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Labor force transitions at older ages: burnout, recovery, and reverse retirement

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Labor Force Transitions at Older Ages: Burnout, Recovery, and Reverse Retirement

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Abstract: Partial and reverse retirement are two key behaviors characterizing labor force dynamics for individuals at older ages, with half working part-time and over a third leaving and later re-entering the labor force at some point. The high rate of exit and re-entry is especially puzzling when considering the flat and declining wage profiles observed at older ages and uncertainty about future re-employment. Using Health and Retirement Study (HRS) data, we document the timing and prevalence of these behaviors and show that reverse retirees resemble permanent retirees across many observables, but differ notably in reported job stress and polygenic scores linked to stress sensitivity. To understand what drives these behaviors, we develop and estimate a dynamic model of retirement that incorporates uncertainty in wages and health, along with a novel "burnout-recovery" process representing the accumulation and dissipation of work-related stress. The model replicates key patterns in the data, accounting for over two-thirds of reverse retirement and 40 percent of transitions to part-time work—patterns that cannot be explained by health or wealth shocks alone. Our findings suggest that reverse retirement is largely a predictable response to recoverable stress rather than a reaction to shocks. Policy simulations show that part-time subsidies and sabbaticals enhance labor force attachment and welfare by reducing burnout, while eliminating the Retirement Earnings Test raises re-entry but also increases stress exposure. Together, these findings highlight the central role of stress dynamics in shaping retirement behavior and inform the design of policies to support work at older ages.

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1. Introduction

For much of the twentieth century, retirement ages were declining and retirement was often characterized as a one-time, permanent withdrawal from the labor force (Lazear, 1987). In recent decades, however, older-age labor force participation has been rising, and retirement has taken on more heterogeneous forms (Cahill et al., 2015). Beyond full and permanent withdrawal, older workers increasingly pursue partial retirement, bridge jobs, and *reverse retirement*—returning to work after a period of retirement (Ruhm, 1990; Maestas, 2010; Cahill et al., 2011). The aim of our paper is to account for these increasingly common patterns, with particular attention to partial and reverse retirement.

In the Health and Retirement Study (HRS) data we study, over one-third of respondents who identify themselves as retired and have ceased working for pay later re-enter the labor force. This figure seems surprisingly high given the well-documented trends of (1) flat or declining earnings in the labor market with age, (2) increasing disutility of work with age or poor health and, at all ages, (3) the nontrivial re-entry costs of returning to work found throughout the retirement literature. We seek to understand this common yet perhaps puzzling behavior by introducing a burnout–recovery process into retirement decisions, extending rich structural models of health, savings, and work decisions at older ages (French, 2005; French and Jones, 2011). In our model, cumulative work-related stress—i.e., burnout—reduces utility from continued employment but can dissipate with time out of the labor force or reduced hours, enabling later re-entry for some, following the process proposed by Maestas and Li (2007). Using data from the HRS linked with polygenic scores, we document that reverse retirees differ from permanent retirees in stress sensitivity and mental health dynamics, but not in most major economic or demographic characteristics. Our model replicates patterns in the data, explaining more than two-thirds of observed reverse retirements and 40 percent of part-time work transitions—magnitudes that cannot be attributed to health or wealth shocks alone.

By embedding this burnout–recovery process in a retirement model, we can capture the mechanisms generating observed dynamics and also evaluate counterfactual policies. We estimate the effect of eliminating the Social Security Retirement Earnings Test, introducing part-time work subsidies, and offering sabbaticals at older ages. These experiments highlight the role of burnout–recovery in shaping labor supply and policies that have the potential to reduce costly exit-and-reentry cycles by allowing workers to recover without leaving the labor force entirely.

This work is, to the best of our knowledge, the first paper to propose and estimate a structural model that seeks to explain reverse retirement. The motivation for our model comes from patterns in the HRS data we find on stress levels, financial and health shocks, and work. We find that those who voluntarily leave work and ultimately re-enter—whom we refer to as *Reverse Retirees*—look remarkably similar on measures of education, income and wealth, health, occupations, how much they report liking both work and retirement compared to those who ultimately remain as *Permanent Retirees*. Our perspective is consistent with Maestas (2010) in that we find little support for reverse retirement being solely a result of financial or health shocks. What does seem to vary, however, are improvements in reported mental well-being, levels of work-related stress for those in part-time versus full-time work, and job stress for those continually working compared to those who voluntarily left and re-entered work. We also find that those who do retire and ultimately re-enter the labor force have polygenic scores related to anxiety and cortisol that indicate higher angst and sensitivity to stress compared to otherwise similar people who retire permanently. This suggests a role for such dynamic preferences over work in explaining common retirement and re-entry behaviors.

This paper contributes to the literature studying the complexity of work decisions at older ages, particularly partial retirement (Gustman and Steinmeier, 1984; Ruhm, 1990; Beehr and Bennett, 2014), health (Bound et al., 1998; French, 2005), and returns to work (Maestas, 2010; Cahill et al., 2011, 2015; Clark et al., 2020). More broadly, this work is in the spirit of Blau (1994), who emphasized the role of dynamic features and preferences in labor supply decisions around retirement.

In addition to its focus on partial and reverse retirement, our research closely relates to recent studies emphasizing workplace stress and mental health as crucial determinants of labor market trajectories. Within studies on retirement timing, Henkens and Leenders (2010), like Maestas and Li (2007), find a measure of burnout that strongly predicts early retirement intentions, emphasizing the roles of workload, autonomy, and social support in the Netherlands. Furuya and Fletcher (2024) show that retirement itself influences well-being and biological aging. Looking across the life cycle, Jolivet and Postel-Vinay (2024) construct a search model with job characteristics to show how job stress affect health and career dynamics. They estimate their model using British data, quantifying the substantial value people place on health, work, and jobs with lower stress. Referencing burnout in particular, Nekoei et al. (2024) provide compelling evidence of the high, long-term economic cost of burnout as it relates to work using administrative data from Sweden.

While we do not consider younger ages, as Jolivet and Postel-Vinay (2024) and Nekoei et al. (2024) do, there is an important connection. The high Frisch elasticity of labor supply measured at older ages and apparent sensitivity to job features at older ages makes it an interesting setting to study a burnout-recovery dynamic in labor force decisions. Generally, those who are older have had time to accumulate assets and become eligible to claim Social Security retirement benefits. All else equal, they are more in a position to leave work altogether if desired before possibly returning, and thus we observe more transitions. A burnout-recovery process may be more broadly applicable and present at younger ages as well. Although more difficult to estimate through labor-supply responses, it may be nonetheless important to consider this type of behavioral response to policy changes, since early-career health shocks and burnout and recovery can shape long-run attachment to the labor force and earnings trajectories. Our focus on older ages provides a first step toward incorporating burnout-recovery into models of labor supply more generally.

Our analysis also relates to insights from studies on job flexibility and worker accommodation at older ages in particular. Ameriks et al. (2020) consider the preferences particularly of older workers, showing that older-age labor supply would be notably higher if people had greater flexibility in their work, while Blau and Shvydko (2011) find that firms offering flexible hours experience lower late-age separation rates. In our study, partial- and reverse-retirement are alternative ways for people to achieve that flexibility. Hill et al. (2016) on accommodation for partially disabled older workers, and they use the "big 5" measures in the HRS to show that those with traits associated with self-advocacy were more likely to receive accommodation. Likewise, we show heterogeneity in sensitivity to work stress or burnout by predisposition through polygenic scores as predictors of stable individual traits in the HRS.

The remainder of the paper is organized as follows. Section 2 presents descriptive statistics from the HRS that motivate our analysis. Section 3 introduces the burnout–recovery framework for work decisions, which builds on the retirement, health, and savings models of French (2005) and French and Jones (2011). Section 4 details the estimation, and Section 5 presents simulation results using parameter values estimated using HRS data. Section 6 uses the estimated model to conduct counterfactual policy analyses of part-time subsidies, sabbaticals, and modifications to the Social Security Retirement Earnings Test. Section 7 concludes.

2. Work Patterns and Respondent Characteristics in the HRS

This section presents novel descriptive evidence from the Health and Retirement Study (HRS), which also motivates our modeling approach. We document two key empirical patterns. First, reverse and partial retirement are prevalent among older individuals and reverse retirees and permanent retirees appear very similar across a range of demographic and economic characteristics. Second, reverse retirees and permanent retirees differ notably in responses to job stress, polygenic scores related to stress sensitivity, and mental health dynamics. These patterns inform the burnout–recovery framework that we incorporate into our structural model to explain labor force re-entry and part-time work in later life.

2.1. Data and Retirement Definition

The Health and Retirement Study (HRS) is a panel survey that includes nationally representative respondents in the U.S. who are at least age 50 and their spouses (Health and Retirement Study (2018)). The first wave of respondents were interviewed in 1992 and approximately every two years since, with later birth year respondents brought into subsequent waves. Respondents are interviewed in detail about their lives across an exceptional range of topics related to health, work, and finances.

We study fourteen interview waves, up to the 2018 interviews. Since the goal of this paper is to analyze the dynamics of labor supply decisions, having sufficient panel observations of individuals at the relevant ages is necessary. We include respondents who were observed for at least five biennial waves, working for pay at least once after age 50, and born between 1931 and 1947. These criteria leave 66.7 percent of men and 61.6 percent of women from the "HRS" (b. 1931–1941) and "War Babies"(b. 1942–1947) cohorts. Our main sample consists of 9,076 respondents and a total of 99,569 person-year observations. More details on the selection and representativeness of this sample are in Appendix A.1.

Table 1 summarizes our main sample of HRS respondents, who were observed for an average of 11 biennial waves (approximately 22 years), typically beginning around age 54 and extending to age 75 by 2018. During this period, respondents experienced multiple transitions in work, health, and marital status—most notably, spousal loss among women at older ages. Several measures and transitions differ significantly by gender, which we highlight where relevant throughout the analysis.

We define a "Reverse Retiree" as someone who exits paid work for at least one year—excluding exits due to permanent or severe disability—and is later observed returning to paid work in a future HRS wave. Respondents who exit and are never observed re-entering are classified as "Permanent Retirees."[1] Among respondents who were working at least once after age 50 and observed in five

[1] We discuss alternative definitions of reverse retirement and the robustness of our classification in Appendix A.2.

Table 1: *Characteristics of the HRS Sample Respondents*

Main Characteristics:		
Number of Respondents	9,076	
Men	4,328	
Women	4,748	
Birth Years	1931–47	
Ages Observed from 1992–2018	50 (min), 87 (max)	
Biennial Waves Observed (s.d.)	11 (2.9)	
Educational Category		
Less than HS	18.3%	
HS or GED	39.0	
Some College	22.0	
College +	20.7	
Percent Ever Reverse Retiring		
Men	35.8%	
Women	34.0	
Characteristics Over Time:		
	First Observed	*Last Observed*
Average Age at Survey (s.d.)	54.4 (4.0)	75.0 (6.3)
Self-Reported Health Status		
Good, Very Good, or Excellent	87.9%	75.9%
Marital Status		
Married or Coupled	83.4%	67.0%
Separated or Divorced	10.6%	10.9%
Widowed	3.4%	19.5%
Never Married	2.6%	2.7%

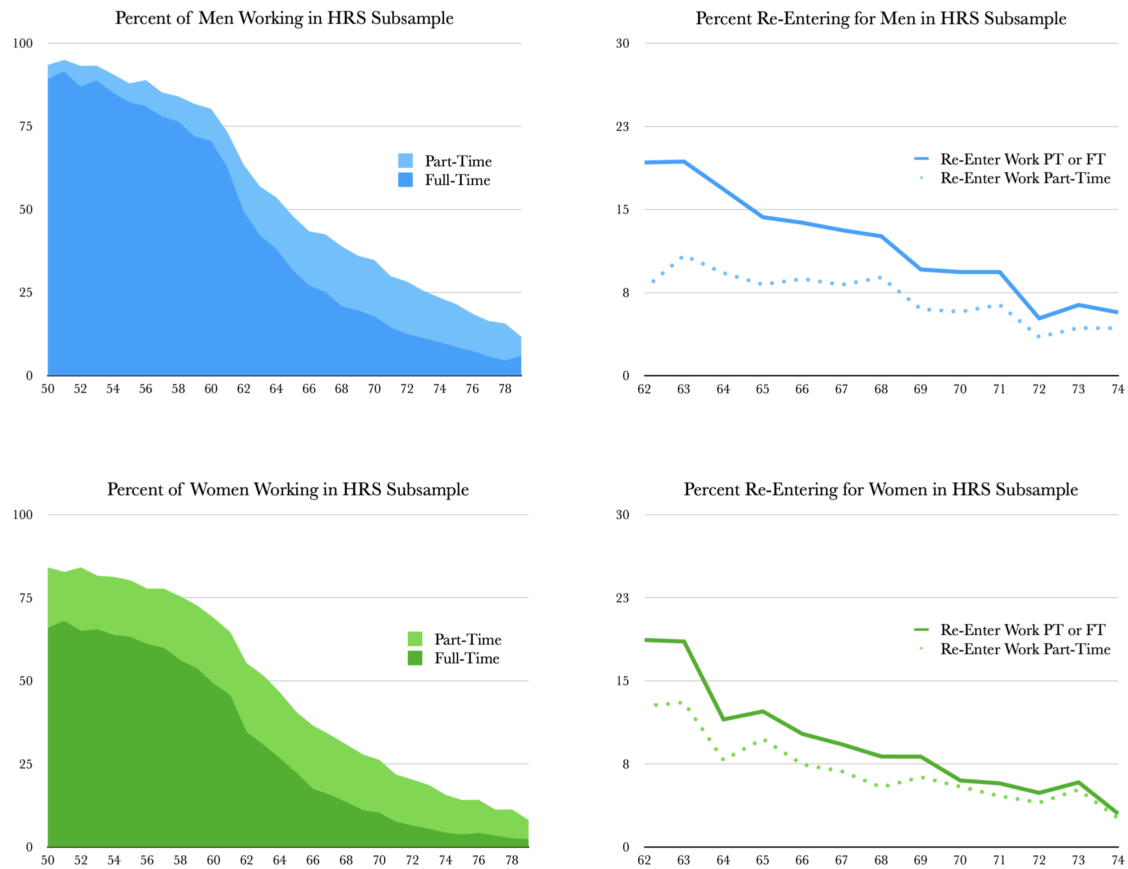
Note: Aside from the number of respondents, these figures are weighted using HRS sample weights, representing 7,130 individuals based on our sample of 9,076. None of the weighted measures here differ significantly from unweighted figures.

or more waves, reverse retirement is common: 35.8 percent of men and 34.0 percent of women in our sample leave and later re-enter the labor force at older ages.[2]

Figure 1 shows the proportion for men and women working full-time and part-time by age (left panels) and the percent of those re-entering into full-time and part-time by age (right panels). A notable feature of work at older ages overall, particularly for re-entrants, is the high proportion of respondents who report "part-time" work of up to 30 hours per week. The percent of respondents who re-enter into paid work by age, conditional on not working, is highest at younger ages and declines with age. For men in their early 60s, re-entry into part-time or full-time work is equally likely. At older ages, re-entry is more likely to be into work that is less than 30 hours per week.

[2]This is similar to Maestas (2010), who, using varying definitions, finds between 25 to 40 percent of retirees "unretire" and an additional quarter of the sample transitions to full retirement through partial retirement or part-time work. Our definition is broader than that of Cahill et al. (2011), who report a 15 percent re-entry rate when focusing only on returns after exiting "career jobs." It is also higher than the 25 percent found by Ruhm (1990) which focuses on over half of all men from the Social Security Administration's Retirement History Longitudinal Survey (RHLS) data, years 1969-1979. Our HRS sample spans up to 22 years of observation and includes only those seen working at least once, as we observe job characteristics and subjective work experience only when respondents are employed.

Figure 1: *Labor Force Status by Age (Left) and Re-Entry (Right)*



Note: Left, labor force participation: 42,447 male and 49,293 female person-years from HRS sample described in text; right, re-entry rate among those not working: 12,068 male and 15,888 female person-years.

These patterns—particularly the high prevalence of reverse retirement and the shift toward part-time work at older ages—are difficult to reconcile with declining wages and deteriorating health in later life. The fact that a substantial share of older individuals re-enter the labor force despite these frictions suggests the presence of additional dynamics. In the next section, we examine similarities and differences between reverse and permanent retirees across a range of characteristics to better understand what might drive these transitions.

2.2. Characteristics of Permanent and Reverse Retirees

2.2.1. Similarities in Health, Education, Retirement Expectations, Income and Wealth

We compare Reverse and Permanent Retirees across observable characteristics, beginning with health and disability, education, and expectations about retirement, followed by assets and income. Across these dimensions, we find surprisingly small differences between the two groups.

Health and Disability. The upper panel of Table 2 shows the percent of respondents who report their health as being "good, very good, or excellent" when ages 50–54 and again at 70–74. While Permanent Retirees are somewhat more likely to report good health at younger ages

Table 2: *Characteristics of HRS Sample of Permanent and Reverse Retirees*

	Permanent Retirees	*Reverse Retirees*
Respondents (unweighted)	6,024	3,052
Self-Reported Health and DI Application		
Good, Very Good, or Excellent Health		
Ages 50–54	91.8%	89.8%
Ages 70–74	79.1	81.8
Ever Applied for SSDI	9.6	10.9
Education		
Less than HS	12.1%	13.3%
GED	4.5	6.1
High School	36.6	36.9
Some College	22.5	22.9
College	24.4	20.8
Feelings about Retirement, First Observed		
Looking Forward	68.9%	69.4%
Mixed Feelings	13.8	13.2
Uneasy	17.3	17.4

(91.8 vs 89.8 percent), and Reverse Retirees report slightly better health at older ages (79.1 vs 81.8 percent), the rates are fairly similar. Chi-squared tests of distributions across Permanent and Reverse Retirees both within men and within women (not shown) suggest there are no statistically significant differences. The percent who report ever applying for Social Security Disability Insurance (SSDI) is only slightly higher for Reverse Retirees (10.9 vs 9.6 percent).[3]

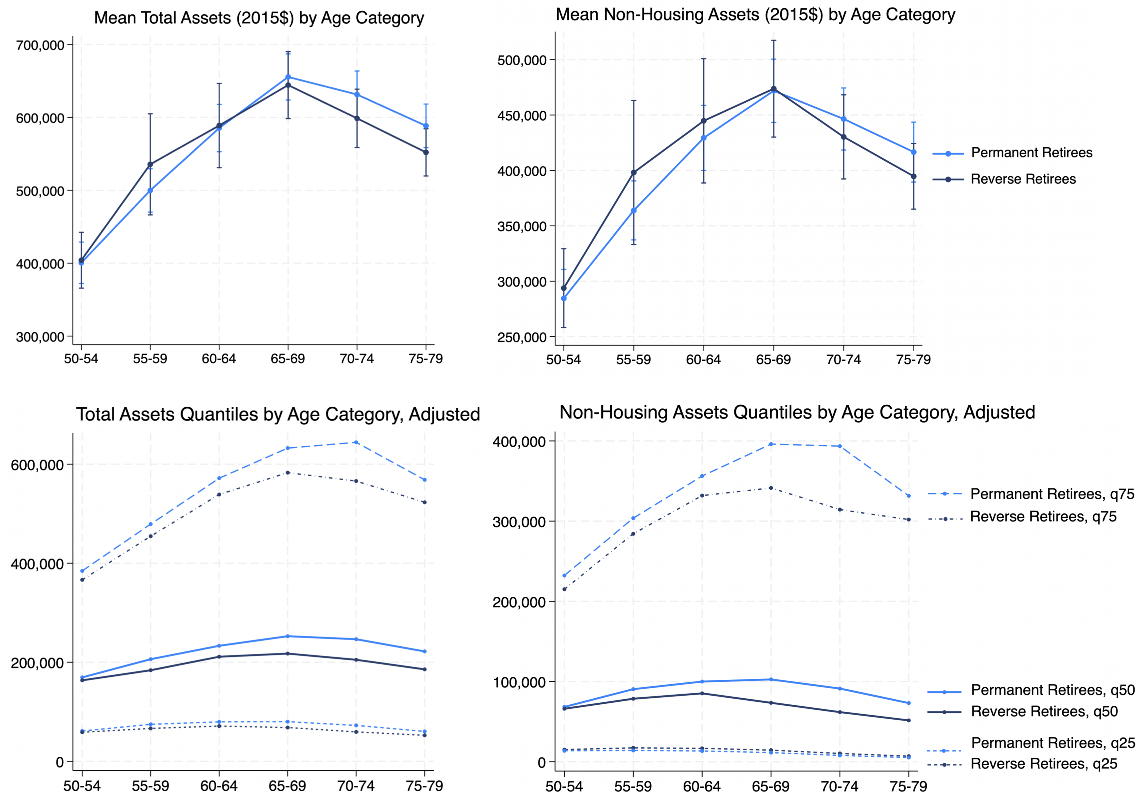
Education. Permanent and Reverse Retirees are distributed very similarly across educational attainment categories, with the greatest difference being in the percent who report a four-year college degree being higher for Permanent Retirees (24.4 vs 20.8 percent). Other categories—less than high school, GED, high school, and some college—show minimal variation.

Retirement Expectations. When first observed in the HRS, respondents were asked how they felt about retirement. Nearly 70 percent of both groups reported "looking forward" to retirement, with similar shares expressing "mixed feelings" or feeling "uneasy." This is notable given the divergent paths the two groups ultimately take.

Assets and Wealth. Figures 2 and 3 compare household wealth and income for Permanent and Reverse Retirees. The top two graphs in Figure 2 show mean levels of total assets (left) and non-housing assets (right) for Permanent and Reverse Retiree households. Mean total and non-housing assets are similar across groups at most ages–they are not statistically different, and we see the high variance typical of mean wealth estimates. However, Reverse Retirees appear to have slightly higher wealth before age 60 and slightly lower wealth after age 70. Percentile comparisons (25th, 50th, 75th) show similar patterns, with some divergence emerging later in life—likely reflecting

[3]Compared to the broader population, relatively few in this sample apply for and are ultimately approved for SSDI benefits, due to both low overall approval rates and the relatively healthy nature of our sample (which includes only those observed for at least 10 years past age 50). Also note that individuals who leave work due to a severe, work-limiting disability but later re-enter are not classified as Reverse Retirees under our definition.

Figure 2: *Household Assets by Age, Total (left) and Non-Housing (right), 2015$*



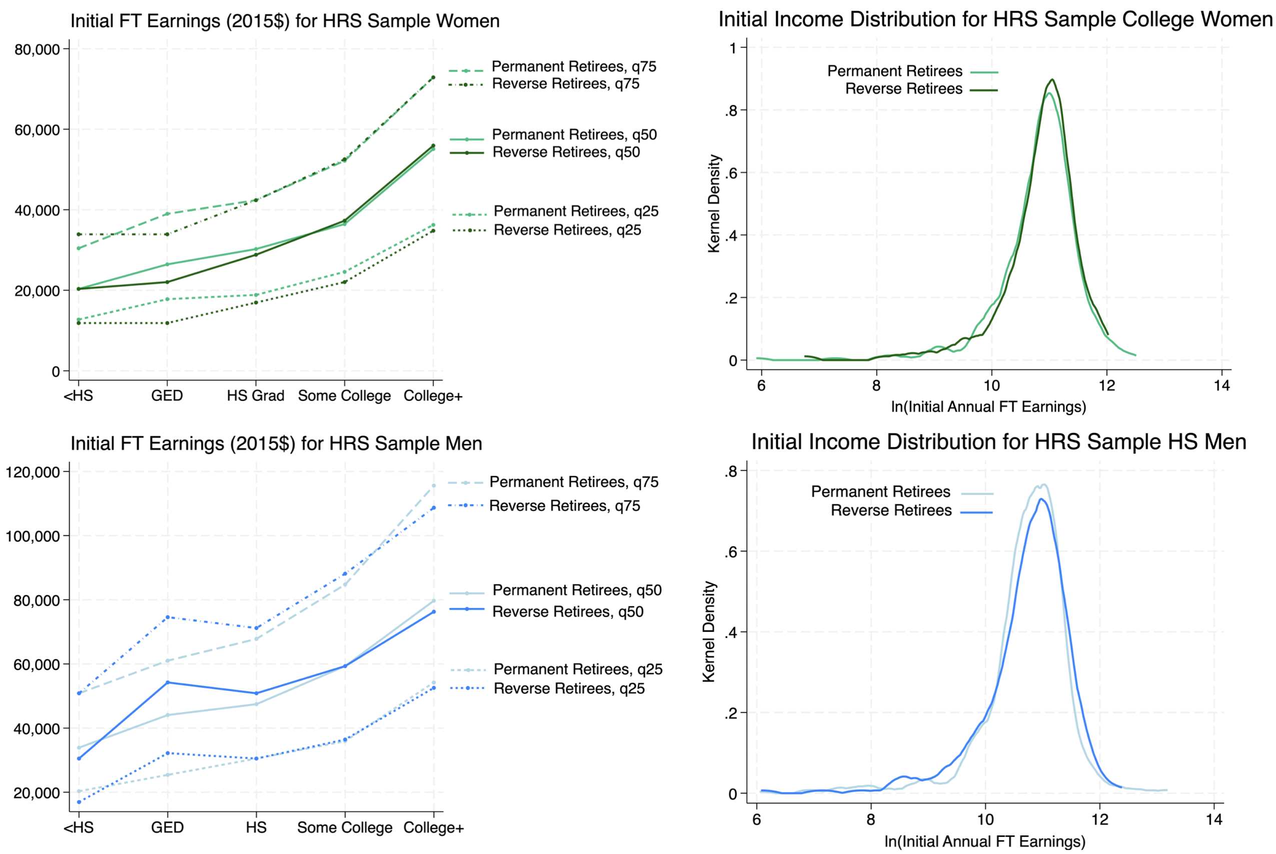
differences in work and drawdown behavior.

Earnings. The graphs in Figure 3 show the average annual earned incomes observed for respondents when first observed working in their early 50s. The upper graphs show mean income by education group (left), and the log distribution of earnings with an education group (right) for Reverse and Permanent Retirees. For women (top row, left), mean income with each education category is slightly higher for Permanent Retirees. The distribution of earnings is not statistically within all education groups, with the female College category—the most similar—shown here (top row, right). The second row shows the equivalent for male earnings, where mean income for Permanent Retirees is only slightly higher for the Some College and College categories. The distribution of earnings for males in the High School education category is shown on the right.

The graphs in the bottom row of Figure 3 show initial full-time earnings at the 25th, 50th, and 75th percentiles for men (left) and women (right) by education categories. Aside for the GED education category, within which there is high variance, earnings within each education category for Permanent and Reverse Retirees are very aligned, both for men and women.

Overall, we find that Permanent and Reverse Retirees are remarkably similar on many of the key observable characteristics. These similarities suggest that observable characteristics alone may not explain why some individuals return to work after retirement while others do not. This motivates our focus on less visible factors—such as job stress, psychological recovery, and stress sensitivity—which we explore in the next section.

FIGURE 3: *Younger-Age Income by Education for (left) and Women (right), 2015$*



Note: Combined Kolmogorov–Smirnov for College Women: 0.1219 0.092; HS men D: 0.0821 p-value 0.320 weakly rejects distinct initial income distributions of Permanent and Reverse Retirees.

2.2.2. Differences in Patterns in Job Stress, Symptoms of Burnout, and Recovery

On a number of major observable characteristics, we have seen that Permanent and Reverse Retirees are quite similar. Given this, what else could be contributing to significant differences in retirement behavior? In the HRS data, we find that on these measures Permanent and Reverse Retirees *do* differ on average: Patterns in job stress and exit, *polygenic risk scores* indicating sensitivity to stressors, and the dynamics of respondents' experiences of depressive symptoms. This suggests a relationship between measures reflective of deep preferences—which may be heterogeneous—systematically contribute to reverse retirement behavior beyond what other observables and health, income, and work preference shocks can explain.

We observe three empirical patterns that motivate the "burnout-recovery" aspect of our model: (i) Those who ultimately reverse retired voluntarily exited work at earlier ages—ahead of high burnout—compared to otherwise similar people and that job stress predicts earlier exit, especially for Reverse Retirees. (ii) Polygenic scores measuring susceptibility to angst or anxiety are predictive of job stress, and the distributions of these scores for Permanent and Reverse Retirees are statistically different. Finally, (iii) there is a reduction in depressive symptoms when not working, and recovery is slightly greater for Reverse Retirees who will ultimately re-enter work. We interpret fact (i) as evidence of "burnout" that can arise as work fatigue culminates, prompting exit, fact (ii) as an indication that some people are more sensitive to stress and respond by exiting earlier than they otherwise would, and fact (iii) as evidence of "recovery" which can diminish the level of burnout when not working or—and to a lesser extent—when working part-time. This recovery contributes to labor force re-entry.

Observation (i): ***Job stress predicts exit from work, especially for Reverse Retirees.***

There are differences in the timing of the initial exit from work for Permanent and Reverse Retirees and the circumstances around the timing of exit. Permanent and Reverse Retirees in this sample are observed working the same total number of years of over all interview waves. However, mechanically, this puts the initial retirement for Reverse Retirees earlier: For women, the average age at first observed exit is 61.8 for Reverse Retirees and 64.4 for Permanent Retirees. For men, average first exits are at 63.5 for Reverse and 65.8 for Permanent Retirees.[4]

Table 3 presents results from a logit regression where the outcome is exit from paid work, with remaining in work as the base category. The strongest positive predictors of exit in any given period are age, being female, and being classified as a Reverse Retiree (whom we necessarily observe exiting at least once). In contrast, being in good to excellent health significantly reduces the likelihood of exit. Job stress is also strongly associated with exit. We find a significant interaction between job stress and Reverse Retiree status: job stress increases the probability of exit, and this effect is especially pronounced for those who eventually return to work.[5] Holding all other covariates at their means, Reverse Retirees exhibit a larger increase in the probability of exit when reporting job stress (22.4 vs. 20.5 percent) compared to Permanent Retirees (12.7 vs. 11.8 percent). These

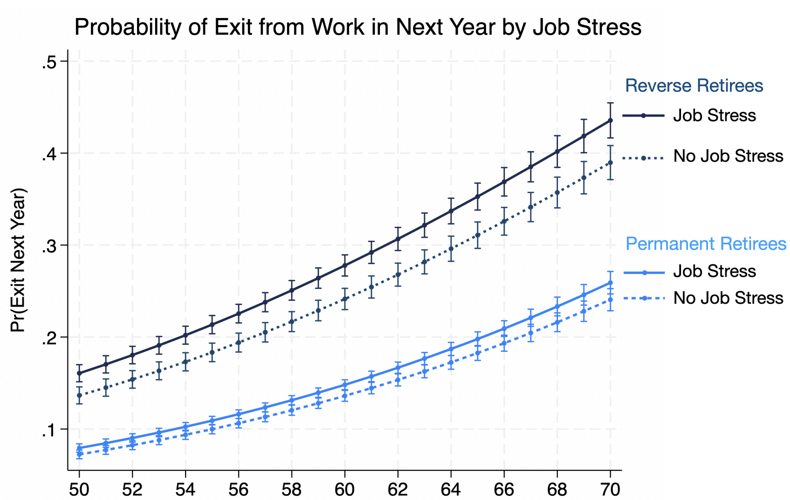
[4]Because the distributions of education, assets, birth year, and longest occupation held are so similar, these figures are unchanged for estimates controlling for these variables.

[5]We use HRS responses on job stress level, where respondents who are working at the time of the interview are asked whether their current job "involves much stress." Responses include Strongly Agree, Agree, Disagree, or Strongly Disagree. We report condensed responses here, where Strongly Agree or Agree indicate "Job Stress" and Disagree or Strongly Disagree indicate "No Job Stress." This is primarily for clearer exposition, but the patterns are not substantively different when using the full scale.

TABLE 3: *Job Stress Predicts Exit from Work, Especially for RRs*

Logit, Outcome: Exits Paid Work	**Coefficient**	**(s.e)**	**P-value**	**Pred. Margin at Means (s.e.) (Prob. of Exit)**
Age	0.075	(0.003)	0.000	
Job Stressful	0.079	(0.047)	0.092	
Ever Re-Enter	0.654	(0.054)	0.000	
Job Stressful × Rev. Ret.	0.147	(0.072)	0.040	.244 (.007)
Not Stressful, Rev. Ret.	-			.205 (.007)
Job Stressful, Perm. Ret.	-			.127 (.003)
Not Stressful, Perm. Ret.	-			.118 (.004)
Female	0.147	(0.042)	0.000	.157 (.003)
Male	-			.138 (.004)
Work Status × ln(Earnings)				
PT $<$ 30 hrs	0.008	(0.023)	0.724	.169 (.006)
FT $\geq$ 30 hrs	-0.012	(0.021)	0.579	.143 (.003)
Self-Rated Health Good to Excel.	-0.473	(0.053)	0.000	.143 (.002)
Fair or Poor	-			.211 (.008)
Constant	-5.845	(1.059)	0.000	
(Occupation Controls)				
(Birth Cohort Controls)				
(Education Level Controls)				
		Observations		25,763
		Log likelihood		-10,806.89
		LR Chi-square (29)		1,657.02
		Pseudo R^2		0.0712

FIGURE 4: *Job Stress as a Significant Predictor of Exit for Reverse Retirees*



Note:

differences in predicted exit probabilities by age and stress level are shown in Figure 4.[6]

These findings are consistent with Nekoei et al. (2024), who show that subjective reports of job stress are highly predictive of burnout—as measured by stress-related sick leave—in administrative data from Sweden. Indeed, they find that subjective stress responses outperform administrative predictors of burnout. Our results suggest that job stress, as a proxy for burnout, contributes to labor force exit decisions, particularly for individuals more sensitive to its effects.

Observation (ii): ***Polygenic Risk Scores predict job stress and their distributions differ between Permanent and Reverse Retirees.***

To explore potential sources of heterogeneity in preferences and responses to stress or burnout, we use Polygenic Risk Scores (PGS) attached to biometric samples collected from HRS respondents, obtained in 2006-12 Ware et al. (2024b). A PGS is a number indicating an estimate of a person's genetic predisposition to particular traits or diseases based on the joint effects of single nucleotide polymorphisms (SNPs). The collection and relative contribution of the SNPs most associated with different traits are identified through genome-wide association studies (GWAS).

While PGSs are not deterministic, they are predictive of a range of behavioral and health outcomes. In this analysis, we focus on two scores: one associated with anxiety (Angst/Anxiety) and another with cortisol regulation. Both variables are standardized to have a mean of zero and a variance of one (though the empirical variance in the HRS sample exceeds one). PGSs are constructed within ancestry groups: African, Hispanic, and European. Because the distribution of polygenic scores differs across these groups, we restrict our presentation here to the largest subsample European ancestry group (77 percent), within which measures are more comparable. Results for African ancestry respondents are similar, while results for Hispanic ancestry respondents exhibit larger variation in our sample. Further details on the construction and interpretation of these scores are provided in Appendix A.1.[7]

Table 4 presents the results of a logistic regression on factors predicting job stress among working respondents. In the upper panel, we see that, all else equal, the probability of reporting job stress is higher for women, and the strongest positive predictors of job stress include working full-time, earning more, and having at least one indicator of depression. The likelihood of reporting job stress decreases with age, and is less likely if one is also in good health.

The second panel shows the difference between job stress for Permanent and Reverse Retirees, and whether that work is continuous or at a time of re-entry for Reverse Retirees. Reverse Retirees report somewhat lower stress while working. Additionally, it is worth noting that while stress does differ somewhat across occupations, the difference between full-time and part-time workers' stress levels within each occupation is substantially larger. This motivates our decision to focus on work status rather than occupation in modeling stress exposure.[8]

At the same time, as shown in Table 3, Reverse Retirees are more likely to exit when experiencing

[6]In alternative specifications, we found no significant interactions between Reverse Retiree status and health, occupation, or education variables.

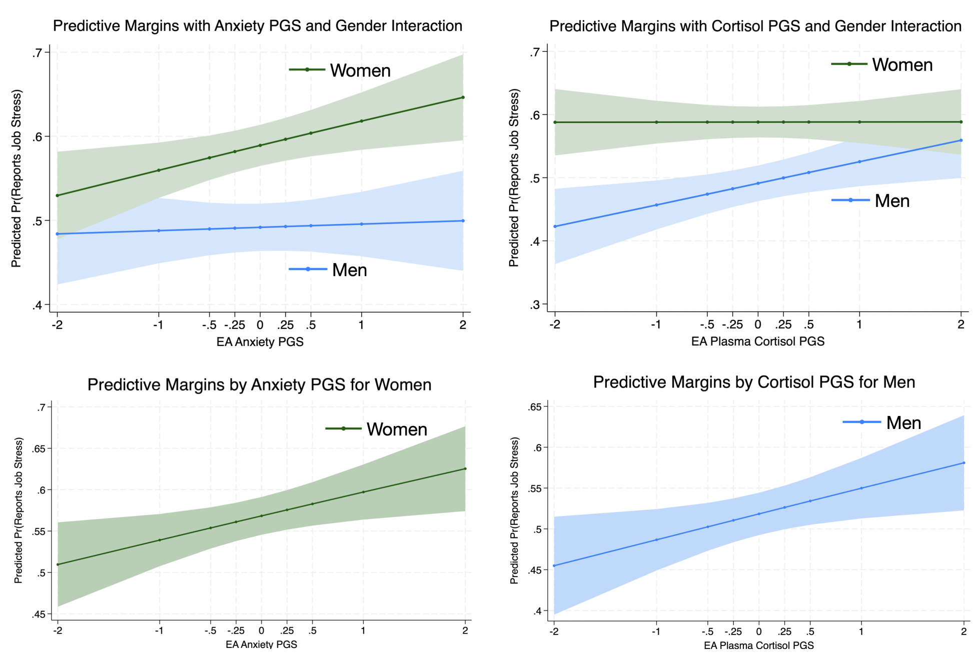
[7]For other applications of PGSs to older-age aging and work, see, for instance, Barth et al. (2020), who show connections between polygenic scores and economic outcomes in the HRS, Schmitz et al. (2022) on the interaction between socioeconomics and epigenetic age acceleration, and Furuya and Fletcher (2024), who use U.K. data to show how retirement affects biological age.

[8]Table A.9 in Appendix A.4 gives job stress reported by occupation category and whether working full time or part time, as well as the proportion within age categories who report that their job is stressful.

Table 4: *What Predicts Job Stress*

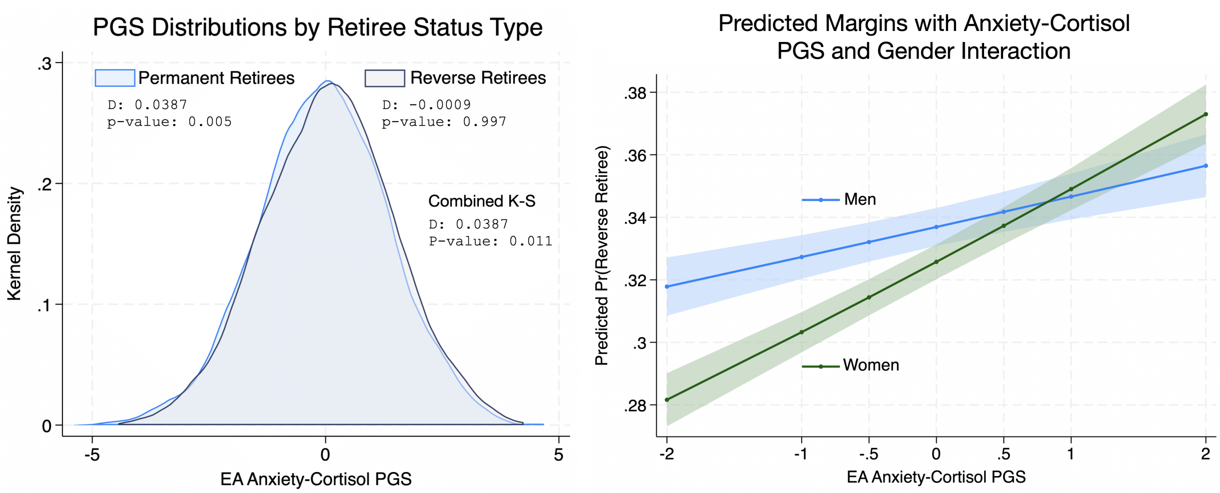
Logit, Outcome: Reports Job is Stressful	**Coefficient**	**(s.e.)**	**P-value**
Age	-0.041	(0.004)	0.000
Female	0.417	(0.044)	0.000
Working Full-Time ($\geq$ 30 hrs/wk)	1.288	(0.427)	0.003
ln(Earnings)	0.284	(0.035)	0.000
Work Status × ln(Earnings)			
FT $\geq$ 30 hrs	-0.046	(0.042)	0.276
CES-D (Depression Indicator)	0.541	(0.039)	0.000
Self-Rated Health Good to Excel.	-0.366	(0.065)	0.000
Ever Rev. Retire, Continuing work	-0.123	(0.040)	0.002
Rev. Retire, Re-entering work	-0.353	(0.121)	0.004
Cortisol PGS	0.097	(0.027)	0.000
Female × Cortisol PGS	-0.044	(0.038)	0.243
Anxiety PGS	-0.043	(0.027)	0.120
Female × Anxiety PGS	0.074	(0.038)	0.054
(Occupation Category Controls)			
Constant	-0.547	(0.457)	0.232
Observations		15,887	
LR Chi-square (21)		2272.34	
Pseudo R^2		0.1043	

Figure 5: *Anxiety-Cortisol PGSs, Gender, and Job Stress*



Note: The upper two graphs are of the predictive margins for job stress across two standard deviations of the Anxiety/Angst (left) and Cortisol (right) PGSs for men and women corresponding to the regression results in Table 4. The lower two graphs include results from a similar logistic regression on men and women separately, with the margins across the Anxiety/Angst PGS for women (left), and Cortisol PGSs for men (right).

FIGURE 6: *Anxiety-Cortisol PGS Distributions and Predictions for Permanent vs. Reverse Retirees*



Note: (Left) Combined Kolmogorov–Smirnov for PGS distributions of Permanent and Reverse Retirees suggests statistically distinct distributions. (Right) Adjusted predictions of whether Reverse Retirees at PGS margin and gender interaction. Controls for education, initial income, marital status, birth year, and occupation.

job stress, suggesting positive selection into continued employment among those who remain. Upon returning to work, Reverse Retirees report lower levels of job stress, consistent with selection into re-entry following a period of recovery. Because job stress is predicted to be much lower for part-time workers and re-entrants, regardless of occupation, a similar process may explain both reverse retirement and the high rates of part-time work observed at older ages despite commonly observed wage penalties for both. Additionally, what predicts job stress within an age band, and measuring primarily continuous workers, we find that eventual reverse retirees are no more or less likely to report job stress. This further supports the idea that it is not baseline stress exposure, but rather differential sensitivity and recovery, that distinguishes the two groups.

Finally, in the third panel of Table 4, we see the contribution of PGSs on Cortisol and Anxiety in predicting job stress. Having a higher Cortisol PGS is a modest though significant predictor of reporting job stress, and the interaction term suggests it does not differ greatly between men and women. A higher Anxiety/Angst PGS does not significantly affect the probability of job stress for men, though it does for women. The marginal effects on the probability of reporting job stress are shown in the graphs in Figure 5.

In addition to the associations between (a) job stress and being a Reverse Retiree and (b) job stress and Anxiety/Angst and Cortisol PGSs, there is also a relationship between (c) being a Reverse Retiree and Anxiety/Angst and Cortisol PGSs. The graph on the left in Figure 6 shows that Cortisol PGS distributions differ between Permanent and Reverse Retirees controlling for several factors. While the difference is not striking visually, a Kolmogorov–Smirnov test for equality of distribution functions rejects the hypothesis that Permanent and Reverse Retirees are drawn from the same distribution. The graph to the right in Figure 6 shows the predictive margins for the interaction term of the Anxiety/Angst and Cortisol PGSs in a logistic regression where the outcome is whether a person is or is not an eventual Reverse Retiree, with full results in Appendix A.4, Table A.7. While most regressors have limited explanatory power in predicting Reverse Retiree status, these

PGSs are among the more significant predictors.

Bringing Observations (i) and (ii) together, there is an apparent relationship between PGS and whether one is a Reverse Retiree, mediated by likelihood of job stress and responsiveness to job stress through earlier exit and later re-entry into work. The model we estimate allows for heterogeneity in preferences, where some types of individuals may place greater weight on the disutility from job stress or burnout. In this framework, PGS serve as predictors of preference type, helping to capture individual differences in stress sensitivity.

Observation (iii): ***CES-D recovery predicts re-entry; recovery slightly greater for Reverse Retirees***

Our final observation motivates the inclusion of a "recovery" process in the model for those leaving work due to increasing burnout. Because responses to whether one's job is stressful can only be observed when an HRS respondent is working, to understand possible recovery in non-work periods we use an indicator of the presence of depressive symptoms, CES-D which is correlated with job stress and collected whether the respondent is working or not. We present a 0-1 binary version of whether any of depression indicators are present where 0 means no depressive symptoms and 1 means at least one symptom is present.[9]

We find that there is a moderate reduction in the CES-D index when not working, with the reduction being steeper for those who will eventually re-enter paid work.

Those Reverse Retirees who would eventually re-enter paid work, overall, were more likely to maintain a CES-D indicating 0 depressive symptoms or were more likely to "recover", going from a CES-D of 1 just before exiting work to 0 after a short time out of work. Table 5 shows transitions in the presence of depressive symptoms across work status changes for Permanent and Reverse Retirees. These are predicted margins from a multinomial logit regression controlling for age at first exit from work, assets, marital status, gender, and health. Among those who will be Permanent Retirees, 49.5 percent were observed having a CES-D of 0 (no depressive symptoms). Of those, 66.7 percent remained having no depressive symptoms in the two years following their exit from work while 33.3 percent developed at least one symptom. Among eventual Reverse Retirees, a somewhat higher 53.2 percent had a CES-D of 0 just before exiting work, and also saw a higher proportion of 70.8 percent continuing to have 0 recorded symptoms after their initial exit. Just over half of Permanent Retirees—50.5 percent—had a CES-D of 1, indicating at least one recorded depressive symptom, before exiting work and 31.2 percent improved to reporting 0 symptoms. Eventual Reverse Retirees were somewhat less likely to have CES-D of 1—46.8 percent—and a higher share, at 38.0 percent, improved compared to Permanent Retirees improved.

A related observation in the HRS data is on the occurrence and timing of re-entry: The probability of re-entering paid work is associated with age, self-reported health, reported satisfaction with retirement, and transitions in CES-D. Table 6 shows results from a logistic regression where the outcome is returning to paid work over the default of remaining out of work. All else constant, the likelihood of returning to work declines with age. Health and its interaction with age are less precisely estimated. Those who report not being very satisfied with retirement are not necessarily more likely to return to work. However, re-entry is more likely in any period for those who either maintained a CES-D of 0 before and after their initial exit from work or recovered from a CES-D

[9] This is variable `RwCESD` from the RAND version of the HRS data, described in Appendix A.1.

Table 6: *Recovery in CESD Increases Probability of Re-Entry*

Logistic Regression with Outcome: Return to Work *Base Outcome: Remain out of work*			
	Coefficient	(s.e.)	**P-value**
Age	-0.162	(0.018)	0.000
Self-rated Health (good or better)	-0.829	(1.289)	0.520
Self-rated Health × Age	0.020	(0.019)	0.295
Years since first exit	0.003	(0.008)	0.730
CES-D transition			
$1 \to 1$	-		
$0 \to 1$	0.014	(0.154)	0.560
$1 \to 0$	0.190	(0.158)	0.093
$0 \to 0$	0.280	(0.140)	0.046
Retirement Satisfaction			
Very satisfied	-		
Moderately or not satisfied	0.039	(0.286)	0.163
(Occupation Category Controls)			
(Education Category Controls)			
(Birth Year Cohort Controls)			
Constant	10.278	(1.348)	0.000
Observations	6,649		
Log likelihood	-1449.34		
LR Chi-square (28)	287.94		
Pseudo R^2	0.090		

Figure 7: *Re-Entry Rates, Predictive Margins by Recovery*

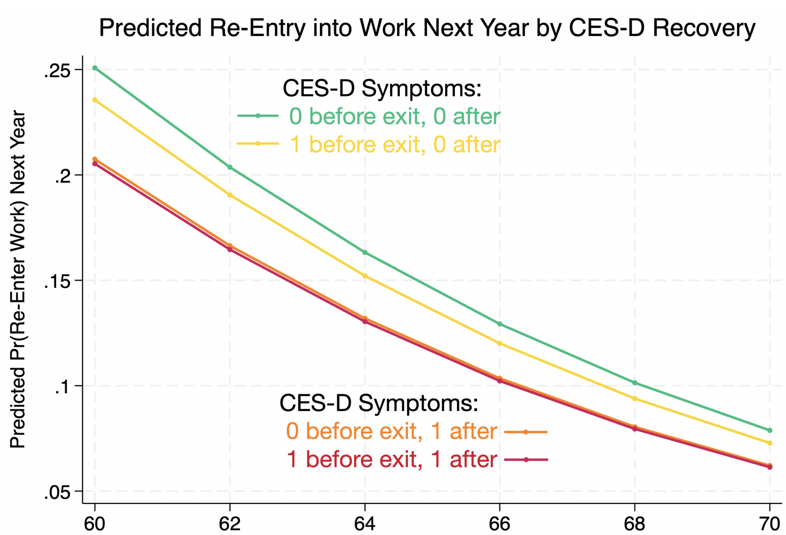


Table 5: *Change in CES-D when Not Working: Greater Recovery for RRs*

	Permanent Retirees	*Reverse Retirees*
Percent with CES-D 0 Before Exit	49.5%	53.2%
0 After Exit	.667	.708
1 After Exit	.333	.292
Percent with CES-D 1 Before Exit	50.5%	46.8%
0 After Exit	.312	.380
1 After Exit	.687	.620

Note: Predictive margins from a multinomial logit controlling for age, assets, marital status, gender, and health. All margins significant at 5% level. These results for recovery holding controls at means look nearly identical to the simple tabulation.

of 1 to 0 after stopping work.

To summarize from our findings on patterns and respondent characteristics in the HRS, we conclude that while Permanent and Reverse Retirees are quite similar on a number of basic demographic characteristics, there are differences in the relationships among job stress and exit from work, polygenic risk scores, and re-entry. Although these factors alone do not determine reverse retirement, these observations suggest a role for heterogeneity in preference types and a burnout-recovery process in work decisions. Together, these observations motivate the inclusion of a burnout–recovery process in model design and estimation, which we turn to in the next section.

3. A Model of Retirement, Burnout, and Recovery

The present framework extends the rich retirement, health, and savings models of French (2005) and French and Jones (2011), which incorporate unobserved heterogeneity in preferences. We build on this foundation by introducing a burnout–recovery process that captures the dynamic relationship between work and psychological strain at older ages. Our emphasis on the dynamic relationship between work and stress is similar in spirit to Jolivet and Postel-Vinay (2024). The estimated model allows us to (1) determine the extent to which a burnout-recovery process matters for generating the high levels of reverse and partial retirement we see in the data, beyond what can be explained by health, financial, or preference shocks alone, and (2) quantify the effects of various policy interventions around typical retirement ages.

We model the decisions of a person making decisions from age 50 on about whether and how much to work, consume and whether to claim Social Security retirement benefits. Decisions are made annually, with each period indexed by age t. At each point in time, individuals make choices based on the distributions of future earnings, job stress, health status, medical expenses, and mortality, conditional on their current state. Each person makes decisions that in expectation maximize current utility and future expected discounted utility, expressed as

$$u(C_t, L_t) + E\left[\sum_{j=t+1}^{T+1} \beta^{j-t}\left(\prod_{k=t}^{j-1} s_k\right)\Big[s_j u(C_j, L_j) + (1-s_j)B(A_j)\Big]\right], \tag{1}$$

where β is the discount factor on future utility; s_t is the probability of surviving to age t conditional on health and having survived to age $t-1$; $B(A_t)$ is the utility value of leaving A_t in assets as bequests in the event of death at age t or reaching terminal age T. The worker maximizes their expected lifetime utility in (1) given the preferences, constraints, and uncertainty outlined below.

3.1. Preferences

The per-period utility is assumed to take a constant relative risk aversion (CRRA) form as

$$u(C_t, L_t) = \frac{1}{1-\nu}\left(C_t^{\alpha_C} L_t^{1-\alpha_C}\right)^{1-\nu} . \tag{2}$$

where C_t denotes consumption, L_t denotes leisure, α_C and ν are preference parameters indicating weight on consumption and degree of risk aversion, respectively.

The work participation decision P_t can take on the values FT (full-time work), PT (part-time work) or R ("retired" or not working) in all periods. The quantity of leisure the worker enjoys, which will also depend on health and whether she was working last period, is given by

$$L_t = L - N_t - \phi_H \mathbb{1}_{H_t=\text{Bad},P_t\neq 0} - \phi_{RE} RE_t - FC_t - \alpha_B B_t \tag{3}$$

where L is the total annual time endowment measured in hours. The hours worked N_t is equal to zero when $P_t = \text{R}$, 1,500 when $P_t = \text{PT}$, and 2,000 when $P_t = \text{FT}$. To capture the empirical fact that health status is correlated with participation and reentry decisions, we allow the quantity of leisure to depend on an individual's health status through ϕ_H where $H_t \in \{\text{Good, Bad}\}$. Workers who leave the labor force then re-enter incurs the time cost of ϕ_{RE}, where RE_t is a 0-1 indicator equal to one when $P_t = \text{FT}$ or PT and $P_{t-1} = \text{R}$. The last two terms capture the fixed costs of working and the burnout-recovery process, respectively, as explained below.

We define the fixed costs of working that vary with age and hours, FC_t in equation (3), as

$$FC_t = (\phi_P + \phi_{P,t})\mathbb{1}_{P_t=\text{PT or FT}} + \phi_{\text{FT}}\mathbb{1}_{P_t=\text{FT}} . \tag{4}$$

Coefficients ϕ_P and $\phi_{P,t}$ in (4) represent the fixed cost components of work participation, which may vary with age t. The final term, with coefficient ϕ_{FT}, captures the differential utility cost that may be experienced with full-time compared to part-time work hours.

Finally, To incorporate the burnout–recovery process into the model, we introduce a disutility term governed by the coefficient α_B in equation (3), which captures the utility cost of accumulated burnout. The stock of burnout at time t, denoted by B_t evolves according to (5). If an individual works in the previous period $t-1$, then B_t increases by α_S^{FT} if work was full-time and stressful (i.e. $\text{str}_t = 1$), and further increases by α_{WL} if the individual exhibited depressive symptoms ($W_t = 1$). For part-time work, burnout accumulates similarly, but we allow the contribution of stressful work to differ, denoted α_S^{PT}.

In contrast, if the worker did not work then B_t is reduced by the recovery parameter R_{WH} in the following period, and further reduced by R_{WH} if lacking depressive symptoms ($W_t = 0$). The wellbeing indicators $W_t = 0$ and $W_t = 1$ correspond to the CES-D indicator in the HRS, described in Section 2.2.2. Formally, the stock of "burnout" is

$$B_t = \begin{cases} B_{t-1} + \alpha_S^{\mathrm{FT}} \mathrm{str}_t + \alpha_{WL} \mathbb{1}_{W_{t-1}=1} & \text{if } P_{t-1} = \mathrm{FT} \\ B_{t-1} + \alpha_S^{\mathrm{PT}} \mathrm{str}_t + \alpha_{WL} \mathbb{1}_{W_{t-1}=1} & \text{if } P_{t-1} = \mathrm{PT} \\ B_{t-1} - R_{WL} \mathbb{1}_{W_{t-1}=1} - R_{WH} \mathbb{1}_{W_{t-1}=0} & \text{if } P_{t-1} = R\,. \end{cases} \tag{5}$$

If death occurs between time $t-1$ and t, or terminal T is reached, the individual bequeaths assets A_t and values this as, following De Nardi (2004),

$$b(A_t) = \frac{\theta_b \left(A_t + K_0\right)^{(1-\nu)\alpha_C}}{1-\nu}\,. \tag{6}$$

In De Nardi et al. (2010), parameter K_0 marks the degree to which assets can be interpreted as intended bequests; without this it is difficult to distinguish bequest motives from consumption-smoothing or precautionary savings. The utility weight on bequests is θ_b

In estimation, described below, we allow for heterogeneity in preferences over the weight on the burnout-recovery process, α_B, the fixed cost of work ϕ_P, and relative risk aversion, ν.

3.2. Budget Constraints

Total income Y_t includes several potential sources: asset income rA_t, where r is the pre-tax interest rate; own income from working; $y_t(P_t)$, spousal income y_t^{sp}; Social Security benefits as function of typical past income PI, $\mathrm{ss}_t(\mathrm{PI})$, if one has applied for them ($\mathrm{ss}_t = 1$); and outside transfers tr_t:

$$Y_t = Y\left(rA_t + y_t(P_t) + y_t^{\mathrm{sp}} + \mathrm{ss}_t(\mathrm{PI}) + \mathrm{tr}_t,\, \tau\right), \tag{7}$$

where τ is the income tax structure. The asset accumulation equation is

$$A_{t+1} = (1+r)A_t + Y_t - C_t\,. \tag{8}$$

To reflect empirical patterns, additional net borrowing is limited:

$$A_t + Y_t - C_t \geq 0\,. \tag{9}$$

Following Hubbard et al. (1995) and French and Jones (2011), outside transfers $\mathrm{tr}_t = \max\{0,\ \underline{c} - (A_t + Y_t)\}$ provide a consumption floor $\underline{c}$ so that $c_t \geq \underline{c} > 0$, which is necessary for estimating risk aversion levels.

Social Security Benefits, importantly, apply the Retirement Earnings Test (RET): If claiming Social Security retirement benefits and also working, earned income beyond a certain threshold results in contemporaneous benefits being reduced and credited back upon reaching one's Full Retirement Age. The adjustment is actuarially fair, though from the perspective of a budget constrained, risk averse person with subjective life expectancy, the delayed benefit is not neutral. These adjustments are part of the tax structure τ and the elimination of the RET is one of three counterfactual policy simulations presented in Section 6. Details about Social Security benefits formula and the Retirement Earnings Test are in Appendix A.3.

3.3. Timing of Decisions and Dynamic Choices

Each period a person chooses consumption, work, and Social Security claiming to maximize current and expected future utility, as in equation (1), denoting these decision variables as $\mathcal{D}_t = \{C_t, P_t, \mathrm{SS}_t\}$. Choices are made with knowledge of state variables but uncertainty over future earnings, job stress, health and wellbeing, and mortality.

Let X_t denote the vector of state variables at time t, which includes

$$X_t = \{A_t, H_t, W_t, P_{t-1}, B_{t-1}, \mathrm{SS}_{t-1}, \mathrm{PI}\} \tag{10}$$

where A_t is assets, H_t is health, W_t is wellbeing (CES-D), P_{t-1} is previous period's work status, B_{t-1} is accumulated burnout, SS_{t-1} is Social Security claiming status, and PI is past income. Table 12 summarizes all variables included in the model.

The value function is given by

$$V_t\left(\mathbf{X}_t\right) \quad = \quad \max_{\mathcal{D}_t}\Big\{u(C_t, L_t(P_t)) + \beta\left(1 - s_{t+1}\right) b\left(A_{t+1}\right) + s_{t+1} EV_{t+1}\left(\mathbf{X}_{t+1}\right)\Big\}, \tag{11}$$

where s_{t+1} is the survival probability to age $t+1$ and the expected continuation value is

$$EV_{t+1}\left(\mathbf{X}_{t+1}\right) = \max_{\mathcal{D}_{t+1}} \int V(\mathbf{X}_{t+1})\, dF(\mathbf{X}_{t+1} \,|\, \mathbf{X}_t, \mathcal{D}_t, t)$$

subject to asset accumulation in (8) and the borrowing constraint in (9). The distribution of next period's earnings, job stress, health and wellbeing, and mortality conditional on current state and choice variables is $dF(\mathbf{X}_{t+1} \,|\, \mathbf{X}_t, \mathcal{D}_t, t)$.

The solution to the individual's problem consists of the decision rules on consumption and participation choices that solve (11) recursively from terminal period T. Next we will describe the procedure for estimating the parameters of this model.

4. Estimation Procedure

We estimate the model using the method of simulated moments (MSM), which allows us to identify the preference parameters that generate simulated life-cycle decision profiles most consistent with those observed in the data. Following a two-stage estimation strategy similar to Gourinchas and Parker (2002), French (2005), and French and Jones (2011), we separate the estimation of structural parameters into two steps to reduce computational complexity. In the first stage, we estimate parameters that can be identified outside the model, including the transition probabilities for state variables such as health, job stress, and wages. In the second stage, we jointly estimate the preference parameters and the parameters governing type heterogeneity, using the first-stage estimates as inputs.

4.1. First-Stage Estimates

In the first stage, we estimate parameters that are determined outside the structural model. These include wage profiles, health transition and survival probabilities, and the distribution of

Table 12: *Summary of Variables*

	Description
State Variables, $\mathbf{X}_t$*:*	
A_t	Total assets
H_t	Health status: good or bad
W_t	Well-being/binary CESD measure
P_{t-1}	Participation decision last period: R, PT, or FT
B_{t-1}	Burnout stock
SS_{t-1}	Began claiming Social Security earnings
PI	Permanent income
Choice Variables, $\mathcal{D}_t$*:*	
P_t	Labor force participation decision, $P_t \in \{\mathrm{R}, \mathrm{PT}, \mathrm{FT}\}$
C_t	Consumption
SS_t	To begin claiming Social Security
Preference Parameters:	
Shared:	
β	Time discount factor
α_C	Consumption weight
θ_B	Bequest weight
K_0	Bequest shifter
ϕ_H	Leisure cost of working with Bad health
ϕ_{FT}	Leisure cost of working full time
ϕ_{RE}	Leisure cost of re-entering work
$\phi_{P,t}$	Fixed cost of working, time trend
α_S^{FT}	Additional B units if FT job is stressful
α_S^{PT}	Additional B units if PT job is stressful
α_{WL}	Additional B units if working and wellbeing is low
R_{WH}	Recovery: Additional reduction in B units if wellbeing is high
Varying by Preference Type:	
ν	Relative risk aversion
ϕ_P	Fixed cost of working
α_B	Weight on burnout-recovery process

work-related stress. These estimates are obtained directly from the data and used to calibrate the state transition processes in the model.

Wages. Measuring earnings towards the end of the work-life cycle and the role of reduced hours are important considerations given our emphasis on accounting for the high rates of part-time work observed at older ages. Although life-cycle earnings are often characterized as "hump shaped" over age, there are many possible contributors to the observed declines at older ages. Casanova (2013) notes that the commonly assumed declining wage-age profile is, rather, a declining *earnings*-age profile that reflects the increasing prevalence of part-time work among older workers, rather than true declines in offered wages. She argues that the correct specification for the offered wage profile may in fact be flat with age. This raises the question of whether older individuals reduce hours due to changing preferences or because productivity declines manifest as reduced hours rather than lower wages. Indeed, Rupert and Zanella (2015) find that for most cohorts in PSID data, wages do not decline with age, and reduced average earnings with age come from both dramatic and gradual reductions in hours approaching eventual retirement.[10] More generally, Chang et al. (2011) show that properly considering part-time work is necessary for getting labor supply elasticity estimates correct: If not accounted for, estimates of the intertemporal elasticity of substitution of labor supply could be biased upwards; Rupert and Zanella (2015) provide adjusted profiles that avert precisely this concern.

We estimate earnings through a two-stage selection model separately for men and women. Letting Work_i be an indicator for whether individual i is working for pay, we estimate selection into work

$$\begin{aligned}\Pr\big(\text{Work}_i = 1 \mid Z_i\big) = \Phi\Bigg(&\alpha_0 + \sum_a \alpha_a \mathbb{1}_{\text{Age Cat}_i = a} + \beta_1 \,\text{ihs}(\text{Initial Assets}_i)\\ &+\beta_2 \ln(\text{Initial Earnings}_i) + \beta_3 \,\text{ihs}(\text{Initial Assets}_i) \times \ln(\text{Initial Earnings}_i)\\ &+\beta_4 \mathbb{1}_{\text{Good Health}_i} + \sum_e \eta_e \mathbb{1}_{\text{Educ}_i = e}\Bigg),\end{aligned} \tag{12}$$

where $\Phi(\cdot)$ is the standard normal c.d.f., age category $a \in$ <50, 50–54, 55–59, ..., 75–79 , education $e \in \{<\text{HS}, \text{GED}, \text{HS}, \text{Some Col}, \text{College+}\}$.

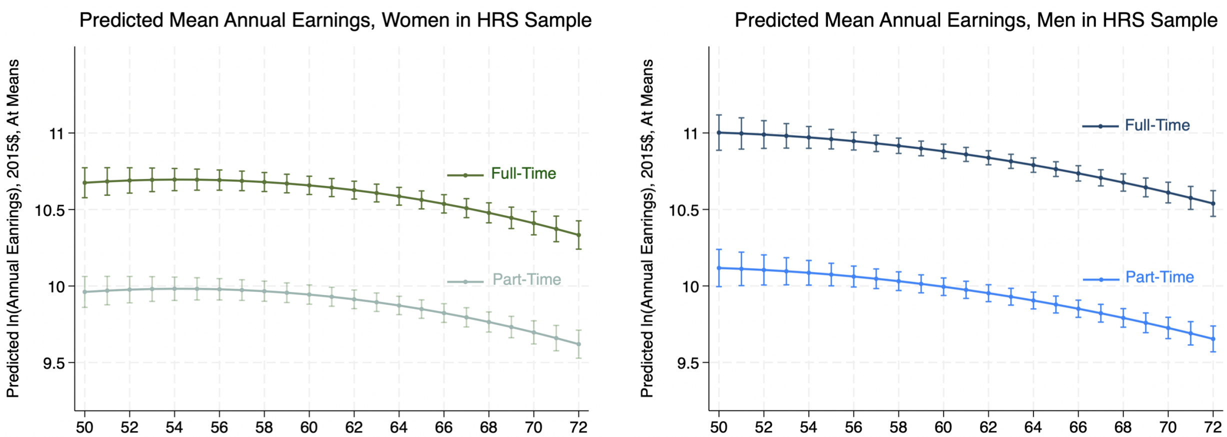
We estimate log annual earnings conditional on selecting into work, ($\text{Work}_i = 1$), through

$$\begin{aligned}\ln(\text{Earnings}_i) = \;&\gamma_0 + \gamma_1 \text{Age}_i + \gamma_2 \text{Age}_i^2 + \gamma_3 \mathbb{1}_{\text{FT}} + \gamma_4 \mathbb{1}_{\text{Good Health}} + \gamma_5 \mathbb{1}_{\text{FT}} \times \mathbb{1}_{\text{Good Health}}\\ &+ \theta_1 \ln(\text{Initial Earn}) \times \mathbb{1}_{\text{Initial LFP=PT}} + \theta_2 \ln(\text{Initial Earn}) \times \mathbb{1}_{\text{Initial LFP=FT}}\\ &+ \sum_a \delta \mathbb{1}_{\text{Age Cat}_i = a} \times \widehat{\lambda}_i + \rho \widehat{\lambda}_i + u_i,\end{aligned} \tag{13}$$

where $\widehat{\lambda}_i$ is the inverse Mills ratio constructed from the probit in (12), and u_i is the second-stage disturbance. Full-time status is $\mathbb{1}_{\text{FT}}$ (baseline: part-time), and "Good Health" includes those self-reporting good, very good, or excellent health. The specification includes interaction of the Mills ratio with age category dummies to reflect possible differences in selection patterns across

[10] Angrisani et al. (2017) argue that it could be the nature of any part-time work is different, in addition to the reduced hours alone providing more work-life balance that people may be willing to pay for, increasingly so with age. While differences in part-time compared to full-time work *within an occupation* are not explicitly accounted for here, this aspect is captured through reduced stress and contributions to burnout in the model.

FIGURE 8: *Predicted Annual Earnings Trajectories*



age and also includes the standalone Mills term. Estimates here align with many findings about lower hourly pay when working part-time at older ages, as described in Casanova (2013), and the difference between part-time and full-time pay being smaller for women, as Aaronson and French (2004) find. Figure 8 shows predicted annual earnings by for full- and part-time work for someone with constant, average characteristics under the estimates of Equations (12) and (13) in Table A.10 in Appendix A.4. All else equal, with these coefficients on age and age squared, wages are declining with age after 50–54.

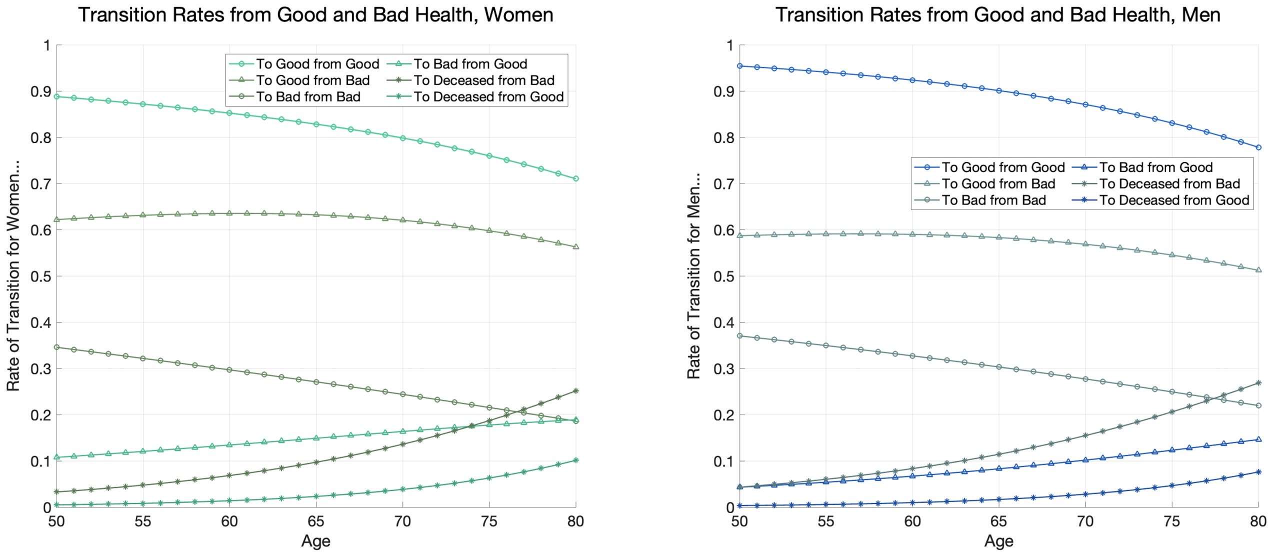
Health and Mortality Transitions. Health transitions are measured through an ordered probit, in which expectations on future health status depend on current self-reported health status and age.[11] The statuses are divided into *"Good, Very Good, or Excellent"*, or *"Fair or Poor"*. While, at most ages, 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 and mortality transition probabilities are shown in Figure 9.

Stress and Wellbeing (CES-D) Transitions. An individual's expected level of stress arising from work depends on whether working full- or part-time, earnings, gender, health, age, and past participation status, with a specification and results similar to those in Table 4. To clarify the role of stress in the model, we treat stress exposure as observable and predictable from these covariates, while the coefficient on stress in the utility function—interpreted as equivalent leisure hours lost—is unobserved and estimated structurally. This stress exposure also informs the initial distribution of burnout B.[12] We also estimate the probability that an individual has any depressive symptoms, represented by wellbeing indicator W_t in the model—Equation (5)—and corresponding to CES-D

[11] Mortality probabilities also come from the HRS data, with the sample broadened to all in birth-years 1924-47. These are conditional on health status, gender, and survival to age 50.

[12] While baseline stress exposure does not differ significantly between Permanent and Reverse Retirees when conditioning on age and work status, as shown in Section 2.2, we do find considerable differences in how stress relates to labor force transitions. Reverse Retirees are more likely to exit work when reporting stress, and report lower stress upon re-entry. These patterns suggest that it is not the average stress levels that differ, but rather the utility cost of stress, which we capture through preference heterogeneity in the burnout–recovery process of the model.

FIGURE 9: Health and Mortality Transition Probabilities



measures in the HRS data, as presented in Section 2.2.2. The presence of at least one depressive symptom (CES-D$\geq$ 1) is predicted by age, work, health, and gender, with interactions among these variables and controls for initial assets, education, and cohort. The estimates are shown in Appendix A.4, Table A.11, with predictive margins across age, health, and gender in Figure A.2.

4.2. Second Stage Estimation

The transition processes from these first-stage estimates are fed into the model in the second stage of the model estimation process, where preference parameters are found. In the second stage, we find the preference and type prediction parameters that generate moments from simulated data that best match the moments from the HRS data using simulated method of moments (SMM). The moments for ages between 50-79 are matched to target the identification of the utility parameters.

Although men and women exhibit somewhat distinct behavior on average, we do not allow preference parameters to vary by gender in order to maintain a parsimonious model and focus on the broader mechanisms driving reverse retirement. Our framework captures gender-related variation through differences in initial state variables, wage trajectories, mortality profiles, and household income. While a richer model could incorporate gender-specific preferences or joint retirement decisions, our current approach is designed to highlight general patterns and the role of burnout–recovery dynamics in later-life labor supply.

These are the HRS data moments we seek to match with the model, which total $9A+2$ moments, where $A = 30$:

- *Assets* (M1): To capture consumption and bequest behavior, we match assets by age (50–79) at the 25$^{\text{th}}$, 50$^{\text{th}}$, and 75$^{\text{th}}$ percentiles, yielding $3A$ moments. The risk coefficient (ν), consumption share (α_C), and time discount (β) parameters are identified from the distribution of assets, which reflects precautionary motives. Bequest parameters (θ_B and K_0) are primarily identified from the upper percentiles, consistent with findings in French and Jones (2011) and De Nardi (2004) that bequest motives are most relevant for wealthier households.

- *Work and Initial Income* (M2): We match rates of full-time work and part-time work by initial income quartile and age (50–79), contributing $2 \times 4A$ moments. Age profiles help identify the cost of full-time work and the fixed and age-varying costs of part-time work (ϕ_{FT}, $\phi_{P,t}$ and ϕ_P), while variation across income quartiles helps further identify the consumption share and risk coefficient (α_C and ν).
- *Work and Health* (M3): To identify the time cost of bad health (ϕ_H), we include work by age (50–79) and health (good or bad), contributing $\frac{1}{2}A + 2 \times \frac{1}{2}A$ moments.
- *Work and CES-D* (M4a-b): To identify burnout and recovery parameters (α_S^{FT}, α_S^{PT}, α_{WL}, R_{WL}, R_{WL}, α_B), we match (a) exit rates from work by age (60–74) and CES-D (presence or absence of symptoms) and (b) Re-entry into work by age (60–74) and CES-D (presence or absence of symptoms), contributing $2 \times \frac{1}{2}A + 2 \times \frac{1}{2}A$ moments.
- *Social Security Claiming* (M5): To further inform β, α_C, we include percent claiming Social Security retirement benefits at the Early Retirement Age of 62 (1 moment).
- *Reverse Retirement* (M6a-b): We match (a) the overall rate of Reverse Retirement, and re-entry into full-time and (b) part-time work by age (60–74), yielding $\frac{1}{2}A + 2 \times \frac{1}{2}A + 1$ moments. These moments help identify the re-entry cost (ϕ_{RE}).

Preference Heterogeneity and Type Prediction

To account for differences in choices due to unobserved preferences, we incorporate permanent preference heterogeneity across individuals. This approach, used in French and Jones (2011) and others, and originating in Heckman and Singer (1984), assumes that each individual belongs to one of a finite number of preference types. These types differ in ways that allow the model to better replicate observed behavior under heterogeneous preferences. In our model, preference heterogeneity helps to account primarily for large differences in (1) assets and (2) susceptibility to burnout from work among individuals who are otherwise similar in observable characteristics.

We jointly estimate the preference type probability parameters with the preference parameters in the second step. Following French and Jones (2011), we assume three discrete preference types and allow variation across types in risk aversion ν, fixed cost of working ϕ_P, and the importance of the burnout-recovery process α_B.[13] We experimented with alternative specifications and found that two types did not provide sufficient flexibility to match the asset distribution, while four types led to redundancy, with two types converging to similar parameter values. The probability of belonging to a given type is modeled as a function of initial conditions, including the anxiety–cortisol PGS, initial assets, income, and whether the respondent reports "enjoying work" when first observed in the data.

Assignment to a preference type i, with $i \in (1, 2, 3)$ is part of the second stage of estimation, and is determined by a multinomial logistic function: $P(\text{Type } i|X) = 1/(1 + e^{-\boldsymbol{\beta}X})$ where

$$\boldsymbol{\beta}X = \beta_0 + \beta_1 \text{PGS} + \beta_2 \text{Enjoys work} + \beta_3 \frac{\text{Initial Assets}}{\text{Income}} . \tag{14}$$

Coefficients in (14) are determined alongside estimation of preference parameters in the second stage of estimation. As an example of the mechanics of this aspect of the model, consider

[13] Note that α_B can be viewed as an amplifier or reducer that affects all burnout and recovery parameters through equations (3) and (5).

the "Enjoys work" variable, where HRS respondents are asked whether they (strongly) agree or (strongly) disagree with the statement "I enjoy work."[14] While this does not tell us directly what a respondent's disutility or fixed cost of working is, it does contribute to the identification of the fixed cost of work, ϕ_P: individuals who report enjoying work are more likely—via a positive coefficient β_2 —to be assigned to the preference type with a lower $\phi_{P,t}$. All else equal, we expect higher labor force participation among these individuals.

Simulated Method of Moments Process

Returning to the estimation procedure, the parameters estimated in the first step are represented by $\widehat{\chi}$. Further, let θ denote the vector of parameters estimated in the second step which includes parameters of utility function, fixed costs of work, and type prediction. The estimator $\widehat{\theta}$ is given by

$$\widehat{\theta} = \underset{\theta}{\operatorname{argmin}} \; \widehat{\varphi}\,(\theta, \widehat{\chi})' \,\Omega\, \widehat{\varphi}\,(\theta, \widehat{\chi}) \tag{15}$$

where $\widehat{\varphi}$ denotes the $9A+2$ vector of moment conditions, and Ω is a symmetric weighting matrix. We use a weighting matrix that contains the inverse of the estimated variance-covariance matrix of the estimates of the sample moments along the diagonal and zero elsewhere.

The solution to (15) is obtained by the following procedure

1. Compute sample moments and weighting matrix Ω from the sample data.
2. From the same data, we generate an initial distribution for health, wages, AIME, assets, accumulated work periods 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 $\widehat{\chi}$, we generate matrices of random health, wage, mortality, burnout from part-time work, and preference shocks. The matrices hold shocks for 10,000 simulated individuals.
4. Each simulated individual receives a draw of assets, health, wages, accumulated work periods, AIME, as well as preference type from the initial distribution, and is assigned one of the simulated sequences of shocks.
5. Given $\widehat{\chi}$ and an initial guess of θ, we 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 (15).
7. Pick a new value of θ, update the simulated distribution of preference types, and repeat steps 4-7 until we find the $\widehat{\theta}$ that minimizes (15).

5. Parameter Estimates and Simulated Behavior

The estimated preference parameters from the second-stage estimation, described in Section 4, are reported in Table 13. Using these estimates—together with the first-stage results and initial distributions derived from the HRS data—we evaluate model fit by simulating key life-cycle profiles, including work re-entry, labor force participation, and asset accumulation. These simulated profiles

[14] We also considered alternative indicators of work enjoyment, such as responses to "Would work even if I didn't need the money," but these were excluded due to limited coverage across HRS waves.

are then compared to their empirical counterparts from the HRS in the figures that follow.

5.1. Parameter Estimates

The upper panel of Table 13 shows parameters that are shared across preference types, while the lower panel shows parameters that vary across three preference types. While our inclusion of novel parameters governing the burnout–recovery process leads to shifts in some parameter values, the overall estimates are broadly consistent with those found in related structural models of retirement, health, and savings behavior broadly (Jones and Li, 2023; French, 2005; French and Jones, 2011; Jones and Li, 2018).

While our primary goal is to understand the role of the burnout–recovery process in explaining reverse retirement, descriptive evidence also suggests that part-time work plays a meaningful role. To capture this, we allow the fixed utility cost of working (ϕ_P) to vary across preference types, while keeping the age-varying cost and the cost of part-time work common across types. This structure reflects the idea that individuals may differ in their baseline willingness to work (the intercept), but share similar responses to age and hours worked (the slope). We also include a separate utility cost (or benefit) of working full-time, ϕ_{FT}, which is estimated to be modest—equivalent to roughly 200 hours of time cost—placing it at the lower end of estimates in the older-age labor supply literature.

In our framework, these fixed and full-time costs interact with the burnout–recovery process, which further shapes labor supply behavior. The parameters α_S^{FT}, α_S^{PT}, α_{WL}, R_{WL} and R_{WH}

Table 13: *Parameter Estimates*

Shared Preference Parameters		*Estimates* (s.e.)		
β	Time Discount Factor	.971 (.021)		
α_C	Consumption Weight	.55 (.04)		
θ_B	Bequest Weight	.044 (.011)		
K_0	Bequest Shifter	\$273K (48K)		
ϕ_H	Leisure cost of working with bad health	202 (18)		
ϕ_{FT}	Leisure cost of working full time	49 (8)		
ϕ_{RE}	Leisure cost of re-entering work	107 (11)		
$\phi_{P,t}$	Fixed cost of working FT, time trend, age $t > 55$	17(t-55) (4)		
α_S^{FT}	Additional B units if FT job is stressful	.25 (.06)		
α_S^{PT}	Additional B units if PT job is stressful	.12 (.02)		
α_{WL}	Additional B units, wellbeing low while working	.22 (.07)		
R_{WH}	Recovery: Reduction in B units, wellbeing high	.88 (.09)		
Type-Specific Preference Parameters		*Type 1* (37.4%)	*Type 2* (47.3%)	*Type 3* (15.3%)
ν	Relative risk aversion	5.76 (.31)	3.37 (.28)	4.65 (.40)
ϕ_P	Fixed cost of working	153 (12)	150 (11)	159 (16)
α_B	Weight on B-R process	98 (7)	126 (7)	85 (6)
Percent of Type Reverse Retiring		.33	.39	.22

Note: Bootstrapped standard errors (s.e.) come from 100 re-samples of 500 simulated individuals.

govern how stress and recovery accumulate and affect utility. For example, the contribution to burnout B_t from working in a stressful full-time job is given by $\alpha_S^{\mathrm{FT}} \times \alpha_B$, where α_B is a type-specific weight on the burnout–recovery process. Based on our estimates, this translates into an additional utility cost equivalent to 24.5 hours for Type 1, 31.5 hours for Type 2, and 21.25 hours for Type 3—indicating that Type 2 individuals are most prone to burnout, while Types 1 and 3 are relatively more resilient.[15]

The estimated cost of re-entering work (ϕ_{RE}) is 107 hours, which is moderate and partially offset by the recovery benefit $R \times \alpha_B$ that accrues when not working. This estimate is comparable to the reentry cost of 94 hours found in French and Jones (2011) and lower than the roughly double cost estimated in Jones and Li (2018) for people aged 62-69. Our model's ability to match observed re-entry rates by age, health, and asset levels suggests that this lower re-entry cost is consistent with the data. This generates overall re-entry rates very close to what is seen in the HRS data.

In the next section, we assess how well the model replicates observed patterns in the HRS data by comparing simulated profiles of work, re-entry, and asset accumulation to their empirical counterparts.

5.2. Model Fit: Simulated vs. Observed Profiles

To evaluate the model's ability to replicate observed behavior, we compare simulated profiles to empirical patterns in the HRS data across several key dimensions: labor force participation (full-time and part-time), health status, asset accumulation, and re-entry into work. These comparisons serve as a test of the model's capacity to capture the mechanisms driving reverse retirement.

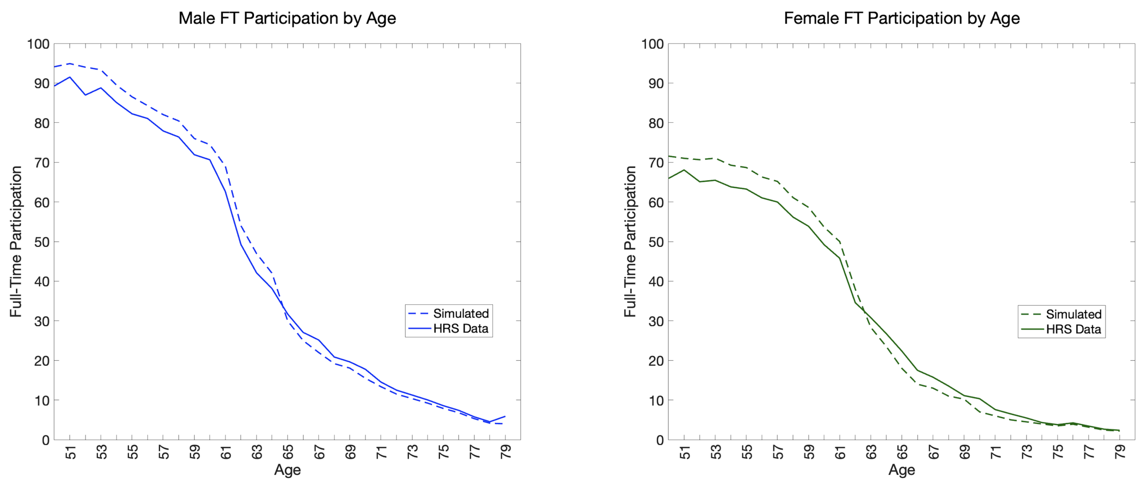
The first set of graphs in Figure 10 show profiles of simulated data compared to HRS data for full-time work rates on the left, and part-time work rates on the right by age for. Rates for men are in the upper panel (A) and for women are in the lower panel (B). The overall rates for men and especially women of these birth cohorts are much higher than for the broader population, as inclusion in the HRS sample requires having been observed working at least once (stronger selection for females) and observed in the HRS data (stronger selection for males). They do, however, show the same overall patterns seen across the population, with declining rates of overall participation and higher proportions of work being in part-time roles with age. Full-time simulated participation rates for both men and women match the HRS data fairly well, with some overestimates in full-time work and underestimates in part-time work at younger ages, which flip beyond ages 62–65. For part-time profiles, the lower estimated part-time earnings seem to result in less part-time work at younger ages than is seen in data. At older ages, the higher simulated rates part-time work compared to what is in the HRS data suggest the effects of the Retirement Earnings Test (RET) pushing those who claim Social Security benefits before the Full Retirement Age to shift to part-time work may be overestimated. Figure 10c shows a similar picture of part-time work from another angle, giving the share among those who are working who are in part-time work. The share of workers who are part-time is relatively low at younger ages, with significant increases in the share past ages 61–62.

At older ages especially, labor force participation is highly dependent on health status. In the

[15] Although these parameters are bounded between 0 and 1 conceptually, they were not constrained during estimation.

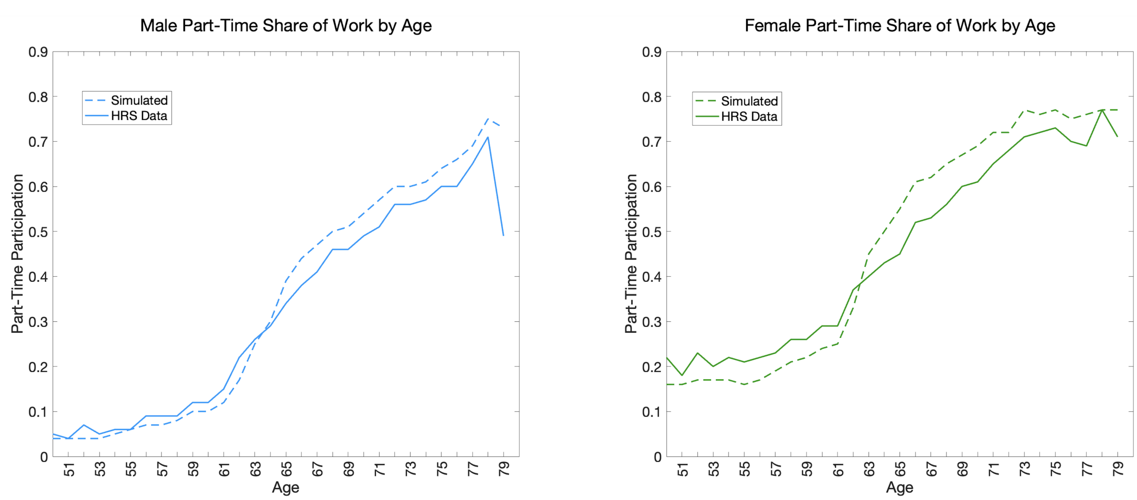
Figure 10: *HRS and Simulated Full- and Part-Time Work by Age*

(a) Full-Time Participation by Age, Men (left) and Women (right)



(b) Part-Time Participation, Men (left) and Women (right)

(c) Share of Total Working Part-Time, Men (left) and Women (right)



model this is generated primarily by the parameter ϕ_H, the leisure cost of working while in bad health in terms of leisure hours lost. This also is a result of lower earnings due to being in bad health; controlling for selection into work, however, this reduction is on net very small. The graphs in Figure 11 show the differences in total (part-time and full-time) rates of paid work for those in good and bad health by age for men (left) and women (right). On these measures, simulated and HRS data rates align quite well. This is important in more precisely estimating the distinct burnout-recovery process. Notice that for both men and women, participation across health states is more distinct at younger ages, and a smaller share of people at these ages would be categorized as having bad health.

In Figure 12, we show simulated and actual HRS non-housing household asset levels at the 25^{th}, 50^{th}, and 75^{th} percentiles by age. While savings behavior is not the primary focus of this study, this is a prominent part of older-age decisions; it contributes especially to estimation of risk aversion parameter ν, consumption weight α_C, bequest parameters K_0 and θ_B, and is sensitive to assumptions about the guaranteed consumption floor $\underline{c}$. We allow for heterogeneity in ν, which is one way to generate the significant spread of assets seen in the data among otherwise similar households. Simulated non-housing assets align reasonably well with levels in the HRS data, though somewhat over-estimated at the median for all ages and under-estimated at the 75th percentile past age 56. The very low simulated assets at the 25th percentile match the HRS data well.

Finally, we have re-entry rates by age among those not working. This is shown for re-entry into any work and part-time work in Figure 13a, and by presence or absence of depressive symptoms in Figure 13b. We had seen that overall shares of work that was part-time increased with age we also see something similar among re-entries into work, where Figure 13a shows an increasing proportion of re-entrants go into part-time work with age. An important set of moments in the model, the simulated data matches overall patterns. There are, however, larger differences between re-entry into part- and full-time work, and simulated rates of re-entry overall are somewhat higher than in the data. While the overall rates of reverse retirement in the simulated and actual HRS data are very close, the model generates more people with more than one re-entry, and this is seen in the overall higher simulated re-entry rates at most ages. Figure 13b shows the re-entry rates by age for those who did and those who did not have depressive symptoms when not working. The measures in the HRS data are somewhat noisy, especially among females, however generally re-entry is higher among those for whom there are no depressive symptoms reported. This is seen in the simulated data, somewhat more starkly, and these movements are influenced especially by estimates of ϕ_{RE}, α_B, R_{WL} and R_{WH}.

Overall, the model performs well in replicating key empirical patterns observed in the HRS data. It captures the age profiles of full-time and part-time work, the influence of health on labor force participation, the distribution of non-housing assets, and the dynamics of re-entry into work—both overall and conditional on depressive symptoms. While some differences remain, the model succeeds in matching the broad profiles of older-age labor supply and savings behavior. These results confirm the model's capacity to analyze the various channels—especially the role of burnout and recovery—that shape late-life labor market dynamics.

Figure 11: *HRS and Simulated Work (Full- or Part-Time) by Health and Age*

Figure 12: *HRS and Simulated Non-Housing Assets by Age at 25th, 50th, and 75th Percentiles*

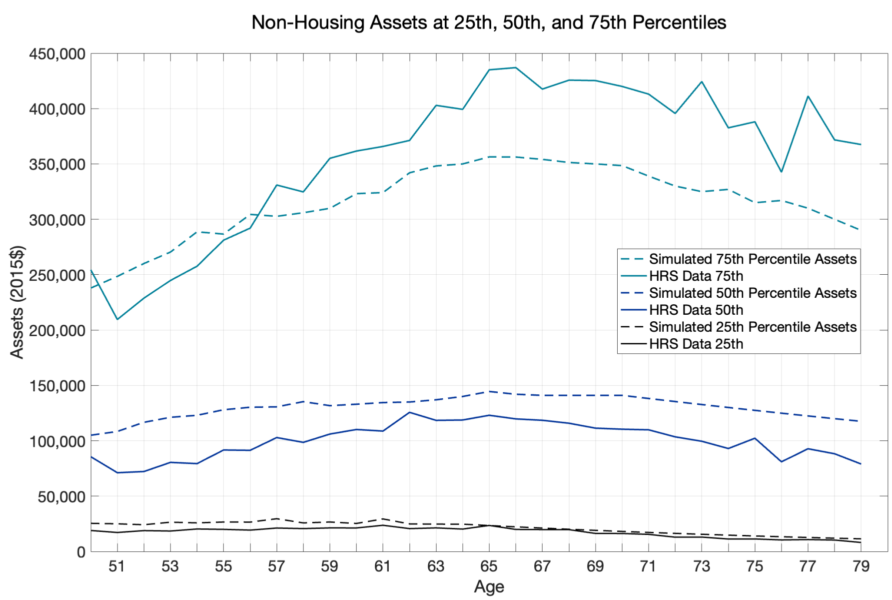
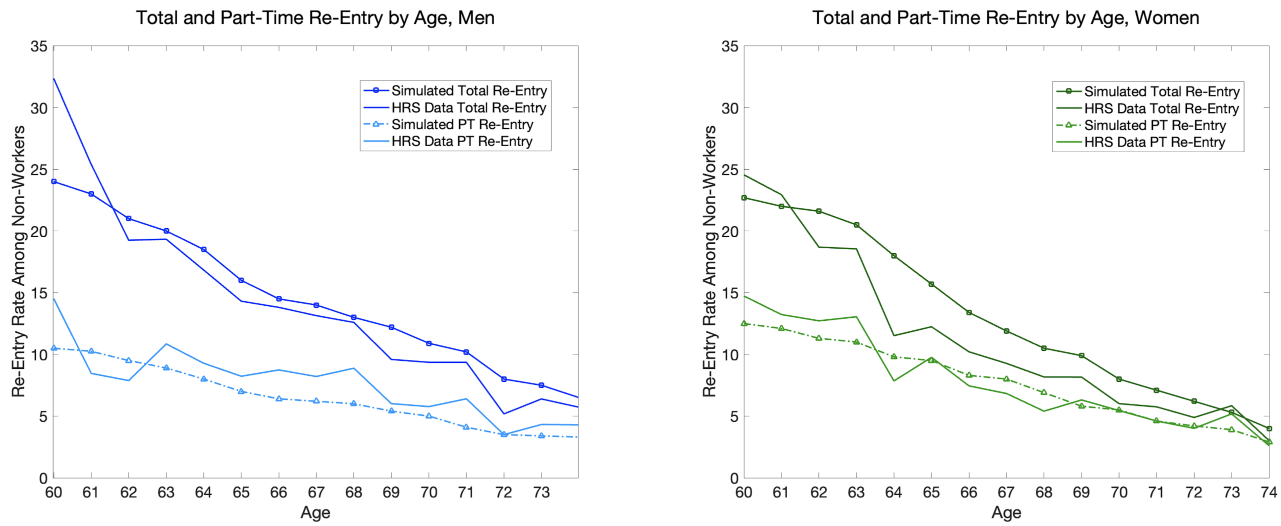
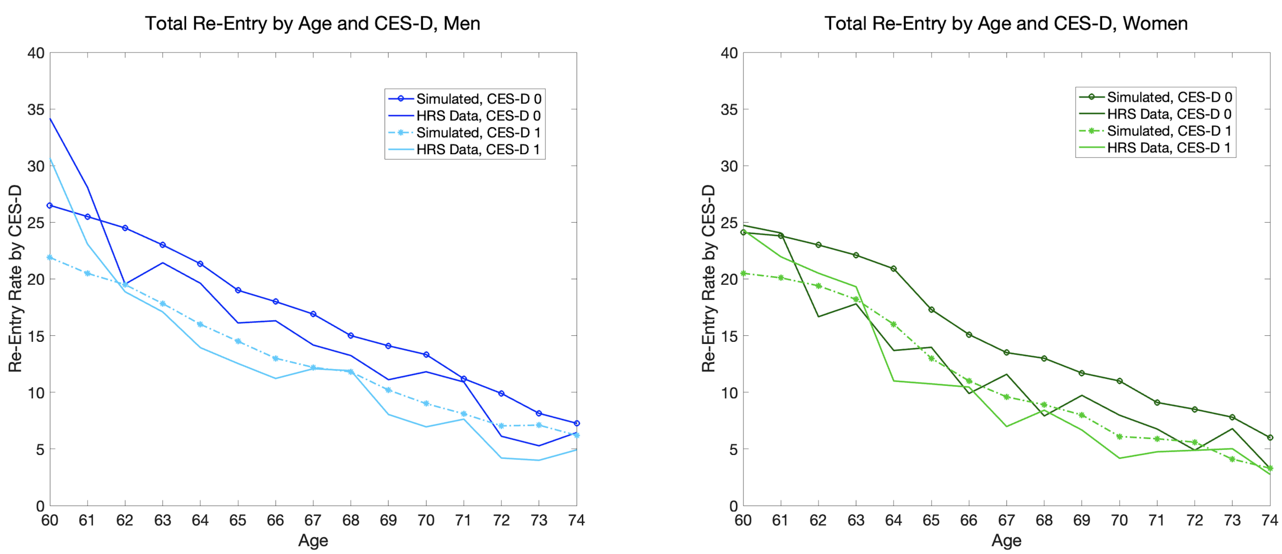


Figure 13: *Re-Entry Rates Among Non-Workers*

(a) *HRS and Simulated Re-Entry Among Non-Workers by Age*



(b) *HRS and Simulated Re-Entry Among Non-Workers by CES-D and Age*



5.3. Alternative Model Without a Burnout-Recovery Process

As reverse retirement and part-time work are two of the main behaviors we study here, we would like to see the extent to which the burnout-recovery aspect of the model is generating simulated moments compared to an otherwise very similar model lacking in this burnout-recovery process. To do so, we look at simulated labor force re-entry behavior and rates of part-time work in a model without all the stress-burnout related parameters (α_B, α_S, α_{nS}, α_R, and ϕ_{FT}). We then compare this to the simulated behavior when the remaining identifiable parameters in Table 13 are re-estimated, with neither part-time work nor re-entry in the HRS data being targeted moments.[16] The main differences in remaining parameters estimated are that: (1) The parameter on relative risk aversion ν is lower than what we estimated in the previous model with the burnout-recovery process. This indicates that, in the absence of a burnout–recovery channel, the model explains significant part-time work through lower curvature in utility over the consumption–leisure composite—implying a greater willingness to trade consumption for leisure. (2) Weight on consumption α_C is higher in the general model without burnout-recovery, generating lower but still substantial part-time work despite the lower hourly earnings.

This suggests that relative risk aversion in a general model without a burnout-recovery process could be an underestimate, because it is picking up a burnout-recovery process that is omitted. Also, a general estimate of α_C consumption might be higher than in a model with a burnout-recovery process in order to explain significant part-time work despite a part-time wage penalty.

Comparing the areas under the simulated and alternative model curves in Figure 14, for both men and women, there is about 40 percent less part-time work as a proportion of all work without the burnout recovery process. Figure 15 shows the rates of re-entry out of retirement by age, as a proportion of all whether working or not. The total and rate-by-age share of those who are reverse retirees is reduced greatly, to about 26 percent of previous rates for men, and 30 percent of previous rates for women. The primary mechanisms for exit and re-entry in this alternative version of the model are shocks to health and earnings. These come through first-stage estimates using the HRS data, and we can infer from this exercise that they are significant, but not the sole, contributors to high rates of reverse retirement. Under both models, the noticeable increase in part-time work around age 62 is due largely to the Social Security Retirement Earnings Test.

Taken together, these comparisons highlight that while health and earnings shocks are important, the burnout–recovery channel is essential for matching the magnitude of reverse retirement and part-time work observed in the data.

6. Counterfactual Experiments

With transition costs associated with changing work status as well costs to retraining from the employers' perspectives, reverse retirement may be an unnecessarily high-cost way to diminish burnout from work. Indeed, Nekoei et al. (2024) estimate the overall costs of workplace-related burnout to be very high. Are there policies that could help avert some of this cost by facilitating reduced burnout while working? We consider this question through three counterfactual simulations—all variations on existing or past policies—in which (i) part-time subsidies are given to older workers, (ii) employers offer "sabbaticals" (modeled as reduced pay but lower transition costs), and (iii) the Social Security Earnings Test prior to normal retirement age is eliminated.

The first two counterfactual policies involve subsidies for two types of work that we attribute in part to burnout reduction or prevention efforts: Part-time work and reverse retirement. In these exercises, part-time earnings are brought up to hourly wages that are closer to hourly full-time wages, and reverse retirement is encouraged through subsidized "sabbaticals". The third counterfactual exercise considers the elimination of the Retirement Earnings Test, which delays about half of any claimed Social Security benefits for those with earned income exceeding an annual

[16] With this change, re-entry costs ϕ_{RE} are not identified, and the time trend on full-time work is now general.

Figure 14: *HRS, Simulated, and Alternative Model Share of Total Working Part-Time by Age*

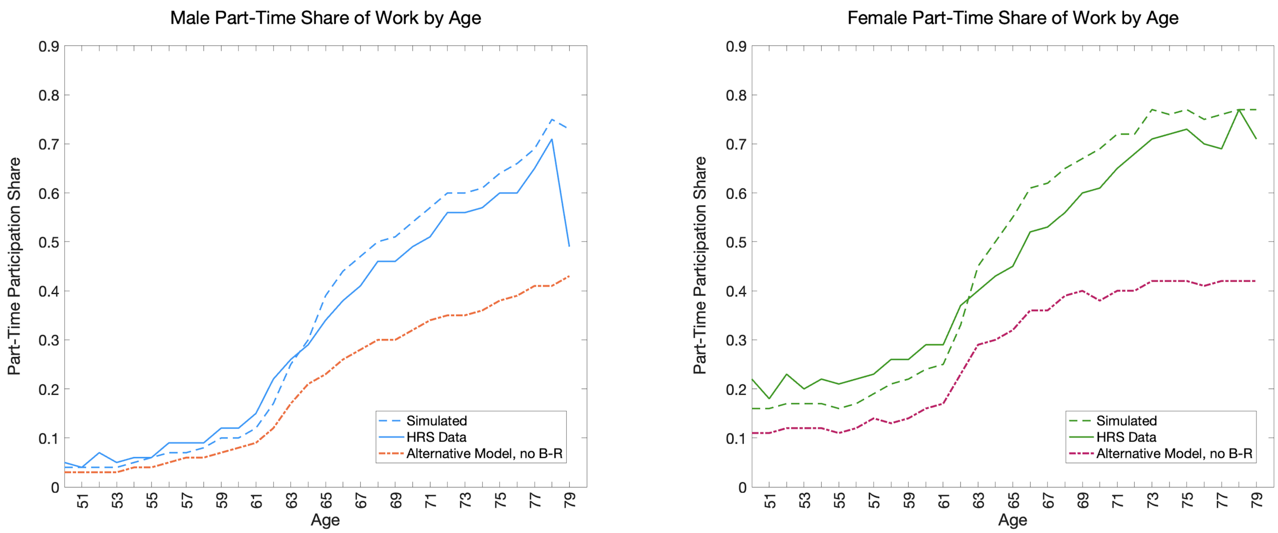
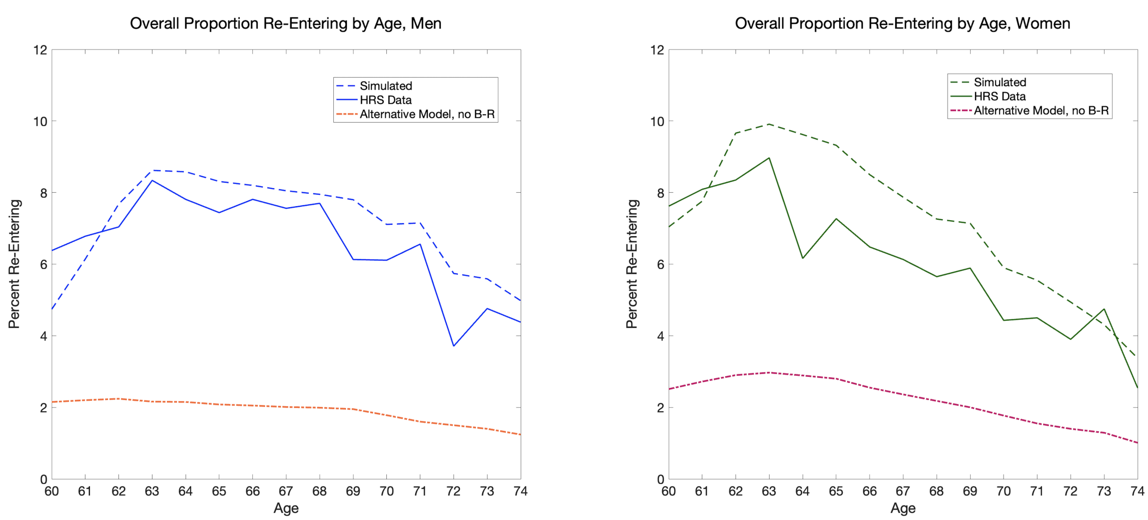


Figure 15: *HRS, Simulated, and Alternative Model Re-Entry Rates by Age*



Note: This shows the rates of re-entry among all (workers and non-workers).

threshold prior to one's Full Retirement Age. We show combined results for men and women, across all estimated preferences types, noting differences that may be of interest.

6.1. Subsidizing Part-Time Work

We found in the HRS data that part-time work is especially common at older ages, and that, controlling for broad measures, those in part-time jobs are less likely to report job stress. Yet part-time positions typically pay lower hourly wages, which constrains their role as a burnout-reducing margin. In this counterfactual, we examine the extent to which the part-time wage penalty limits the use of part-time work for reducing burnout.

This counterfactual policy gives an hourly wage subsidy of 15 percent, the amount that would reduce the part-time penalty by about half of what many estimates show, as reported in Casanova (2013) for older workers, and Aaronson and French (2004) more broadly. While the observed wages in part-time work might in part reflect a willingness to accept less pay per hour in exchange for reduced hours and greater "work-life balance", Angrisani et al. (2017) shows that the nature of part-time work is also different. Not all jobs are linearly scalable, and these differences are difficult to control for. Because of this, our 15 percent counterfactual subsidy reflects a very conservative estimate of the true reduction in hourly wages associated with part-time work.

This policy generically models a part of the Dutch disability system, in which one might be eligible for varying degrees of benefits depending on one's condition—including burnout or "psychological overstrain" (*psychische overbelasting*) —and capacity to work, applicable under the Work and Income (Capacity for Work) Act, or WIA.[17] There is required medical verification of the condition of burnout, which is relatively straightforward for initial sick leave, however moderately difficult to meet the criteria for WIA long-term partial disability. It also approximates a pre-2010 German policy of partial retirement *Altersteilzeit*, which allowed those aged 55 and above to halve their working hours, with wage "top-ups" of at least 20 percent of the part-time wage and increased pension contributions. While this program is no longer in place, there are significant hiring subsidies (*Eingliederungszuschuss*) for older unemployed workers—especially those who are health limited—for up to several years. Our generic counterfactual policy gives a subsidy that would correspond to less generous benefits, but requires no application and verification process.

The main effects of the part-time wage subsidy are shown in Figures 16 and 17. The left two graphs in Figure 16 show the percent of people working either full- or part-time by age, while the graphs on the right show the proportion of those workers who are part-time; the top panel shows rates for men and the lower panel shows rates for women. These groups respond differently to the policy, having different state variable distributions and estimated preference type distributions. For males, the policy results in a higher percent working at all ages, occurring more at older and younger simulated ages, corresponding to about 1.1 years additional years working either full- or part-time over this period. The share of these workers who are part time increases significantly, especially between the ages of 60 and 69. Without the subsidy, these participation rates by age translate to an average of 4.0 years in full-time work, and 1.6 years in part-time work across ages

[17]Returning to work for the partially disabled is part of the WGA (*Werkhervatting Gedeeltelijk Arbeidsgeschikten*) and involves, depending on degree of disability, Wage-Related Benefits or Wage Supplement Benefits The WIA, however applies only after 2 years; prior to this, employers provide up to 70 percent of income under a separate sick leave system.

60–69. With the subsidy, this shifts to 3.1 full-time and 2.9 part-time work years on average. Among women, for whom part-time work was relatively more common, the part-time subsidy leaves total full- and part-time participation almost unchanged, and results in a total increase of only about 0.1 years worked. Without the subsidy, between ages 60 and 69, they worked an average of 3.1 years full-time, and 2.0 years in part-time work. With the subsidy, average years in full-time work falls to 1.7 and average part-time work years increases to 2.9 while age 60–69.

For both men and women, part-time work becomes much more common. The patterns in the timing of the shift to part time work do differ, as seen in the right two graphs in Figure 16. The model predicts that women on average will shift to part-time work as a percent of all work across ages more uniformly. For men, the model predicts only a modest shift prior to age 62, and significantly more part-time work thereafter.

6.2. Subsidizing Sabbaticals

We have characterized reverse retirement as a mechanism that contributes to a reduction in burnout, however one that is costly for the individual and potentially employers as well, who lose the firm-specific expertise of a person exiting earlier due to burnout. Under this policy, a person leaving paid work for a one-year "sabbatical" could do so incurring neither a full loss of income nor switching costs. As with the part-time subsidy counterfactual policy, this policy has motivation similar to the Dutch disability system with return to work. It is again less generous, but designed for broad eligibility without any verification of burnout required.

Results vary by the structure of the sabbatical, but in general it is most financially attractive at younger ages. In this exercise, a person could receive 40 percent of their past earnings up to mean earnings by age, and 10 percent of their earnings that exceed the mean up to the level of twice mean earnings.[18] Take-up is heterogeneous: those with higher ν (who place greater weight on maintaining consumption) and lower burnout B_t are less likely to find the sabbatical attractive, as the reduction in earnings dominates the value of additional leisure and stress relief.

The left two graphs in Figure 16 show the the sabbatical subsidy results in significantly less work prior to the ERA of 62 for both men and women, with more remaining in work at older ages. Of those who work at older ages, a somewhat higher share will be in full-time work past age 62. Total years worked (excluding the sabbatical) during ages 60–69 goes from 5.6 to 6.1 for men all through more net full-time years, and stays at 5.1 years for women under this policy change. There are about one-third fewer reverse-retirees overall, excluding sabbatical time from this count. The policy is more costly but not on net more welfare-improving per dollar relative to part-time subsidy.

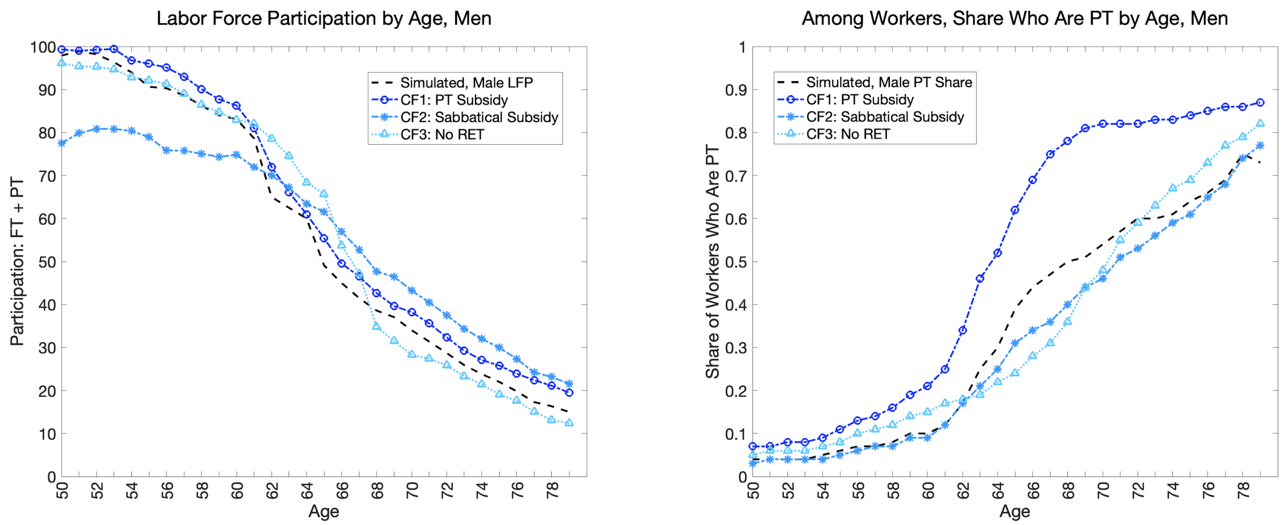
6.3. Eliminating the Retirement Earnings Test

For our third counterfactual policy exercise, we estimate the effects of eliminating the Retirement Earnings Test (RET), also referred to as the Annual Earnings Test (AET). The RET reduces the Social Security retirement payment amount for those claiming by $1 for every $2 dollars a person makes in earned income past a certain threshold before reaching their Full Retirement Age (FRA).

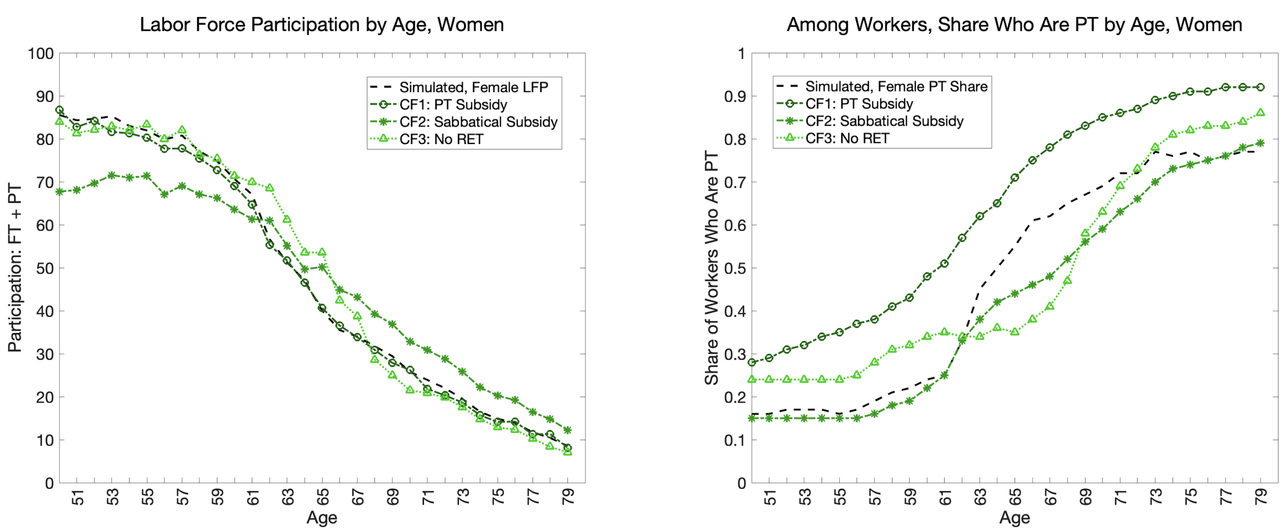
[18] We chose to illustrate the effects of 40 percent earnings replacement as this is approximately the average rate of income replacement for Social Security retirement benefits, with its progressive formula also resulting in lower replacement rates for those with above-average earnings histories.

Figure 16: *HRS, Simulated, and Counterfactual Policy Labor Force Participation and Share PT*

(a) Total LFP by Age among Men, Total (left) and Share Part-Time (right)



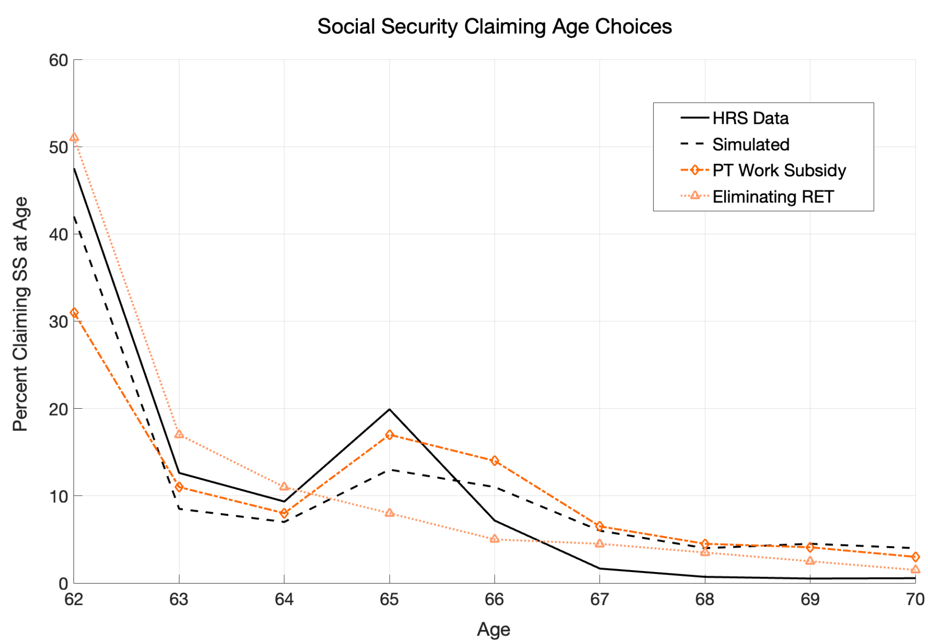
(b) Total LFP by Age among Women, Total (left) and Share Part-Time (right)



The entire amount withheld due to the RET is credited to a beneficiaries' future Social Security payments after they FRA is reached in a way that is actuarially fair given the life expectancy of the average person. In 2024 the earned income threshold was $22,320 in years prior to reaching one's FRA.

Before the year 2000, the RET was also applied to earned income up to age 70 for anyone claiming Social Security benefits. There are several studies studying the effects of this policy change, showing that the RET led to meaningful reductions in labor supply at older ages; work generally increased after the elimination of the RET for the prior FRA of 65 up to 70 (Gelber et al., 2022; Engelhardt and Kumar, 2014; Friedberg and Webb, 2009; Song and Manchester, 2007). Although the RET offset is actuarially fair on average, both subjective life expectancy and preferences for work and over time differ across people; for an individual, the policy is unlikely to be neutral. Our current model accounts for the RET, and for this counterfactual we look at the effects of simply eliminating the RET for Social Security benefits for all ages. Given the high rates of work and Social Security benefit claiming for ages 66 and younger, we expect that this counterfactual policy change would result in much larger effects than were observed when the RET was eliminated for anyone who had reached their FRA and older.

FIGURE 17: *HRS, Simulated, and Counterfactual Social Security Claiming Ages*



Our estimates show that the elimination of the RET increases work between the ages of 60–69 more than either the counterfactual part-time or sabbatical subsidies, and reduces the share and total amount of work that is part-time at those ages for both women and men. This is shown in Figure 16. Work between the ages of 60–69 for men increases from 5.6 to 6.2 years, and remains at about 5.1 years for women. The share of those who are reverse retirees decreases by about 4 percentage points.

Figure 17 shows, noticeably, that the sharp increases in claiming around the FRAs of 65 and 66 are no longer present when the RET is eliminated. The only moment targeted in estimation was the share claiming at age 62; indeed, what had generated peaks in this model was not through preferences but had come through the RET. Under this counterfactual policy, even more people claim at the ERA of 62, and there is a steady decline in the proportion from age 63 on.

Consistent with prior studies, eliminating the RET shifts work and claiming behavior. By incorporating burnout–recovery, our model introduces an additional dimension of heterogeneity. As a result, even though the RET offset is actuarially fair on average, the policy change may not be fiscally neutral once differences in preferences, subjective life expectancy, mortality gradients, and burnout–recovery dynamics are taken into account, as also demonstrated by Jones and Li (2023).

7. Conclusion

In this paper we developed and estimated a structural model of retirement that incorporates a burnout–recovery process, offering a new explanation for reverse and partial retirement at older ages. Our descriptive analysis of the Health and Retirement Study data showed that reverse retirees and permanent retirees are strikingly similar on many observable demographic characteristics, including education, assets, and health. They do, however, differ in responses to job stress, polygenic indicators of stress sensitivity, and patterns of recovery. Embedding these dynamics into a model of work allows us account for a significant amount of the increasing level and share of part-time work at older ages, beyond what arises in a model from financial, health, or preference shocks alone. In our framework, part-time work is not simply more leisure—it also represents jobs with lower stress and reduced burnout risk.

Incorporating the burnout-recovery process changes both parameter estimates and their interpretations. Without this channel, high rates of re-entry would instead be attributed to low fixed costs of work or to lower risk aversion. By including burnout–recovery, we show that heterogeneity in sensitivity to stress explains much of the variation in retirement patterns. The resulting estimates for risk aversion, the utility of consumption, and fixed costs fall within ranges consistent with the broader literature, but with a richer behavioral foundation.

Our three policy counterfactuals underscore the policy relevance of managing burnout in work decisions. Part-time subsidies increase labor force attachment and reduce stress-induced exits, while employer-provided sabbaticals allow recovery without permanent exit, yielding modest increases in years worked but large welfare gains. By contrast, eliminating the Retirement Earnings Test increases re-entry and full-time work but also raises stress exposure. Together, these exercises highlight that policies designed to retain older workers may have very different implications once burnout dynamics are taken into account.

Several extensions could further enrich the framework. Joint household retirement decisions, work-hour rigidities, and occupational differences in stress exposure would add new dimensions to the model. Incorporating these features could clarify how burnout interacts with labor supply elasticity and job attributes across the life cycle.

In sum, reverse retirement and rising part-time work at older ages are striking features of the data, with important implications for pension systems and workforce policy. By modeling burnout and recovery explicitly, we show that stress dynamics are central to understanding labor supply decisions at older ages. While our analysis focuses on retirement transitions, the burnout–recovery process may also be relevant at younger ages—for instance, in explaining job switching, career breaks, and demand for flexible work arrangements—pointing to a broader role for stress and recovery in shaping labor supply.

Our framework provides a first step toward incorporating job stress dynamics into models of labor supply—an area of growing importance as attention to the role of mental health and well-being at work continues to expand.

A. Appendix

A.1. The HRS Data and Sample Selection

The primary sample we analyze from the Health and Retirement Study (HRS) includes men and women born between 1931 and 1947 who were observed in the panel as a respondent in at least five waves and working in at least one. We will discuss the rationale for our sample choice here.

The sample includes those whose birth years brought them in to the study as part of the "HRS" (born 1931–41) and "War Babies" (born 1942–47) cohorts. Both cohorts were interviewed biennially from 1992 to 2018, the latest interview wave included in our analysis. The age range while observed for those in the HRS cohort was 50 to 88, while for the War Babies it was 44 to 77. Although the study is of Americans ages 50 and up, one can be brought into the study as a younger spouse of a respondent who is at least 50. While those from older and younger birth year cohorts are part of the HRS, the age ranges for other cohorts were less suited to our research question around reverse retirement. The nearest older to the HRS cohort, the "Children of the Depression" (CODA), born 1924–30, were first observed at age 61 at the earliest, leaving out meaningful observations from their younger ages. The nearest cohort younger than the War Babies is the "Early Boomers", born 1948–53, observed at maximum ages between only 65 and 71, which are some of the most relevant ages for the behavior we seek to study here.

We also include only those who were observed for at least five waves and reporting that they worked for pay in at least one of those waves. This allows a reasonable amount of time to observe the work dynamics of interest for the relevant population, at least somewhat attached to the labor force. This makes our sample not representative of the HRS data, which is, when weighted, representative of the older U.S. population. The criteria of being observed at least five times can be accounted for through the existing HRS sample weighting, which factors in some attrition due to poor health and different rates of mortality across subpopulation. The criteria of being observed working at least once is not corrected for by this weighting, and selects differently across subpopulations.

Of the 10,512 men and women in the HRS cohort, 34 percent of men and 41.9 percent of women do not meet the criteria of being observed for at least five waves. For the War Babies cohort, 31.1 percent o men and 29.6 percent of women do not meet the criteria. In Table A.1 on the left, we see that men in these cohorts that were excluded were more likely to have not been observed for at least five waves compared to women, and women excluded more likely to have not been observed working a least once. The columns on the right show that our criteria excludes disproportionately those who were in fair or poor health when first observed, especially for men (not broken out here).

This leaves 9,076 individuals, 99,569 person years, with the sample observed as respondents for nearly 11 biennial survey waves (22 years) on average. Applying analytical weights, which we do for many descriptive figures and for the initial distribution of simulated individuals, this is about 7,130 individual and 81,180 person-years. More information about the HRS sample frame can be found at `https://hrs.isr.umich.edu/documentation/survey-design`.

Variable Descriptions. We use the RAND HRS Data (2020) version of the HRS variables as well as some variables not available in the RAND version, which we take from the original Health and Retirement Study (2018) version. Below are descriptions of select RAND HRS variables used here. Further descriptions can be found through RAND HRS Data (2020) and Health and Retirement

Table A.1: *Main Selection Criteria HRS and War Babies Cohorts*

Group	Gender: Male	Gender: Female	Total (% in row)	Health Status: Excl./VG	Health Status: Fair	Health Status: Poor	Total (row total %)
Included:							
Obs ≥ 5 and work > 0	4,328 (66.68%)	4,748 (61.59%)	9,076 (63.92%)	7,880 (86.82%)	972 (10.71%)	224 (2.47%)	9,076 (100.00%)
Excluded:							
No work & obs < 5	531 (8.18%)	597 (7.74%)	1,128 (7.94%)	475 (42.11%)	290 (25.71%)	363 (32.18%)	1,128 (100.00%)
Work > 0 but obs < 5	996 (15.34%)	768 (9.96%)	1,764 (12.42%)	1,417 (80.33%)	269 (15.25%)	78 (4.42%)	1,764 (100.00%)
Obs ≥ 5 but no work	636 (9.80%)	1,596 (20.70%)	2,232 (15.72%)	1,233 (55.24%)	534 (23.92%)	465 (20.83%)	2,232 (100.00%)
Total	6,491 (100.00%)	7,709 (100.00%)	14,200 (100.00%)	11,005 (77.50%)	2,065 (14.54%)	1,130 (7.96%)	14,200 (100.00%)

Study (2018)[19]

- *Participation*: A respondent is considered to be participating in the labor force if he or she answers that he is "working for pay" and not participating in the labor force if he is "not working for pay" (HRS variable `RwWORK`). These binary responses are fairly consistent with similar questions in the Study, such as whether respondents considers themselves retired (HRS variable `RwSAYRET`) or labor force status (`RwLBFR`).
- *Non-Housing and Housing Financial Wealth*: `HWATOTA` The net value of non-housing financial wealth in 2015 dollars is calculated as the sum of the appropriate wealth components less debt: Stocks, checking account balance, CDs, bonds, and other non-housing wealth minus debt. (HRS variables `(HwASTCK + HwACHCK + HwACD + HwABOND + HwAOTHR) - HwADEBT`.)
- *Earnings*: Annual earnings from work come from the HRS variable `RwIEARN`. The nominal reported amounts are converted to 2015 dollars using the CPI. `RwIEARN` is the sum of a respondent's wage or salary income, bonus and overtime pay, commissions, and tips. Retirement earnings come from variables `RwISRET` includes annual Social Security income, including retirement, spouse, or widow benefits, but not including benefits received due to disability, and `RwIPENA`, income from pensions and annuities.
- *Physical Health*: In the HRS there are five categories of self-reported health (variables `RwSHLT`): *Excellent*, *Very Good*, *Good*, *Fair*, and *Poor*. In estimation, physical health status is divided into two categories: "Good", which includes *Excellent*, and *Very Good*, and *Good*, and "Bad", which includes *Fair* and *Poor* self-reported health.
- *Job Stress*: RAND HRS variable `RwJSTRES`, binary version of whether respondent, if working, considers job stressful.
- *CES-D*: `RwCESD` is based on The Center for Epidemiologic Studies–Depression (CES-D) scale and screens for symptoms associated with depression. From the RAND HRS Data (2020)

[19] RAND documentation at:
https://www.rand.org/well-being/social-and-behavioral-policy/centers/aging/dataprod/hrs-data.html and the HRS Question Concordance page:
https://hrs.isr.umich.edu/documentation/question-concordance.

Table A.2: Education Distribution by Sample

	All Sample		Has PGS		Euro PGS	
Education Category	Freq.	Percent	Freq.	Percent	Freq.	Percent
<HS	1,779	19.6	1,092	18.1	541	11.6
GED	456	5.0	299	5.0	234	5.0
HS graduate	2,887	31.8	1,983	32.8	1,620	34.8
Some college	1,998	22.0	1,328	22.0	1,075	23.1
College+	1,956	21.6	1,336	22.1	1,192	25.6
Total	9,076	100.0	6,038	100.0	4,662	100.0

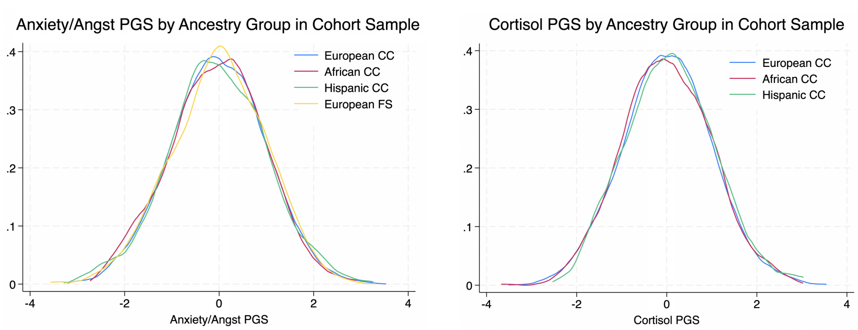
documentation: "The CES-D score (RwCESD) is the sum of five 'negative' indicators minus two 'positive' indicators. The negative indicators measure whether the respondent experienced the following sentiments all or most of the time: depression, everything is an effort, sleep is restless, felt alone, felt sad, and could not get going. The positive indicators measure whether the respondent felt happy and enjoyed life, all or most of the time."

Polygenic Risk Scores in the HRS

From our analysis sample of 9,076 HRS respondents, polygenic scores (PGSs) are available for 6,038. Respondents with genetic data are broadly representative of our subsample (restricted to those born in eligible cohorts, observed at least five times, and working in at least one wave). Table A.2 shows that the distribution of reported education groups is similar to the full analytic sample. PGSs are considered most comparable within broad ancestry groups as the underlying GWAS weights used to construct them were derived from European-ancestry populations (Martin et al., 2017; Ware et al., 2024b,a). Accordingly, predictive power is higher in European-ancestry groups, while portability to other groups is more limited. Figure A.1 shows the distribution of the anxiety/angst and cortisol PGSs across ancestry groups in our sample. In our sample with available PGSs, we observe 863 respondents of African ancestry, 513 respondents of Hispanic ancestry, and 4,662 respondents of European ancestry.

Because the European ancestry group is the largest and most directly comparable, our main analyses use the European-ancestry PGSs. Specifically, we use the variables `E5_ANXFS_ANGST16`: Anxiety/Angst, based on the Anxiety NeuroGenetics Study 2016 GWAS) and `E5_CORTISOL_CORNET14`: Plasma Cortisol, based on CORNET 2014 GWAS (Ware et al., 2024a). Compared to the full sam-

Figure A.1: Anxiety/Angst and Cortisol PGS Distribution by Ancestry Groups



ple, the European-ancestry group has somewhat higher educational attainment on average, also in Table A.2

A.2. Categorizing Retirement and Reverse Retirement

What Does "Retirement" Mean?

A surprisingly high proportion of people, whether we categorize them as reverse-retirees or not, say that they plan to continue paid work after retirement, as seen in Table A.3. In Table A.4, we see whether one's response to "Do you consider yourself retired?" tells us anything about participation in future Waves. We can see that, combining the respondents (to include RRs and Perm-Rs), 11.9 percent of this who consider themselves "Completely Retired" are working in the next Wave, while slightly higher numbers are working in future periods.

There are a number of possible ways to define reverse retirement occurrence. For instance, we could look at changes in the statuses of (1) whether one subjectively considers himself retired, (2) whether he reports working for any pay, (3) hours worked, or (4) level of income.[20] We'll compare responses for the first two definitions, as the later two require more judgement about what the cutoff levels should be, though we may look at these measures further in the future.

We categorize over one-third of the sample as being "Reverse Retirees" or RR. Though the definition of retirement is not straightforward as retirement may or may not indicate labor force participation, we will use "Reverse Retiree" to identify an individual who, nearing what might be colloquially understood as retirement age, ceases to work for pay ("retires") and later begins working for pay again ("reverses" his decision to stop working). Individuals whom we do not observe

TABLE A.3: *Post-Retirement Intentions*

	Perm-R	RR
Stop Paid Work	25.4%	20.3%
Continue Paid Work	74.6%	79.7%
Observations	4,170	2,161

TABLE A.4: *What Does Considering Oneself Retired Mean for Future Participation?*

	Percent Working...				
	Next Wave	+2 Waves	+3 Waves	+4 Waves	Obs.
Perm-R					
Not Retired	.863	.741	.631	.532	8,426
Completely Retired	.026	.022	.020	.024	6,671
Partially Retired	.688	.576	.484	.392	2,506
RR					
Not Retired	.727	.655	.611	.553	2,850
Completely Retired	.323	.363	.368	.359	2,904
Partially Retired	.601	.529	.465	.434	2,030

[20] These correspond to HRS variables (1) `rWsayret`, (2) `rWwork`, (3) `rWhours`, and (4) `rWiearn`.

Table A.5: *Reverse Retirement Occurrences: Comparing Definitions*

Reverse Retirement Occurrences	Change in "Working for Pay"	Change in "Considers Self Retired"
0	64.5	66.7
1	30.2	25.3
2+	5.3	8.0

exiting and subsequently re-entering work are "Permanent Retirees" or Perm-R.[21]

Table A.5 gives the percent who un-retire—which, in the data, we observe from 0 to 4 times for an individual—during the time they are observed in the HRS under two definitions. Under the first, a change in the "Working for Pay" status from not working to working for pay, over 35 percent reverse retire at least once in our observations of them. Using the second definition, in which a respondent says he considers himself completely or partially retires one period and not retired in the next period, more than 33 percent reverse retire.

The definition of reverse retirement we will use in many the descriptive statistics that follow, unless otherwise noted, is a change from "Not Working for Pay" to "Working for Pay". In some ways a change in whether one considers himself retired is somewhat more interesting; if retirement is more a "state of mind" it's surprising that there would be so many reversals. However, the responses to whether one considers himself retired and whether he is working for pay align surprisingly well, and if we look at the later, we are more likely to get the wage observations necessary if looking at periods in which respondents say they are "Working for Pay".

In another pattern that motivates some underlying burnout-recovery process, we see in the Health and Retirement Study (HRS) data that (1) these re-entry rates remain nearly as high at older ages when excluding those who initially left work involuntarily and (2) respondents report much lower job stress levels upon restarting work than those who had been working and continue to work.

Table A.6: *Why Respondent Stopped Working*

Reason for Stopping Work	Permanent Retirees	Reverse Retirees
Laid Off / Firm Reorg.	18.2%	17.3%
Poor Health, Disability	17.8%	20.3%
Business Closed	6.4%	6.2%
Retired	40.5%	31.1%
Bored	8.2%	11.6%
Family	1.4%	1.7%
Family Moved	1.1%	1.7%
Find Better Job	0.6%	0.9%
Other	5.8%	9.1%

Notes: "Other" includes family reasons or relocation, refused, doesn't know travel, pension incentive, and others.

[21] Using this survey response, for a person to be counted as a reverse retiree over three Waves (working-not working-working), time out of the labor force could conceivably range from being out of the labor force on the day of the second of the three survey Waves for up to the nearly four years between the first and third of the three surveys.

Table A.6 gives respondents' reasons for stopping work, separated into those who are Permanent Retirees and Reverse Retirees. We can see that those who do return to work were slightly less likely to have stopped working due to being laid off (17.3 percent versus 18.2 percent), but somewhat more likely to have left work initially due to health reasons (20.3 percent versus 17.8 percent). The less precise "retired" was a more common reason cited among those who never return to work (40.5 percent) than among those who do return (31.1 percent). Still, it is somewhat surprising that over 30 percent of those who ultimately reverse retire said they were stopping because they were retiring. We suspect they either do not think of retirement as the state of no longer working or they find that, unexpectedly, they do not like not working and would rather return to work.[22]

A.3. Social Security

Benefits Calculations.

Social Security retirement or old-age benefits are a function of past covered earnings and the age at which an individual claims. The benefit amount is based on one's Average Indexed Monthly Earnings (AIME), which is an average of a worker's highest 35 years of earnings, adjusted based on an index of wage growth nationally over time. AIME is then translated into a Primary Insurance Amount (PIA) using a progressive, piecewise-linear formula with "bend points." The formula replaces a higher fraction of pre-retirement earnings for low earners than for high earners. The PIA is the monthly benefit payable at an individual's Full Retirement Age (FRA), which is 65–66 for the birth cohorts in our sample (rising to 67 for later cohorts). This is also the amount one receives if awarded Social Security Disability Insurance benefits before their FRA. Otherwise, claiming retirement benefits before one's FRA reduces the monthly benefit permanently: for example, someone with an FRA of 65 who claims at 62 would receive benefits of about 80% of their PIA. Conversely, delaying claiming until after one's FRA increases benefits through delayed retirement credits, up to a maximum at age 70. For someone with an FRA of 65, by claiming at 70 one would receive benefits of 124% of his or her PIA. Currently, the average monthly retired-worker benefit is about $2,000 Social Security Administration (2025), though the PIA varies widely by lifetime earnings and claiming age. In addition to this, spousal benefits allow for "dual eligibility", where someone who has been married for at least ten years is eligible for the higher of: (a) benefits based on his or her own earnings history, or (b) up to 50% of the spouse's PIA. Widow(er)s may also receive up to 100% of the deceased spouse's benefit (subject to claiming age adjustments).

Retirement Earnings Test Example. As an example of how the Retirement Earnings Test (RET) affects benefits, we can consider the following: Suppose a person has an FRA of age 66 and claims Social Security retirement benefits at the earliest possible age of 62, which are for him $30,000 annually, while he continues to work for one year with an earned income of $50,000. His Social Security benefits for the year he is working are reduced by $13,840 (50 percent of earnings past the threshold) to $16,160. The way in which it is credited past the FRA is to adjust benefits to the amount he would get by having claimed later than 62. The $13,840 that was withheld is equivalent to about 5 months of Social Security benefits, and his new permanent benefit amount

[22] Indeed, as we see in Table A.3, a high proportion—over three-quarters—of respondents, whether reverse retirees or not, say they intend to "continue paid work" post-retirement. Evidently, "retirement" does not imply "not working" to most respondents *ex ante*. At the same time, responses in the HRS for whether the respondent considers himself retired line up quite well with whether he is "working for pay" or not.

starting at age 66 would be equivalent to what he would have received if he had claimed at age 62 and 5 months. Benefits are reduced by 5/9 of 1 percent for every month early one claims prior to one's FRA. While claiming at age 62 (48 months early) permanently reduced his benefits by 25% relative to if he had claimed at his FRA of 66. The RET credit makes the reduction fall to around 23% when he reaches his FRA, adjusting benefits as if he claimed only 43 months early.

A.4. Additional Tables and Figures

Table A.7: *Logistic Regression Results: Predictors of Whether Reverse Retiree*

Outcome: Reverse Retiree Variable	Coefficient	(s.e.)	P>|z|
ANX-COR PGS	0.063	(0.033)	0.059
Female	-0.066	(0.079)	0.405
ANX-COR PGS × Female	0.069	(0.046)	0.130
Age at 1st Exit	-0.000	(0.005)	0.995
Initial Marital Status			
Married/Partnered	-		
Separated/Divorced	-0.050	(0.111)	0.649
Widowed	-0.304	(0.181)	0.092
Never Married	-0.200	(0.220)	0.364
ln(Initial Earnings)	-0.081	(0.034)	0.017
Education			
<HS	-		
GED	0.220	(0.172)	0.203
HS graduate	-0.097	(0.115)	0.400
Some college	0.025	(0.125)	0.844
College+	-0.023	(0.136)	0.869
Occupation			
Managerial/Specialty	-		
Prof./Technical	-0.089	(0.107)	0.405
Sales	0.104	(0.128)	0.416
Clerical/Admin.	-0.173	(0.115)	0.132
Farming/Forestry/Fishing	-0.072	(0.265)	0.787
Mechanics/Repair	0.101	(0.184)	0.583
Construction/Extractors	-0.041	(0.200)	0.839
Precision Production	-0.105	(0.189)	0.580
Armed Forces	0.564	(0.294)	0.055
Services	0.010	(0.137)	0.940
Operators	-0.004	(0.131)	0.975
Cohort			
AHEAD	1.102	(1.216)	0.365
CODA	1.002	(1.120)	0.371
HRS	1.274	(1.108)	0.250
War Babies	0.999	(1.108)	0.367
Early Baby Boomers	0.253	(1.109)	0.819
Mid Baby Boomers	0.328	(1.124)	0.771
Late Baby Boomers	0.166	(1.231)	0.893
Constant	-0.791	(1.186)	0.505
Observations	4,644		
LR $\chi^2(13)$	175.13		
Prob > χ^2	0.000		
Pseudo R^2	0.0298		

Table A.8: *Exit from and re-entry into occupations*

Occupation Before Exiting:	Occupation upon Re-entering: Managerial/Spec.	Prof./Technical	Sales	Clerical/Admin	Farm/Forest/Fish	Mech./Repair	Constr./Extract.	Precision Prod.	Services	Operators	Total (from occ.)
Managerial/Specialty	36.04	11.00	11.48	17.22	6.38	1.44	3.19	0.00	7.02	6.22	14.13
Prof./Technical	7.54	58.20	10.00	10.16	1.97	0.00	1.31	2.62	5.57	2.62	13.74
Sales	7.10	4.11	52.71	11.78	1.50	0.00	0.37	0.75	14.21	7.48	12.05
Clerical/Admin.	4.28	6.55	11.76	61.10	1.34	0.53	0.00	1.60	6.42	6.42	16.85
Farming/Forestry/Fishing	6.80	0.00	2.72	5.44	59.18	3.40	1.36	0.00	5.44	15.65	3.31
Mechanics/Repair	3.25	6.50	1.63	1.63	8.13	21.14	10.57	1.63	4.88	40.65	2.77
Construction/Extractors	0.00	0.00	6.80	0.00	2.72	2.72	64.63	0.00	9.52	13.61	3.31
Precision Production	0.00	3.05	9.16	3.05	1.53	0.00	4.58	31.30	29.01	18.32	2.95
Services	3.19	1.96	5.64	5.88	1.23	0.49	0.74	0.98	73.53	6.37	18.39
Operators	4.33	1.81	5.42	5.42	3.97	0.72	6.50	2.17	11.73	57.94	12.48
Total (to occupation)	9.15	12.01	13.68	17.62	4.62	1.26	4.24	2.14	21.02	14.26	100.0

Table A.9: *Occupations and Reverse Retirement*

	Whether Reverse Retires		*Considers Job Stressful*		
Longest Observed Occupation	Perm. Retiree	Reverse Retiree	Part-Time	Full-Time	All
Managerial/Specialty	70.2%	29.8%	.41	.72	.66
Prof./Technical	72.2	27.8	.42	.71	.63
Sales	69.7	30.3	.35	.63	.53
Clerical/Admin.	75.6	24.4	.31	.63	.54
Farming/Forestry/Fishing	64.6	35.4	.28	.60	.50
Mechanics/Repair	72.2	27.8	.23	.58	.54
Construction/Extractors	69.1	30.9	.28	.48	.44
Precision Production	70.1	29.9	.23	.58	.52
Services	74.4	25.6	.30	.55	.44
Operators	73.0	27.0	.34	.50	.47
All	72.3%	27.8%	.34	.63	.54
Observations, weighted	6,130 (persons)		35,810 (person-years)		

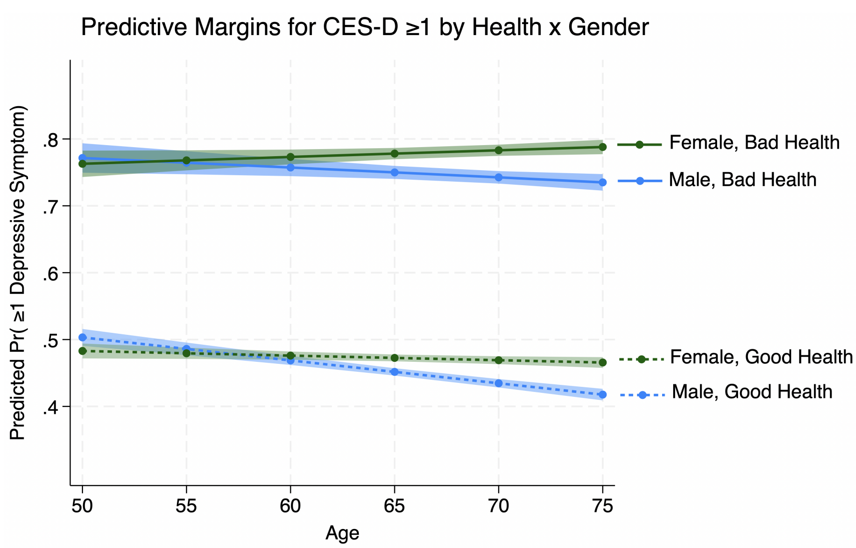
Table A.10: *Earnings Estimates with Selection*

	Women		Men	
	Coef.	(s.e.)	Coef.	(s.e.)
Second stage: Log(earnings)				
Age	0.100	(0.032)	0.091	(0.038)
$\text{Age}^2/10$	-0.091	(0.026)	-0.090	(0.031)
FT > 30 (baseline PT)	0.623	(0.036)	0.662	(0.045)
Good Health	0.044	(0.045)	-0.336	(0.051)
FT>30 × Good Health	0.116	(0.038)	0.250	(0.048)
Initial LFP: Part-Time	0.534	(0.008)	0.590	(0.009)
Initial LFP: Full-Time	0.520	(0.008)	0.563	(0.008)
Mills (overall)	0.005	(0.146)	0.959	(0.164)
× 50–54	-0.017	(0.046)	0.015	(0.098)
× 55–59	-0.002	(0.066)	0.107	(0.113)
× 60–64	-0.012	(0.092)	0.403	(0.130)
× 65–69	-0.265	(0.165)	0.849	(0.164)
× 70–74	-0.828	(0.284)	1.381	(0.218)
× 75–79	-1.008	(0.608)	2.656	(0.416)
Constant	1.594	(0.990)	1.018	(1.201)
Observations	18,498		17,153	
R^2	0.410		0.411	
Adj. R^2	0.410		0.410	
Root MSE	0.766		0.809	
First stage: Probability of Working (Probit)				
Age Category				
<50	-		-	
50–54	-0.240	(0.071)	0.289	(0.157)
55–59	-0.592	(0.068)	-0.192	(0.154)
60–64	-1.219	(0.068)	-0.887	(0.153)
65–69	-1.861	(0.068)	-1.504	(0.153)
70–74	-2.242	(0.068)	-1.850	(0.154)
75–79	-2.594	(0.070)	-2.224	(0.154)
Education				
<HS	-		-	
GED	-0.040	(0.036)	-0.125	(0.035)
HS graduate	0.021	(0.021)	-0.000	(0.021)
Some college	0.062	(0.023)	0.046	(0.023)
College+	0.087	(0.024)	0.238	(0.023)
ihs(Initial Assets)	0.054	(0.012)	0.053	(0.013)
ln(Initial Earnings)	0.119	(0.015)	0.054	(0.016)
Assets × Initial Earn.	-0.006	(0.001)	-0.005	(0.001)
Good Health	0.542	(0.018)	0.501	(0.018)
Constant	-0.105	(0.161)	0.249	(0.222)
Observations	45,393		41,092	
Pseudo R^2	0.268		0.255	

Table A.11: *Probit Results for Presence of Depressive Symptom (CES-D $\geq$ 1)*

Logit, Outcome: CES-D $\geq$ 1	**Coefficient**	(s.e.)	**P-value**
Age	-0.005	(0.002)	0.014
Health			
Bad	-		
Good	-0.535	(0.142)	0.000
Female	-0.428	(0.172)	0.013
Age × Good Health	-0.004	(0.002)	0.054
Age × Female	0.008	(0.003)	0.002
Good Health × Female	0.032	(0.190)	0.868
Age × Good Health × female	-0.001	(0.003)	0.699
ihs(Initial Assets)	-0.015	(0.001)	0.000
Education			
<HS	-		
GED	-0.223	(0.022)	0.000
HS graduate	-0.267	(0.013)	0.000
Some college	-0.378	(0.014)	0.000
College+	-0.528	(0.014)	0.000
Cohort			
HRS	-		
War Babies	0.024	(0.010)	0.016
Constant	1.436	(0.129)	0.000
Observations	92,355		
Log likelihood	-58,911.7		
LR $\chi^2(13)$	9941.7		
Prob > χ^2	0.000		
Pseudo R^2	0.078		

Figure A.2: *Predicted Probability of CES-D $\geq$ 1, Health × Gender by Age*



Note: All other variables are held constant at means.

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