	Poor	.12	.34	.54
Age=72	G/VG/E	.82	.15	.02
	Fair	.39	.39	.22
	Poor	.11	.32	.57

4.1.2. Wage Estimates

This model allows for the wage processes to depend differently on functional limitations for those in Low- and High-PI jobs, which drives the differences in participation at older ages; indeed, wage estimates here confirm the process differs.

The annual earnings offers faced by individuals depend on age, functional limitations, whether the work is Low- or High-PI, and whether part- or full-time. Log annual earnings for individual i at time t with selection into work are estimated as

$$\ln W_{it} = W(a_{it}, F_{it}, PI_{it}) + \varphi N_{it} + f_i + \gamma_{it} \quad (8)$$

where N_{it} indicates full-time work, f_i represents an individual-specific effect, and γ_{it} is an idiosyncratic error term at time t .

Estimates of this equation, controlling for education level, year, and Census division, are shown in Table 8. First, the estimated coefficients on age and age squared, earnings peak at age 51 and decline thereafter. Second and of great interest here is the fact that those in Low-PI jobs will not see any change in wage offers upon the arrival of a functional limitation; those in High-PI jobs, on the other hand, face nearly an 8 percent decline in wages.

Table 8: *Wage Estimates*

Outcome: ln <i>Annual Earnings</i>		
<i>Variable</i>	<i>Coefficient</i>	<i>(s.e.)</i>
Age (years), a_{it}	.1130	(.0225)
Age ²	-.0011	(.0002)
Functional Limitation, F_{it}		
Low-PI	-.0093	(.0162)
High-PI	-.0785	(.0197)
Full-Time Work, N_{it}	.8109	(.0202)
Inv. Mills	-.1267	(.0394)
Constant	6.7948	(.6506)
$\hat{\rho}$ (var. due to f_i)		.4601
$\hat{\sigma}_\gamma^2$		.6364
$\hat{\sigma}_\varepsilon^2$ (trans.)		.6894

n=18,052, individuals=5,216

Controls for education level, year, and Census division.

Being just above Early and Full S.S. claiming age used as exclusion restrictions.

4.1.3. Mortality Profiles

Both Casanova (2010) and French (2005) compute their conditional survival probabilities using Bayes' Rule, with

$$s_t = P(\text{Survive}_t | H_{t-1} = H) = \frac{P(H_{t-1} = h | \text{Survive}_t)}{P(H_{t-1} = H)} \times P(\text{Survive}_t) \quad \text{for } H=\text{VE, F, P.}$$

I assume that individuals die with probability one at age 100 regardless of health status, so $P(\text{Survive}_{100} | H_{99} = H) = 0$ for all H .¹¹

4.2. SECOND STAGE

In the second stage, parameter vector $\hat{\theta}$ solving equation (7) is found through the procedure described above, using first-stage estimates $\hat{\chi}$ and moments φ .

4.2.1. Moment Conditions

The moments from the data comprising vector φ are chosen on the basis of their describing behaviors that I most want the model to be able to capture, given the questions on which this paper is focused. The parameters found will be those that generate moments

¹¹Survival probabilities are obtained from the U.S. Social Security Administration's *Office of the Chief Actuary* reports: Actuarial Study 120, "Life Tables for the United States Social Security Area 1900-2100" by Felicitie C. Bell and Michael L. Miller. Available at <http://www.ssa.gov/oact/NOTES/as120/L0T.html>. These give one-year survival probabilities at age t by sex and birth year cohort, conditional on survival up to age t . I use the 1945 birth year cohort (the birth years in the sample ranging from 1938 to 1953).

from simulated data that are closest—in the sense of minimizing the distance between the true and simulated data as in equation (7)—to the same moments from the HRS data using simulated method of moments techniques. The following $12T$ moments are “matched” to the data for each age between 60-72 ($T = 13$), for a total of 156 moments:

1. Full-time and part-time participation by age ($2T$ moments)
2. Exit rates by age (T moments)
3. Occupation type by age (T moments)
4. Participation (full-time and part-time) by occupation type and age ($2T$ moments)
5. Participation (full-time and part-time) by health and age ($2T$ moments)
6. Participation (full-time and part-time) by preference index and age ($3T$ moments)
7. Assets (“high” or “low” relative to income) by age (T moments)

4.2.2. Preference Heterogeneity

To account for unobservable differences among reverse and non-reverse retirees, I allow permanent preference parameter heterogeneity across individuals. This approach was first introduced by Heckman and Singer (1984), and adapted by many other such as Keane and Wolpin, (1997) and (2007), and French and Jones (2011). Each individual is assumed to belong to one of a finite number of preference types, here one of two types. The probability of belonging to a particular preference type is given by a logistic function of the individual’s initial state vector, which includes age, initial wages, functional limitation status, AIME, and a work enjoyment index described below.

The type probability parameters are estimated jointly with the preference parameters in the second stage. The two preference types allow for differences by preference type in the elasticity of substitution between consumption and leisure, η , time discount factor β , taste for leisure α_L , and fixed cost of work parameters for participation, ϕ_P , re-entry, ϕ_{RE} , and switching occupation ϕ_{OCC} . The probability of being a certain type will depend on income, initial health, assets, age, and one’s work enjoyment index level.

4.2.3. Social Security and Pensions

In future versions, the Average Indexed Monthly Earnings (AIME), which is used to determine an individual’s Social Security Primary Insurance Amount (PIA), will come from the HRS restricted data. In place of this, I currently take the AIME to be an individual’s

average earnings between the ages of 50 and 60.¹² Pensions are not included in the current estimation, but will be in future versions.

4.2.4. Work Enjoyment Index

The work enjoyment preference index is used as a measure of “willingness to work” as in French and Jones (2011). They construct a work preference index based on responses to three HRS questions given in Wave 1 interviews and our is very similar but not identical. While there may not be a strong connection with this preference index and re-entry, it will allow us to better assign types and match levels of labor force participation. In Appendix B are present responses to these questions, also noting how the responses, and thus the preference index constructed from them, are independent of whether one is in a particular occupation type.

5. ESTIMATION RESULTS

Table 9 gives preliminary parameter estimates. These include estimated that are allowed to vary for the two preferences types, as well as parameters that are restricted to be the same across the two types. These shared parameters includes α_c , which is the weight on utility from consumption relative to leisure hours, the leisure cost of bad health, $\phi_{H^{Bad}}$, measured in terms of hours, and bequest parameters α_B and K_0 .

Parameters varying by preference type include η , which is the curvature of the utility over leisure and consumption and relates to the intertemporal elasticity of labor supply, time discount factor β , as well as costs of working more than zero hours, re-entering the labor force, and switching occupation types, all measured in terms of hours.

¹²The (2010) formula for calculating the PIA an individual receives upon claiming his Social Security benefits can be obtained at: <http://www.ssa.gov/oact/cola/bendpoints.html>.

Table 9: *Parameter Estimates*

<i>Shared Preference Parameters</i>		<i>Estimates</i>	
α_c	consumption weight	.49	
$\phi_{H^{Bad}}$	leisure cost of bad health (hours)	381	
α_B	scales the bequest	.03	
K_0	bequest shifter (\$1,000)	771	
<i>Type-Specific Preference Parameters</i>		<i>Type 1 (39.3%)</i>	<i>Type 2 (60.7%)</i>
η	substitution between consumption and leisure	2.1	2.4
β	time discount factor	.98	.97
ϕ_P	fixed cost of work	402	433
ϕ_{RE}	cost of reentry	49	20
ϕ_{OCC}	cost of switching occupation type	199	105
<i>Fixed Parameters</i>			
τ	tax structure	-	
L	Total leisure hours available	5,000	
r	interest earned on assets, before taxes	.05	

5.1. SIMULATED PROFILES

Profiles of some of the moments from the true HRS data and those simulated by the (very preliminary) estimated parameters of the model are shown in the graphs in Figure 4. In the two uppermost graphs, we see the labor force participation rates of those initially in both High- and Low-PI type jobs. The second row includes the percent working with (black line) no functional limitations and (blue) at least one functional limitation. The last row gives the percent, among those working, who are in full-time and part-time work.

5.2. TYPE PREDICTION PARAMETERS

In the second stage of estimation the type prediction parameters are also found. There are two generic types: Type 1 and Type 2. The interpretation is that one type, Type 1, experiences lower disutility of working (relatively lower taste for leisure α_L) and experiences a lower fixed cost of work (ϕ_P). I estimate logistic function

$$P(\text{Type 1}|X) = \frac{1}{1 + e^{-\beta X}}$$

where

$$\begin{aligned} \beta X = & \beta_1 \text{Index}^{high} + \beta_2 \text{Index}^{low} + \beta_3 \mathbb{1}_{\{H_{initial}=\text{Poor}\}} + \beta_4 \mathbb{1}_{\{H_{initial}=\text{Fair}\}} \\ & + \beta_5 \text{Wage}_{initial} + \beta_6 \text{Assets}_{initial} + \beta_8 \text{Age} . \end{aligned}$$

We expect that those with the higher work enjoyment index (Index^{high}) are more likely to be Type 1, as are those in better health.

Figure 4: *Simulated and True Data Moments*

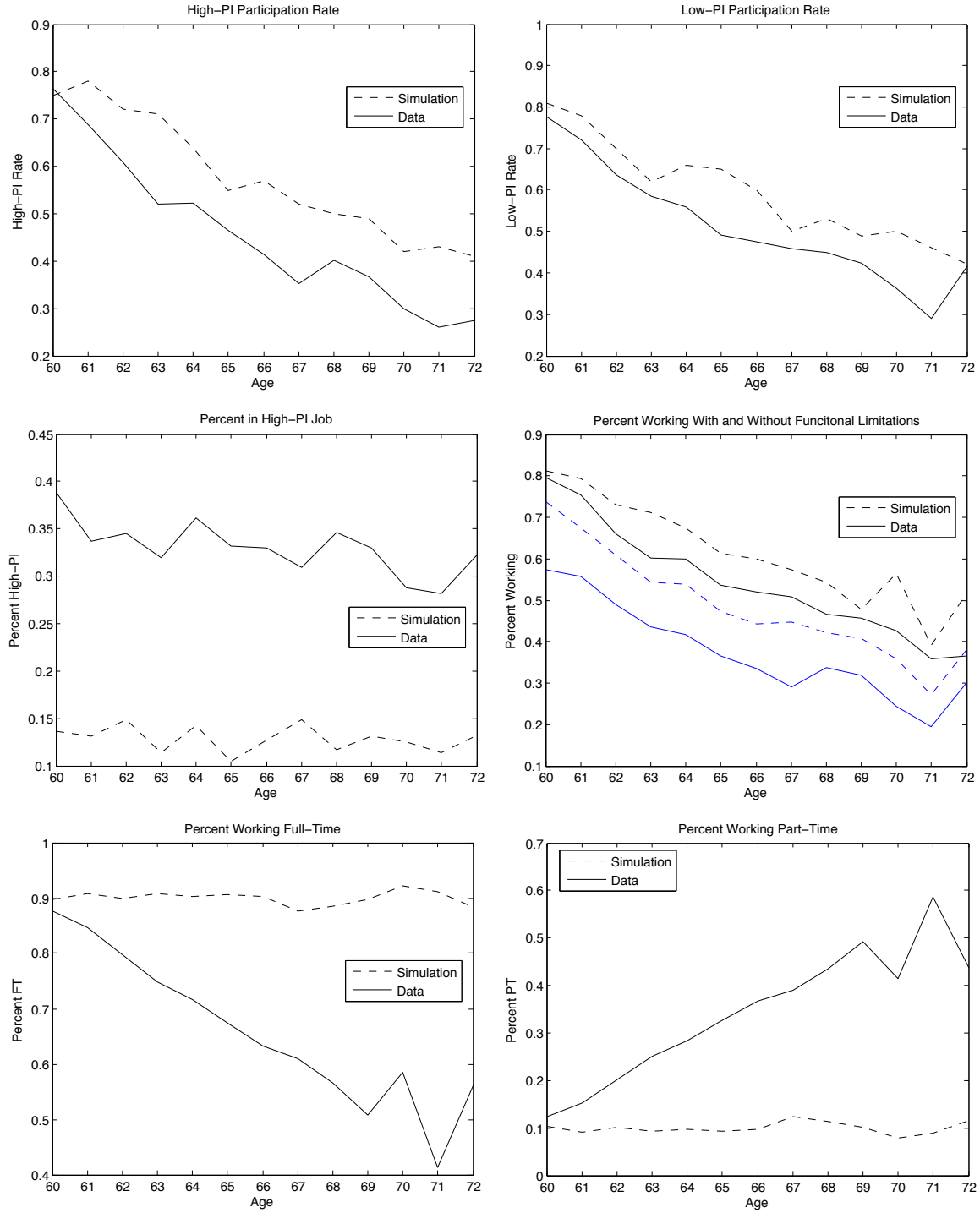


Table 10: Type Prediction Estimates

<i>Coefficient</i>			<i>Estimate</i>		
<i>Coefficient</i>			<i>Estimate</i>		
High Preference Index	β_1	0.37	Initial Earnings*	β_5	-1.89
Low Preference Index	β_2	0.25	Initial Assets*	β_6	0.13
Initial Health: Bad	β_3	-0.94	Age	β_8	0.11
Initial Health: Fair	β_4	-0.21			

*Variables are expressed in 10,000 dollars.

5.3. COUNTERFACTUAL EXPERIMENTS

These counterfactual experiments are in progress. In the first counterfactual scenario, I look at changes in labor force behavior and savings decisions arising from Social Security benefit structure changes. The “full retirement” claiming age increases in the counterfactual—as is being gradually implemented—inducing early transitions to less physically demanding jobs and, even with these transitions affects those initially in physically demanding jobs more adversely, highlighting one inefficient aspect of the Social Security structure. A second counterfactual changes the initial composition of jobs to be less physically demanding to see the extent to which aggregate participation increases as we see in the data.

6. DISCUSSION AND FUTURE WORK

The aim of this paper has been to model the relationship among the physical demands of jobs, health, and work at older ages. In this paper, I estimated a discrete choice dynamic programming model, in which I can explicitly model health transitions and interactions with productivity in different types of jobs. This model can account for not only differences in patterns of labor force participation at older ages for those in different types of work, but also incorporates the decision to switch job types to account for the tendency towards working in less physically demanding jobs with age. With data from the Health and Retirement Study, I showed how those in physically demanding occupations retire sooner and, before exiting, switch to less physically intense jobs.

This structural life-cycle model allows us to predict retirement behavior under counterfactual policy settings and relate the decline in physically demanding jobs with the trend of increasing labor force participation among older individuals. One counterfactual experiments show that the changing occupational type composition explains part of the trend of higher participation rates at older ages, helping also to inform the labor supply behavior we might expect to see in the future. A second counterfactual allows us to see the welfare loss associated with Social Security contributions and benefits not differing by occupation

type.

In summary, the goal of this study was to contribute to the broader literature on the labor supply decisions of older individuals by incorporating the effects of occupational requirements and health on productivity into the modeling of these decisions. Considering what job requirements mean for productivity and hence participation at older ages decisions will enable us to better measure and evaluate policy effects and anticipate overall participation trends for this growing, significant population.

APPENDICES

A. APPENDIX A

The relationship between education and the physical intensity of one’s job is shown in Table 11. We can see that there is some relationship between the two; those in the “Some College” and “College+” categories are more likely to work in Low-PI jobs, while those in other education categories are more likely to be in High-PI jobs.

There is also a relationship between education and labor force participation *at all age levels*, including the later-life span studied in this paper (not shown). I have two reasons, however, for not focusing on education: (1) The relationship between education and the physical intensity of work, while it indeed exists, is far from direct and (2) when controlling for education category, we still see the differences in labor force participation by those in different job types. Furthermore, the job types explanation for difference in labor force exit patterns relates more clearly to transitions with age in health and limitations, while the relationship between education and work at older ages is more a human capital explanation. The decisions of which may be more difficult to study here, given the earliest age at which respondents in this data are observed.

Table 11: *Education and Physical Intensity of Work*

Education Category (%in Cat.)	Physical Effort Over All Periods Observed Working				
	<i>High-PI</i>		<i>Low-PI</i>		Not Reported
	Always	Often	Sometimes	Never	
Less than HS (18.0%)	30.34%	18.80	16.34	6.14	28.38
GED (4.9%)	22.07	16.67	22.97	14.86	23.42
HS (26.6%)	24.61	20.22	28.00	12.76	14.42
Some College (24.3%)	14.25	15.52	29.31	28.49	12.43
College+ (26.2%)	5.13	6.81	22.04	58.03	7.99
Total (100.0%)	17.89%	15.13	24.42	27.37	15.20

Note: 4,534 observations.

The relationship between DOT 2-digit occupation and the physical intensity of jobs is shown in Table 12. While DOT occupation is not used in the model, this table is to motivate the inclusion of the HRS physical effort response. Note that those occupations with the highest proportion in Low-PI jobs are the ones in which the highest proportions report working in ages 70–72.

Table 12: *HRS Respondents' Earnings and Physical Effort Required by Occupation Category*

Occupation (percent of sample) ^a	Med. Earnings ^b	Proportion with Job Requiring Physical Effort ^c				Age 70-72 Working ^d
		High-PI		Low-PI		
		Always	Often	Sometimes	Never	
Managerial, Specialty (19%)	\$ 97,698	.08	.09	.29	.53	.358
Professional, Technical (16%)	\$ 91,888	.05	.06	.30	.59	.367
Sales (9%)	\$ 71,882	.11	.14	.33	.42	.373
Clerical, Admin. (6%)	\$ 52,376	.17	.14	.30	.38	.205
Services ¹ (7%)	\$ 41,686	.30	.22	.31	.17	.237
Farming, Forestry, Fishing (4%)	\$ 28,464	.43	.25	.24	.08	.366
Mechanics, Repair (8%)	\$ 52,662	.27	.25	.38	.10	.167
Construction, Extractors (8%)	\$ 51,744	.41	.29	.23	.07	.266
Precision Production (5%)	\$ 54,131	.26	.22	.36	.15	.243
Operators: Machine, Trans. ² (19%)	\$ 43,521	.37	.22	.28	.13	.249

¹ Services includes Household, Food Prep., Cleaning, Protection, Personal Services categories.

² Operators combines Machine, Transport, Handlers, etc. operator types.

^a Longest occupation listed. Percent is of the – person-years given.

^b Median annual income of working respondents ages 50 to 60. 12,628 person-years given. 2010 USD.

^c Self-reported measure of physical effort for working respondents ages 50 to 60. 11,146 person-years.

^d Percent working for respondents ages 70-72 in each occupation. 859 person-years total.

B. APPENDIX B: WORK ENJOYMENT INDEX

The work enjoyment index is constructed using three HRS questions. The first of the three questions asks whether the respondent would continue working even if he did not need the income from his job.¹³ Overall, nearly 70 percent of respondents either “agree” or “strongly agree” with the statement. These responses are given in Table 13.

The second question used to construct the work enjoyment index asks respondents whether they are looking forward to retirement.¹⁴ The results are in the second panel of Table 13. While most people say they would continue to work if the income from their jobs was not needed, as we see in the first panel of the table, at the same time a majority also look forward to their retirement. Fewer than 20 percent said the idea of retirement made them “uneasy”.

The third question that informs the French and Jones (2011) preference index—here, the enjoyment index so as not to be confused with preference parameter types—asks respondents how much they enjoy their jobs on a scale of 0 (dislike) to 10 (like a great deal).¹⁵ This question was not asked of most respondents—only 146 in our sample. I will not use this as part of the index due to the low number of responses, though the results are in the

Table 13: *Whether Respondent Would Work if the Income Was Not Necessary*

Would Work Even if Income Wasn't Necessary	
Strongly Agree	14.1%
Agree	54.0%
Disagree	23.0%
Strongly Disagree	9.0%
<i>Observations</i>	2,170
Feelings about Retirement	
Looking Forward	69.1%
Mixed Feelings	13.7%
Uneasy	17.2%
<i>Observations</i>	1,670
Like or Dislike Current Job?	
Dislike (0 to 3)	1.4%
Neither Like nor Dislike (4 to 6)	15.0%
Like (7 to 10)	84.6%
<i>Observations</i>	146

¹³Question V3319 in the HRS files.

¹⁴HRS question V5009.

¹⁵HRS question V9063.

last panel of Table 13.

These HRS questions were only asked in the 1992 Wave 1. As in French and Jones (2011), the index is first constructed by regressing participation in future Waves 4 onwards on responses to the “would work even if I didn’t need the money” and “look forward to retirement” questions, as well as age, average income ages 50 to 60, future participation levels, health, and interactions of these terms. The preference index is then the responses times the coefficient estimates. I divided the index into *low* (about 63 percent of the sample) and *high*, where the highest index individuals would have responded that they “strongly agree” with the statement “I would work even if I didn’t need the money” and that they do not look forward to retirement.

The preference index will not inform occupation choice directly, only whether the individual is more likely to work or not in any given period and which preference parameter type he is more likely to be assigned to.

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