Online Appendices: Why Are Older Men Working More? The Role of Social Security

Zhixiu Yu*

1. DATA

The bulk of my model estimation is based on the 1968 to 2015 waves of the Panel Study of Income Dynamics (PSID). I also use data from the Medical Expenditure Panel Survey (MEPS) for medical spending analysis. This section provides information for these data sets.

1.1. Panel Study of Income Dynamics (PSID)

The PSID is a longitudinal study of a representative sample of the U.S. population. It provides high-quality information on, among other things, labor market behaviors, income, health, and wealth. In 1968, about 4,800 families were first interviewed, with information gathered on these families and their descendants from that time onwards. Individuals are followed and interviewed annually (biennially since 1997) to maintain a representative sample of families.

The original 1968 PSID sample consists of 1,872 low-income families from the Survey of Economic Opportunity (SEO) and a nationally representative sample of 2,930 families designed by the Survey Research Center (SRC) at the University of Michigan. I select all individuals in the SRC sample who are interviewed in the waves 1968-2015. Since the PSID has stopped following most families from the SEO sample after 1997 and to make data more representative to the U.S. population, I drop the SEO sample. Further, I keep male household heads and their spouses, if present, and individuals age between 20 and 90. I pick male household heads born in 1920-1935 as the 1930s cohort and male heads born in 1945-1960 as the 1950s cohort.

Table 1 reports the sample selection and sample size. The resulting sample includes 984

*Affiliations: Louisiana State University. Address: 2300 Business Education Complex South, 501 South Quad Drive, Baton Rouge, LA 70803. Email: zhixiuyu@lsu.edu. I gratefully acknowledge fellowship support from grant RDR18000003 from the US Social Security Administration (SSA) funded as part of the Retirement and Disability Research Consortium. The opinions and conclusions expressed are solely those of the author and do not represent the opinions or policy of SSA, any agency of the Federal Government, or National Bureau of Economic Research (NBER).

Table 1: PSID Sample Selection

Selection	Individuals	Observations
Initial sample	76,880	3,075,200
Non-SEO sample	36,430	1,457,200
Household heads and spouse if present	21,225	265,743
Male household heads	10,472	123,650
Age 20 to 90	10,407	122,730
The 1930s cohort	984	20,091
The 1950s cohort	2,844	45,945

individuals and 20,091 observations for the 1930s cohort. I use data from the PSID to estimate the health status transition, wage process, survival probabilities, wife's earnings, initial distribution over state variables, and the moment conditions that my model is estimated to match.

1.2. Medical Expenditure Panel Survey (MEPS)

The MEPS is a nationally representative survey of families, individuals, their medical providers and employers across the United States. It contains individuals of all ages but age is top coded at age 85. The medical spending reported in the MEPS is at the individual level and cross-checked with medical providers and insurance companies, which improves the accuracy of the data. I use data from the 1999-2012 waves of MEPS, drop observations with missing values of age, medical spending, health insurance information during the working periods, or health status, and keep household head above age 20 only. The resulting sample comprises 120,731 persons and 211,709 person-year observations, as shown in Table 2.

I use data from the MEPS to estimate the life-cycle profiles of out-of-pocket medical expenses by health status for a representative population.

Table 2: MEPS Sample Selection

Selection	Individuals	Observations
Initial sample	259,263	491,795
Household heads	130,978	231,866
Age above 20	125,587	222,495
With insurance information at 25-65	121,385	213,005
Non-missing health status	120,731	211,709

2. Labor Supply Trends By Demographic Groups

This section discusses the trends and changes in labor supply across different demographic groups, specifically focusing on the differences between the 1930s and 1950s cohorts. Using the data from the PSID, the analysis finds that there have been compositional changes in education and occupation across the two cohorts and increases in labor supply at older ages across both educational and occupational groups. However, the increases in the older-age labor supply do not differ significantly across either educational or occupational groups.

2.1. Education

Men born in the 1950s have a higher share of individuals with a college degree than the 1930s cohort over their lifetime (ages 30-70). Figure 1 illustrates this trend, showing that there is a more than 15 percentage point higher share of people with a college degree at older ages in the 1950s cohort compared to the 1930s cohort.

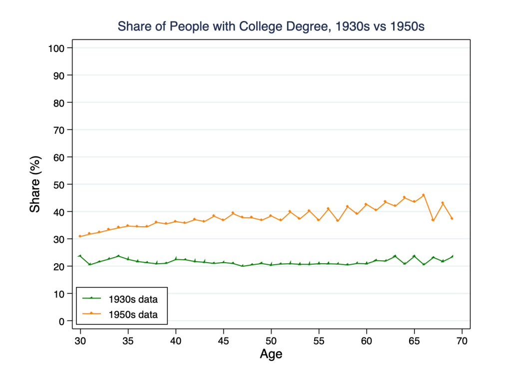
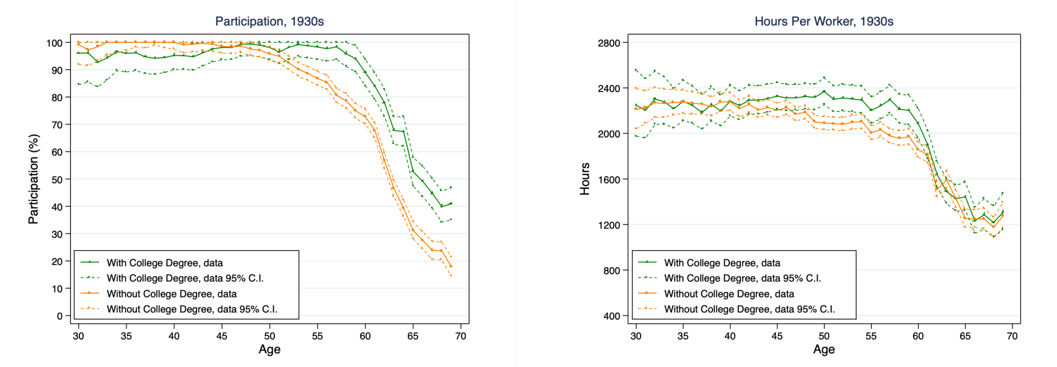


Fig. 1. Shares of People with College Degree, 1930s vs 1950s

Notes: Shares of people with college degree over ages 30-70, comparing the 1930s cohort (green) and the 1950s cohort (orange) for American men.
Data Source: Panel Study of Income Dynamics, author's calculations.

The analysis also looks at the relationship between educational attainment and labor supply. Figure 2 (panel a and panel b) shows the life-cycle profiles of labor force participation and hours worked per worker of the 1930s cohort by educational groups (green: with a college degree; orange: without a college degree). We find that the effect of college educational attainment on hours worked per worker at older ages is not statistically significant, but its impact on labor force participation is large after age 50. For example, the participation rates of people with a college degree is over 20 percentage points higher than those without a college degree at age 65.



(a) Labor Force Participation

(b) Hours Worked by Workers

Fig. 2. Labor Supply Across Educational Groups

Notes: Panel a and panel b display the life-cycle profiles of labor participation and hours worked by workers in the 1930s cohort, comparing educational groups: with a college degree (green) and without a college degree (orange) for American men. The 95% confidence intervals are represented by dotted lines.

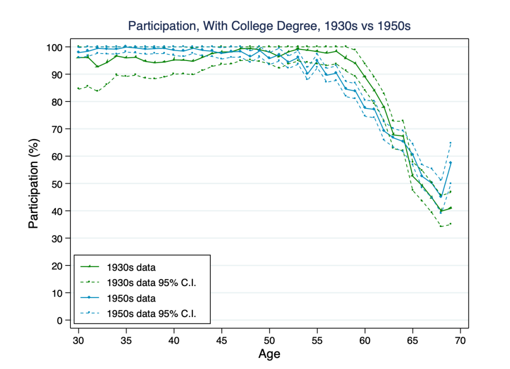
Data Source: Panel Study of Income Dynamics, author's calculations.

When comparing labor supply behaviors across the two cohorts by educational groups, as shown in Figure 3 (panels a-d), the analysis finds that the 1950s cohort has higher participation rates and hours per worker at older ages than the 1930s cohort, but these increased labor behaviors between the two cohorts at older ages do not differ significantly across educational groups.

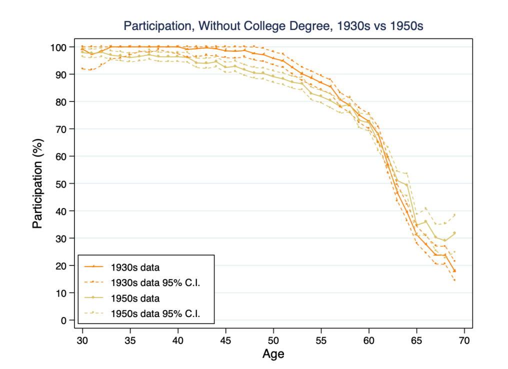
2.2. Occupation

This section documents changes in occupation across different age ranges for the 1930s and 1950s cohorts. The PSID data sets have eight occupation categories, as outlined in Table 3. The analysis finds that when comparing the composition of the eight occupational categories across the age range of 30-70, there are no significant changes between the two cohorts in, e.g., professional and self-employment sectors. However, when looking at the composition of the occupations at older ages, specifically 60-70, the 1950s cohort is found to have higher shares of individuals in the occupation groups of "Professional, technical and kindred workers" and "Self-employed businessmen," and fewer individuals in the groups of "Clerical and sales workers" and "Craftsmen, foremen, and kindred workers" than the 1930s cohort.

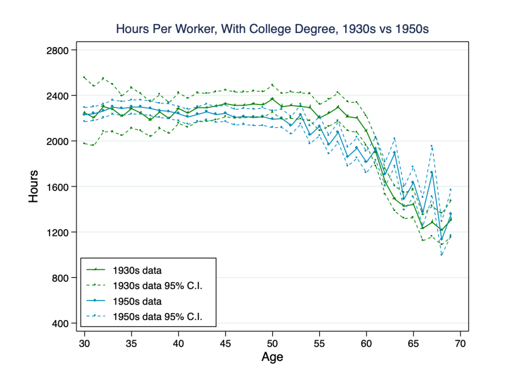
To further investigate labor supply changes in manufacturing and professional sectors between the two cohorts, the analysis defines men working in manufacturing as those belonging to "Clerical and sales workers" and "Craftsmen, foremen, and kindred workers," and those in professional as those belonging to "Professional, technical and kindred worker." As it is difficult



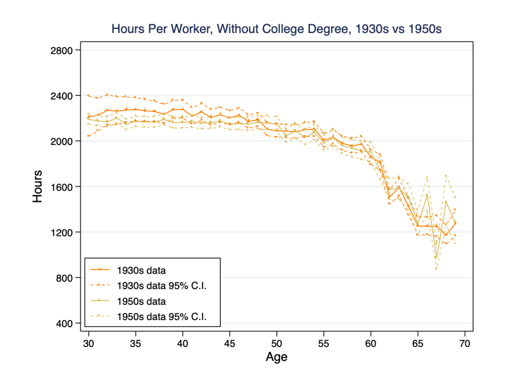
(a) Labor Force Participation, College Degree



(b) Labor Force Participation, No College Degree



(c) Hours Worked by Workers, College Degree



(d) Hours Worked by Workers, No College Degree

Fig. 3. Labor Supply Across Cohorts and Educational Groups

Notes: Panel a and panel b display the data profiles of life-cycle labor participation across cohorts, comparing men with and without a college degree. Panel c and panel d display the data profiles of life-cycle hours worked by workers across cohorts and educational groups. Green lines indicate the profiles of the 1930s cohort, while blue lines indicate those of the 1950s cohorts. The 95% confidence intervals are represented by dotted lines.

Data Source: Panel Study of Income Dynamics, author's calculations.

Table 3: Compositional Changes in Occupation

Occupation Category	Ages 60-70 1930s (%)	Ages 60-70 1950s (%)	Ages 30-70 1930s (%)	Ages 30-70 1950s (%)
1. Professional, technical and kindred workers	17.82	20.57	17.30	17.01
2. Managers, officials and proprietors	17.84	17.08	16.32	15.75
3. Self-employed businessmen	18.73	19.94	18.39	18.58
4. Clerical and sales workers	10.40	9.31	8.66	10.12
5. Craftsmen, foremen, and kindred workers	20.42	17.94	21.33	21.68
6. Operatives and kindred workers	10.76	10.81	13.40	12.87
7. Laborers and service workers, farm laborers	3.92	4.36	4.33	3.86
8. Farmers and farm managers	0.10	0.00	0.28	0.13

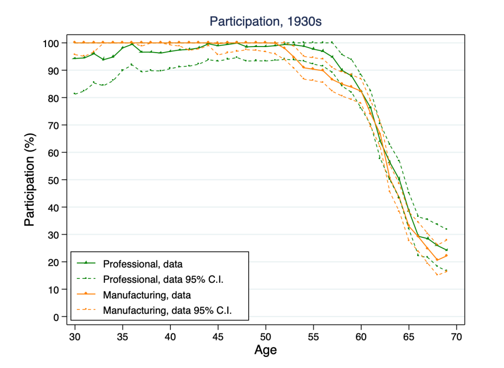
Source: Panel Study of Income Dynamics, author'scalculations.

to identify which individuals are working in manufacturing in, e.g., "Self-employed businessmen," I only choose the categories that are representative of manufacturing or professional jobs.

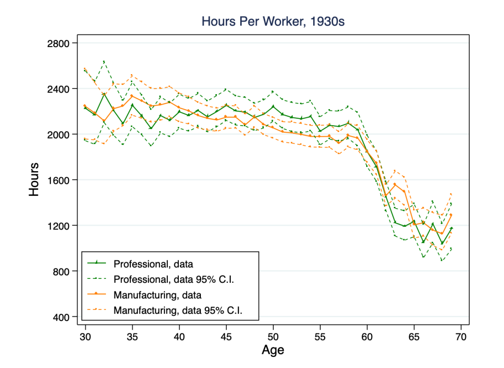
Figure 4 (panels a and b) displays the life-cycle profiles of labor force participation and hours worked per worker of the 1930s cohort by these occupational groups (green: professional; orange: manufacturing). The analysis finds that the effects of employment sectors on labor participation and hours worked per worker at older ages across cohorts are not statistically significant.

Comparing the labor supply behaviors between the 1930s and the 1950s cohorts, Figure 4 (panels c-f) shows that the 1950s cohort has higher participation rates and hours per worker at older ages than the 1930s cohort. Similar to the patterns seen in labor supply by educational groups, these increased older-age labor behaviors do not differ across professional and manufacturing sectors.

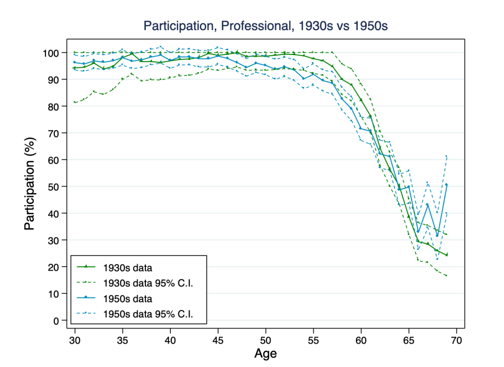
In summary, the analysis finds that there are distinct changes in the composition of education and occupation across the two cohorts. However, it is found that increases in labor supply at older ages do not present significant differences across those demographic groups. This is consistent with the findings of Cajner et al. (2021), which use data from the CPS and HRS and document that the increase in labor force participation of American men at older ages does not differ across either educational or occupational groups.



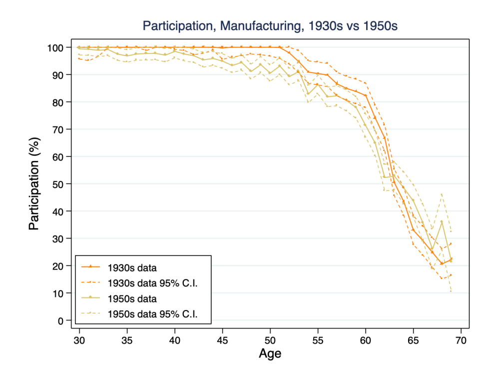
(a) Labor Force Participation, 1930s



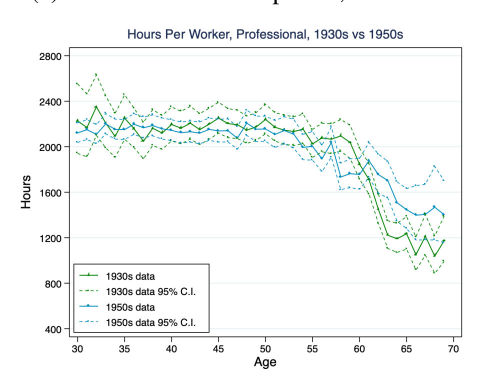
(b) Hours Worked by Workers, 1930s



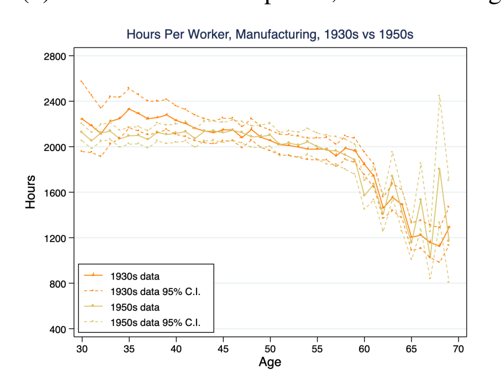
(c) Labor Force Participation, Professional



(d) Labor Force Participation, Manufacturing



(e) Hours Worked by Workers, Professional



(f) Hours Worked by Workers, Manufacturing

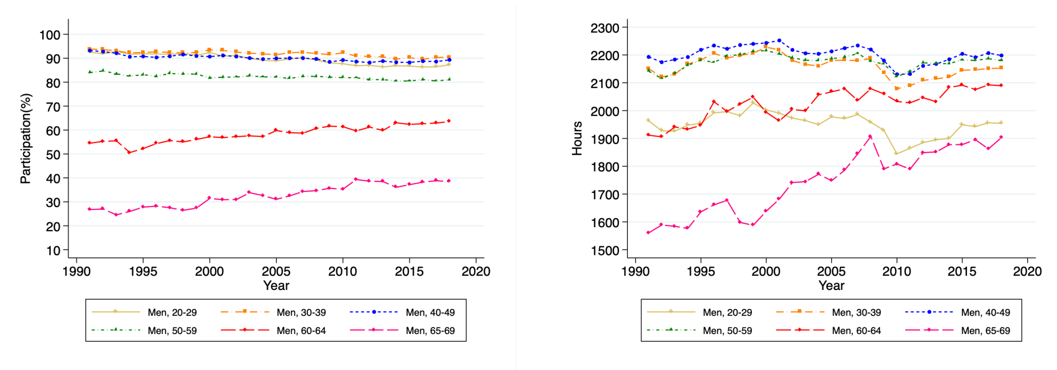
Fig. 4. Labor Supply Across Occupation Groups and Cohorts

Notes: Panels a and b: Data profiles of life-cycle labor participation (panel a) and hours worked by workers (panel b), comparing occupational groups: the professional (green) and the manufacturing (orange) for American men, the 1930s cohort. Panels c-f: Data profiles of life-cycle participation in the occupation groups: professional (panel c) and manufacturing (panel d), and profiles of hours per worker: professional (panel e) and manufacturing (panel f), comparing the 1930s and the 1950s cohorts for American men. The 95% confidence intervals are represented by dotted lines.

Data Source: Panel Study of Income Dynamics, author's calculations.

2.3. Supplemental Figures and Tables

The section presents supplementary evidence on labor supply trends using different data resources. Figure 5 and Figure 6 display the labor supply trends of men and women in different age groups using data from CPS. Figure 7 plots the life-cycle profiles of labor supply between the 1930s and the 1950s cohorts by health status using data from HRS. Additionally, Table 4 and Table 5 provide the regression using the HRS and the PSID to support the plotted labor supply trends.



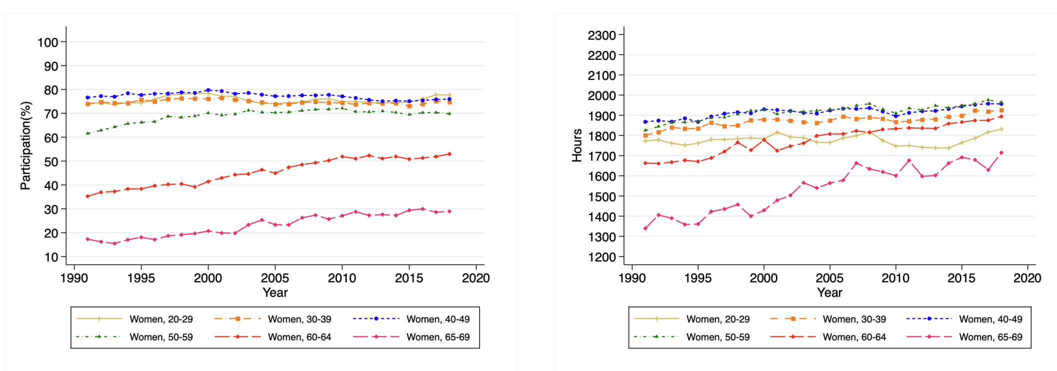
(a) Labor force participation trends

(b) Hours worked trends

Fig. 5. Labor Supply Trends of Men by Age Groups

Notes: Panel a shows the trends in labor force participation of men by age groups. Panel b shows the trends in hours worked conditional on participation of men by age groups.

Source: March Current Population Survey (through IPUMS, see Flood et al. (2020)), author's calculations.



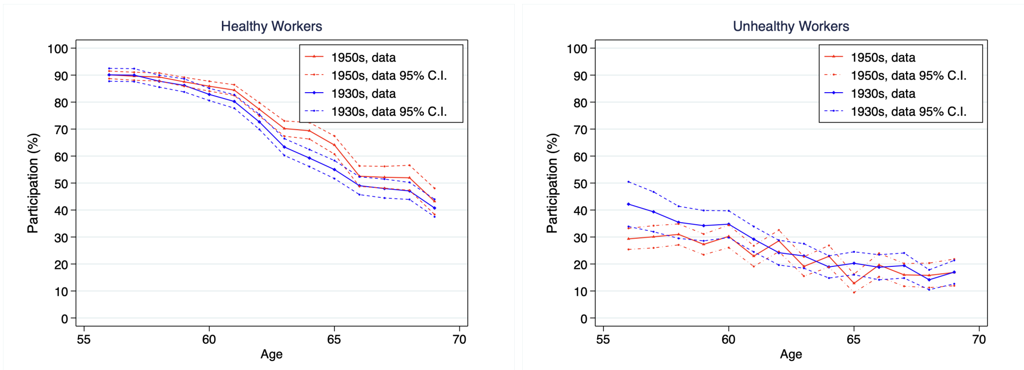
(a) Labor force participation trends

(b) Hours worked trends

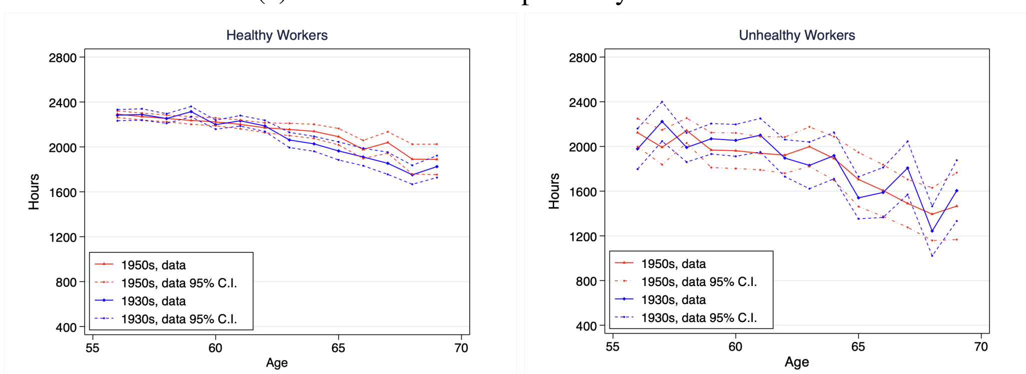
Fig. 6. Labor Supply Trends of Women by Age Groups

Notes: Panel a shows the trends in labor force participation of women by age groups. Panel b shows the trends in hours worked conditional on participation of women by age groups.

Source: March Current Population Survey (through IPUMS, see Flood et al. (2020)), author's calculations.



(a) Labor Force Participation by Health Status



(b) Hours Worked by Health Status

Fig. 7. Labor Supply Across Cohorts By Health Status

Notes: Data profiles of life-cycle labor participation (panel a) and hours conditional on working (panel b), comparing the 1930s (blue) and the 1950s (red) cohorts for healthy people (left panels) and unhealthy people (right panels). The 95% confidence intervals are represented by dotted lines.
Data Source: Health and Retirement Study, author's calculations.

Table 4: Regression on Labor Supply of Older Men using HRS

	Coefficients	S.E.
A. Employment Rates		
Age	-0.3160***	(0.0214)
Age^2	0.0022***	(0.0002)
$Health(good)$	0.2906***	(0.0059)
$Cohort(1950s)$	0.0702***	(0.0061)
$Health(bad) \times Cohort(1950s)$	-0.1552***	(0.0102)
$Constant$	11.6837***	(0.7198)
Observations	37,197	
B. Hours Worked Per Worker		
Age	-330.5391***	(69.5164)
Age^2	1.9865***	(0.5205)
$Cohort(1950s)$	45.1902***	(16.1699)
$Health(good)$	234.4596***	(25.0404)
$Health(bad) \times Cohort(1950s)$	-135.0028***	(43.8290)
$Constant$	14658.89***	(2312.849)
Observations	14,366	

[1] Notes: Dependent Variables: A. Older men's employment rates; B. Older men's hours worked conditional on working. Standard Errors in parentheses. $*p < 0.10, **$ $p < 0.05, ***p < 0.01$.

[2] Source: Health and Retirement Study, author's calculations.

Table 5: Regression on Labor Supply of Men using PSID

	Coefficients	S.E.
A. Employment Rates		
Age	0.0422***	(0.0005)
Age^2	-0.0006***	(0.0000)
$Cohort(1950s)$	-0.0272***	(0.0027)
$Health(good)$	0.2473***	(0.0043)
$Age(55-75) \times Cohort(1950s)$	0.0761***	(0.0046)
$Health(bad) \times Cohort(1950s)$	0.0242***	(0.0057)
$Constant$	0.0443***	(0.0113)
Observations	69,964	
B. Hours Worked Per Worker		
Age	63.9744***	(1.5314)
Age^2	-0.8123***	(0.0183)
$Cohort(1950s)$	-27.0235***	(6.9828)
$Health(good)$	228.6858***	(14.6240)
$Age(55-75) \times Cohort(1950s)$	62.3883***	(14.1394)
$Health(bad) \times Cohort(1950s)$	38.9079**	(18.1890)
$Constant$	862.3294***	(33.9788)
Observations	58,950	

[1] Notes: Dependent Variables: A. Older men's employment rates; B. Older men's hours worked conditional on working. Standard Errors in parentheses. $*p < 0.10, **$ $p < 0.05, ***p < 0.01$.

[2] Source: Panel Study of Income Dynamics, author's calculations.

Table 6: Labor Supply Elasticity to a 20% Wage Increase

Working Hours	Temporary Wage Increase				Permanent Wage Increase			
	Age 40	Age 50	Age 60	Age 65	Age 40	Age 50	Age 60	Age 65
In the year of wage change								
Overall	0.43	0.60	1.16	3.97	0.27	0.46	1.06	3.78
Healthy	0.42	0.49	1.00	4.03	0.26	0.37	0.89	3.79
Unhealthy	0.52	1.35	1.98	3.80	0.36	1.10	1.94	3.76
After the year of wage change								
Overall	-0.02	-0.00	0.15	0.87	0.25	0.61	1.81	3.65
Healthy	-0.01	-0.01	0.12	0.89	0.23	0.54	1.70	3.72
Unhealthy	-0.03	0.03	0.27	0.81	0.39	1.07	2.34	3.48
Participation	Temporary Wage Increase				Permanent Wage Increase			
	Age 40	Age 50	Age 60	Age 65	Age 40	Age 50	Age 60	Age 65
In the year of wage change								
Overall	0.01	0.12	0.56	3.12	0.01	0.10	0.57	2.82
Healthy	0.01	0.02	0.39	3.20	0.10	0.02	0.40	2.81
Unhealthy	0.05	0.79	1.35	2.91	0.04	0.65	1.39	2.84
After the year of wage change								
Overall	-0.02	-0.03	0.03	0.65	0.08	0.35	1.39	2.80
Healthy	-0.02	-0.03	0.01	0.67	0.06	0.28	1.28	2.78
Unhealthy	-0.04	-0.01	0.12	0.60	0.17	0.74	1.85	2.82

3. Recursive Formulation and Numerical Methods

The life cycle can be divided into three stages for each individual. The first stage is between ages 25 and 61: individuals are not eligible for pension and Social Security retirement benefits and only decide on consumption and hours worked (including participation).

Let $X_t = (a_t, w_t, h_t, aime_t)$ denotes the vector of state variables at age t, In recursive form, the individual's problem in state (X) and age t can be written as:

$$\begin{aligned} V_t(X_t) &= \max_{c_t, n_t}\{u(c_t, l_t) + \beta s_{t+1} E_t[V_{t+1}(X_{t+1})] + \beta(1 - s_{t+1})B(a_t)\} \qquad \text{(OA.1)} \\ &= \max_{c_t, n_t}\{\frac{1}{1-\nu}(\ c_t^\gamma\ [L - n_t - \theta_p^{h_t} p_t - \phi \mathbb{1}_{\{h_t \neq 0\}}]_t^{1-\gamma}\ )^{1-\nu} \\ &\quad + \beta s_{t+1} \int V_{t+1}(X_{t+1}) dF(X_{t+1}|X_t, t, c_t, n_t) + \beta(1 - s_{t+1})B(a_{t+1})\} \end{aligned}$$

subject to Equations (3)-(16) in the main content. The parameter β is the discount factor. Individuals with higher values of β are more patient and more willing to defer their consumption and leisure. The function $F(\cdot|\cdot)$ determines the conditional distribution of state variables, given (3)-(16).

The second stage is between ages 62-69, a transition period where individuals choose consumption, labor supply, and whether to apply for Social Security retirement benefits. The value function of the individual in state (X_t) is described as:

$$
\begin{aligned}
V_t(X_t) = \max_{c_t,n_t,b_t} \{ & \frac{1}{1-\nu}(\, c_t^{\gamma} \, [L - n_t - \theta_p^{h_t} p_t - \phi \mathbb{1}_{\{h_t \neq 0\}}]_t^{1-\gamma} \,)^{1-\nu} \\
& + \beta s_{t+1} \int V_{t+1}(X_{t+1}) dF(X_{t+1}|X_t, t, c_t, n_t, b_t) \\
& + \beta(1 - s_{t+1}) B(a_{t+1}) \}
\end{aligned}
\tag{OA.2}
$$

subject to Equations (3)-(16). The state vector is $X_t = (a_t, w_t, h_t, b_{t-1}, aime_t)$, and the indicator b_{t-1} denotes Social Security benefits claim status.

The third stage is between ages 70-95, an entire retirement period where individuals only decide on consumption. Since Social Security rules provide no incentive to delay retirement benefit application after reaching age 70, I assume that all workers retire and apply for Social Security benefits by age 70, i.e., for $t \geq 70, b_t = 1, n_t = p_t = 0$. Then the individual's value function during the entire retirement period is given as follows:

$$
\begin{aligned}
V_t(X_t) = \max_{c_t} \{ & \frac{1}{1-\nu}(\, c_t^{\gamma} \, [L - \phi \mathbb{1}_{\{h_t = 1\}}]_t^{1-\gamma} \,)^{1-\nu} \\
& + \beta s_{t+1} \int V_{t+1}(X_{t+1}) dF(X_{t+1}|X_t, t, c_t) + \beta(1 - s_{t+1}) B(a_{t+1}) \}
\end{aligned}
\tag{OA.3}
$$

subject to Equations (3), (6)-(15). The vector of state variables is $X_t = (a_t, h_t, aime_t)$.

The model is solved backwards using value function iteration. An individual's decisions in period t depend on his state variables X_t, preferences $\Theta = (\gamma, \nu, \theta_p^{h=0}, \theta_p^{h \neq 0}, \phi, L, \beta, \theta_b, \kappa)$, and parameters that determine the data generating process for the state variables $\chi = (r, \sigma_\eta^2, \rho, W(h_t, t + 1), \{\pi_{h_{t+1}, h_t, t}\}_{t=1}^T, \{s_t\}_{t=1}^T, \{ys_t\}_{t=1}^T, \{m_t\}_{t=1}^T, \{pb_t\}_{t=1}^T, \{ss_t\}_{t=1}^T, \{db_t\}_{t=1}^T, Y_t(\cdot))$.

The solution to a male household head's problem consists of sequences of consumption rules $\{c_t(X_t, \Theta, \chi)\}_{1 \leq t \leq T}$, hours worked rules $\{n_t(X_t, \Theta, \chi)\}_{1 \leq t \leq T}$, and Social Security benefit application rules $\{b_t(X_t, \Theta, \chi)\}_{1 \leq t \leq T}$ that solve problems (OA.1)-(OA.3). The labor force participation rules at t, $p_t(X_t, \Theta, \chi)$, are equal to zero when $n_t(X_t, \Theta, \chi) = 0$ and equal to one otherwise. Assets in the next period, $a_{t+1}(X_t, \Theta, \chi)$, can be obtained by inserting these decision rules into the asset accumulation equation (12).

The decision rules are solved numerically using value function iteration, starting at the period T and working backward to the first period. At time T, consumption decision c_T is made by solving the above problem $V_T(X_T)$ with the terminal value $V_{T+1} = B(a_{T+1})$. Given the decision rules and value function at time T, I then solve decision rules at time $T - 1, T - 2$, ..., 0.

I discretize the state variables into a finite number of points within a grid. I directly compute the value function at these points and integrate the value function with respect to the innovation of wages using five-node Gauss-Hermite quadrature (see Judd (1998)). Also, I use linear interpolation within the grid and linear extrapolation outside of the grid to evaluate value function at points that can not be directly computed. The grid consists of 30 asset states, $a_j \in [\$0, \$660000]$; 10 wage states, $w_j \in [\$3, \$60]$; 10 AIME states, $\text{AIME}_j \in [\$2000, \$43800]$ (in 1987 dollars); 2 Social Security application states; and 3 health states (good health, bad health, disabled state). In particular, I solve the value function at 9,000 different points at the first stage; 18,000 points at the second stage; and 900 points at the third stage. Following French (2005), since changes in assets, wages, and AIME are intended to cause larger behavioral responses at low levels of these state variables, the grid is more finely discretized at these levels. In addition, I discretize the the consumption and hours worked decision space and find the optimal decisions by searching over the grid. There are 180 points for consumption, and the hours worked grid is broken into 300-hour intervals.

I then use the decision rules to generate simulated life-cycle histories of individuals using forward induction. For instance, given the realized state variables X_0, I can find an individual's decision at time 0 using the decision rules at $t = 0$. Then given time-0 decisions, the state variables X_1 can be obtained using χ_0 and shocks at time 1, the same for $t = 2, ...T$.

4. Method of Simulated Moments

I proceed with the MSM in the following steps. First, I estimate the life-cycle profiles for labor force participation, hours worked, and assets by health status from the data. Second, I estimate the initial distribution for relevant state variables and a set of parameters that determine the data generating process for the state variables, χ, as in the first step. Then taking as given χ, generate matrices of health and wage shocks. Third, I iterate on the following procedure for different values of Θ until the minimum distance, as in Equation (19), has been found.

1. Given Θ, solve the model and generate the simulated life-cycle profiles for decision variables.
2. Compute moment conditions and calculate the distance between the simulated profiles and data profiles described in Equation (19).
3. Pick a new vector of preference parameters, Θ_{new}, and repeat the above two steps.

4.1. Target Profiles

The target profiles of labor force participation, hours per worker, and savings for healthy and unhealthy men in the 1930s cohort are constructed using the data from the PSID and by running the fixed-effects regression equation (OA.4), following the procedure adopted in French (2005).

Labor force participation is a dummy variable and counted as one if the individual's annual hours worked are more than 300 hours per year. Hours worked are measure with self-reported working hours from the survey. Respondents in survey year t report their total hours of work in year $t-1$. Hours are counted as zero if the reported annual hours worked are below 300 hours.

The measurement of assets includes real estate, the value of a farm or business, vehicles, stocks, mutual funds, IRAs, Keoghs, liquid assets, bonds, and investment trusts, net of mortgages and other debts. It does not include pension or Social Security wealth. I define assets as the sum of all above asset types, plus the value of home equity, and net of debts. I exclude the extremely wealthy or poor observations in the top 5% and bottom 1% of the sample. Assets in the PSID have only been observed in 1984, 1989, 1994, 1999, 2001, 2003, 2005, 2007 PSID wealth surveys, and 2009, 2011, 2013, 2015 PSID family files.

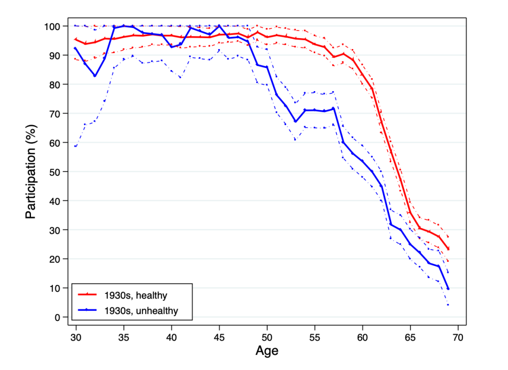
To impute the assets in the missing years, I run the fixed-effect regression for assets on a set of variables, including age polynomials, its interaction with health status, and with log wages, family size, education, unemployment rates, a dummy for health status, its interaction with unemployment rates, and with log wages (e.g., Borella et al. (2019b)). I then use the imputed and the actual observations to estimate the assets profiles by health status that are used as target moments and to compute the initial joint distribution.

I estimate the target profiles by running the following fixed-effects regression:

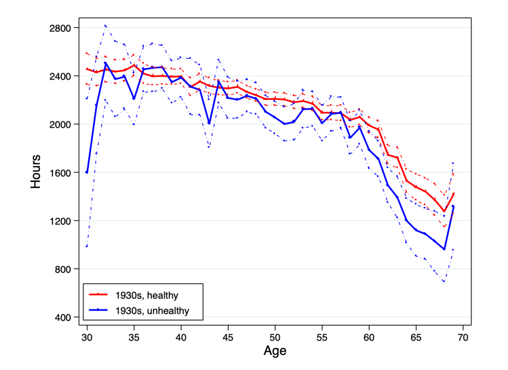
$$\begin{aligned} Z_{it} = f_i + &\sum_{k=1}^{T} B_{gk} I\{age_{it}=k\} \times I\{h_{it}=0\} + \sum_{k=1}^{T} B_{bk} I\{age_{it}=k\} \times I\{h_{it}\neq 0\} \qquad \text{(OA.4)} \\ &+ \sum_{f=1}^{F} B_f \text{familysize}_{it} + B_u U_t + u_{it} \end{aligned}$$

where Z_{it} represents the data observation of either assets, hours worked, or participation for individual i at age t; f_i denotes an individual-specific effect; familysize_{it} is family size dummies; U_t is the unemployment rate; and $\{\{B_{gk}\}_{k=1}^{T}, \{B_{bk}\}_{k=1}^{T}, \{B_f\}_{f=1}^{F}, B_u\}$ are parameters. To make those target profiles are not contaminated by family, year, and individual-specific effects, following French (2005), I control for family size and year (business cycle) effects by setting the family size to 3 and the unemployment rate to 6.5%. Further, I use the mean individual-specific effect for individuals who are age 50, have the average level of health at age 50, and were born in 1930, to control for birth-year (cohort) effect and correlation between person-specific effect and health status for the 1930s cohort. Profiles are estimated by healthy ($h=0$) and unhealthy ($h\neq 0$) status due to limited observations with disability in the data.

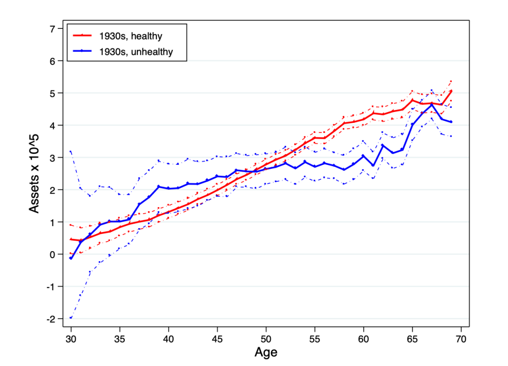
Figure 8 presents the estimated target profiles by health status. As mentioned in Section 2, health plays a significant role in the life-cycle labor supply. The participation rates of healthy individuals start declining in their 60s, while those of unhealthy individuals begin to decline in their late 40s (panel a). One possible explanation for this could be that disability benefits provide some



(a) Labor force participation



(b) Hours worked by workers



(c) (Non-Pension) Assets

Fig. 8. Target Profiles

Notes: Panel a shows the profiles of labor force participation by health status. Panel b shows the profiles of hours worked by health status. Panel c shows the profiles of assets by health status. The red lines represent the profiles for healthy people ($h = 0$). The blue lines represent the profiles for unhealthy people ($h = 1, 2$). Monetary values are expressed in 2016 dollars.

Source: Panel Study of Income Dynamics, author's calculations.

unhealthy individuals opportunities to drop out of the labor market before their retirement age.

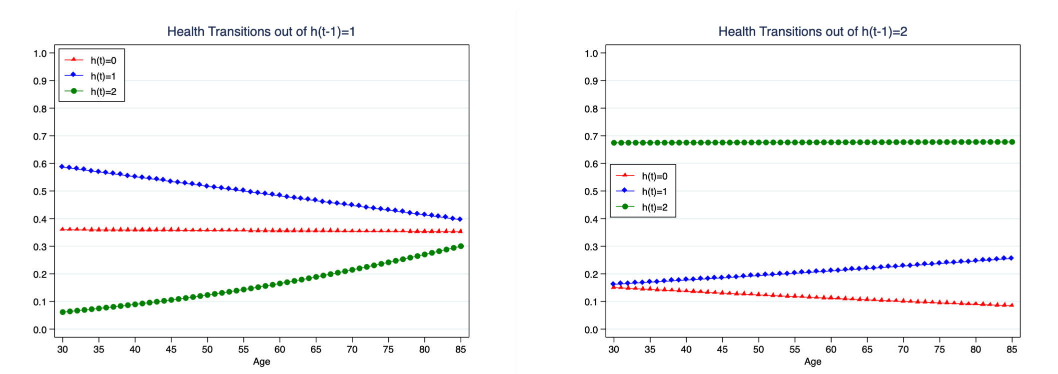
In Figure 8 (panel b), hours worked conditional on participation begin to decline around age 60 for both healthy and unhealthy workers. Health does not have a notable impact on annual working hours during the prime working years (ages 30-59), but it does affect labor behaviors after age 60, when workers begin working fewer hours. For example, at age 65, an average healthy worker works about 400 hours more than an average unhealthy worker.

Figure 8 (panel c) illustrates that health also has a large impact on savings behaviors for individuals after age 50. For example, an average healthy individual has about $120,000 (in 2016 dollars) more than an average unhealthy individual at age 60. This difference can partially be attributed to medical expenditure, which is more expensive for unhealthy individuals at older ages.

4.2. **First-Step Estimation**

4.2.1. **Health Transitions**

Health and disability status is measured based on the following set of self-reported work limitation questions from the PSID. Since there are three health states, $h_t = \{0, 1, 2\}$, we have nine transition patterns, $Pr(h_t = j|h_{t-1} = i),\ i, j \in \{0, 1, 2\}$. I estimate the evolution of health for individuals in the 1930s cohort by running a probit regression for an indicator $(h_t = j|h_{t-1} = i)$ on age dummies using the sample with $(h_{t-1} = i)$. The predicted values of these probit regressions are the estimates of $Pr(h_t = j|h_{t-1} = i),\ i, j \in \{0, 1, 2\}$. I linearly interpolate the probabilities of transitioning in three states across ages so that the transition matrices changes smoothly over the life cycle. The remaining age-specific health transitions out of bad health $Pr(h_t|h_{t-1} = 1)$ and disabled state $Pr(h_t|h_{t-1} = 2)$ are displayed in Figure 9.



(a) Health transition out of bad health (b) Health transition out of disabled state

Fig. 9. Remaining Health Transitions

Notes: Panel a shows the probabilities of transitioning out of bad health. Panel b shows the probabilities of transitioning out of disability status. The red line shows the transition probabilities to good health. The blue line shows the transition probabilities to bad health. The green line shows the transition probabilities to disability status.
Source: Panel Study of Income Dynamics, author's calculations.

4.2.2. **Survival Probabilities**

Age- and health-dependent survival probabilities are estimated by running a logistic regression for the indicator of survival on age polynomial, previous health status, and interaction between cohort dummies and these variables whenever they are statistically significant, using data from the PSID. The estimated coefficients are reported in Table 7.

Table 7: Estimated Coefficients for the Survival Probabilities

	Coefficients	S.E.
Age^2	-0.0006***	(0.0000)
Health_{t-1}	-1.0586***	(0.1202)
Cohort	1.2168***	(0.3214)
Cohort$\times$Age^2	-0.0002***	(0.0001)
Cohort$\times$Health$_{t-1}$	-0.6850***	(0.2081)
Constant	6.9298***	(0.2051)
Observations	57,549	

[1] Notes: Estimated Coefficients of Logistic Regression. Dependent Variable: Indicator of survival. Robust Standard Errors in parentheses, clustered at the individual level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

[2] Source: Panel Study of Income Dynamics, author's calculations.

4.2.3. **Out-of-Pocket Medical Expenses**

The out-of-pocket medical expenses are computed as total medical expenditure net of the amount covered by health insurance programs, using data from the MEPS. Health status is measured based on self-perceived health rank (e.g., Pashchenko and Porapakkarm (2019)), which ranges from 1 to 5. Refer to Appendix A for detailed measurement. I estimate the out-of-pocket expenditure in the following steps.

First, following the procedure used by Pashchenko and Porapakkarm (2019) I estimate the profiles of total medical expenses by running a weighted regression on age dummies and year dummies, separately for individuals in each health status, using the cross-sectional weights and longitudinal weights. Then I estimate the profiles of insurance coverage by regressing them on age dummies and year dummies, separately by health status. For working-age individuals (age 25-64), the medical coverage is computed as the amount paid by insurance programs. In contrast, for individuals who are 65 or older, the coverage is calculated as the expenses paid by Medicare. Next, I compute the out-of-pocket expenditure as the product of estimated coinsurance rates and total medical expenses at each age and health status. Following De Nardi et al. (2018), the estimated medical expenses are multiplied by 1.60 for people younger than 65 years old and by 1.90 for people who are 65 or older to make medical spending consistent with the aggregate medical expenditures from the National Health Expenditure Account (NHEA). Last, I smooth my estimated profiles by regressing them on a quadratic function of age.

4.2.4. **Hourly Wages**

Hourly wages are computed as annual earnings divided by annual hours worked, using data from the PSID. Respondents in year t report their annual earnings and hours worked in year $t - 1$.

Since wages are only observed for labor market participants in the data, to adjust selection bias in observed wages, I estimate the age and health-specific hourly wage profiles using the Heckman selection model (Heckman (1976)), as adapted by most recent studies, e.g., Guner et al. (2012) and Borella et al. (2019a).[1] Specifically, in the first step, I estimate the selection equation (labor force participation) by running a probit regression using all observations from the PSID, and an inverse Mill's ratio is generated. In the second step, I estimate hourly wage by running a regression on age polynomials, the intersection of health and age polynomials, and the inverse Mill's ratio obtained from the first step. The estimated coefficients of the two-stage procedure are reported in Table 8.

I estimate the stochastic components of hourly wages, (ρ, σ_ρ^2), using the wage residuals from the above steps. Following the procedure described in Borella et al. (2019b), I limit the age range between 30 and 75 and drop the highest 0.5% residuals to avoid large outliers that inflate the variance. The estimation process is performed by Maximum Likelihood and standard Kalman Filter recursions. The estimated results for (ρ, σ_ρ^2) in wages are (0.99, 0.0125), which are consistent to the estimates of French (2005) and Borella et al. (2019b). The estimated stochastic components of wages and deterministic age- and health-specific profiles are used in Equation (4) to simulate wages and fed into the model estimation.

4.2.5. **Spousal Earnings**

Spousal earnings are defined as annual earnings from the PSID. Respondents in year t report their wife's total annual earnings in year $t-1$. I estimate $ys(\cdot)$ by running a fixed-effects regression on male household head's age polynomial, logarithm hourly wages, and health and disability status. To estimate the average profiles, I treat wife's earnings as zero for individuals who are single. The estimated coefficients are reported in Table 9.

4.2.6. **Social Security Policy Rules and Taxes**

From the SSA, the 1930s cohort face the ERA of 62, NRA of 65, DRC of 4.5% on average, bend points in the PIA formula \$3,720 and \$22,392, and the maximum AIME of \$43,800.[2] The tax rate and exempt amount of earnings test are different for the following two age groups under age 70: (1) For beneficiaries under age 65, \$1 in retirement benefits will be withheld for each \$2 of labor income above the annual exempt amount, \$6,000; (2) For beneficiaries aged 65 and over, \$1

[1] Some previous studies, instead, estimate the parameters of wage equations by matching profiles of labor market participants using the model to adjust the same selection bias problem in observed wages (e.g., French (2005) and French and Jones (2011)). I estimate the wage parameters using the Heckman selection model since it could make my model match the targeted moments well while saving computation time.

[2] Monetary values are expressed in 1987 dollars. The DRC faced by the 1930s cohort varies from 3% to 6%, depending on the year of birth. I take the average DRC, 4.5%, into my model estimation. The bend points in the PIA formula and the maximum AIME are taken from the rules of 1987.

Table 8: Estimated Coefficients for the Logarithm of Hourly Wages

	Coefficients	S.E.
	Wage Equation	
Age	0.0688***	(0.0164)
Age^2	-0.0007***	(0.0002)
Health×Age	-0.0101***	(0.0022)
Health×Age^2	0.0001***	(0.0000)
Constant	1.2145***	(0.3808)
	Selection Equation	
Age	-0.0034	(0.0182)
Age^2	-0.0009***	(0.0001)
Health	0.3449***	(0.0633)
Health×Age	-0.0567***	(0.0025)
Health×Age^2	0.0007***	(0.0000)
Family Size	0.0115	(0.0094)
Birth Year	-0.0135***	(0.0031)
Constant	30.1581***	(6.0534)
Inverse Mill's Ratio	0.0494	(0.0984)
Observations	16,438	

[1] Notes: Estimated Coefficients of Two-Stage Heckman Selection Model. Dependent variable of wage equation: logarithm of the wages. Dependent variable of selection equation: indicator of labor force participation. Robust Standard Errors in parentheses, clustered at the individual level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

[2] Source: Panel Study of Income Dynamics, author's calculations. To control the minimum wage and high wage outliers, observations with hourly wages below \$6.50 or above \$250 (in 2016 dollars) were dropped.

Table 9: Estimated Coefficients for the Spousal Earnings

	Coefficients	S.E.
Age	1027.5790***	(78.8423)
Age^2	-8.0476***	(0.7428)
$Health$	2774.508*	(1421.4030)
$Health \times Age$	-57.0864**	(24.6183)
$Wages$	15.8867	(10.7239)
$Constant$	-24567.8700***	(2046.0310)
Observations	12,947	

[1] Notes: Dependent Variable: Wife's annual earnings. Robust Standard Errors in parentheses, clustered at the individual level. $*p < 0.10, **p < 0.05, ***p < 0.01$.

[2] Source: Panel Study of Income Dynamics, author's calculations.

in benefits will be withheld for each \$3 of labor income above the exempt amount, \$8,186.

For disability benefits, I assume that disabled individuals can receive the disability benefits if they are over age 50 and their labor income is less than \$3,600. This assumption captures the monthly substantial gainful activity amount of \$300, which the SSA sets for the non-blind disabled people to be eligible for the disability benefits.

Further, individuals have to pay federal tax and payroll tax on total income and labor income. The effective time-varying marginal tax rates on American men's total income are estimated using data from the PSID for the 1930s cohort (see, e.g., Borella et al. (2019a)). For the time-varying payroll tax rates and threshold values on labor income, I take the tax rates for Social Security's Old-Age, Survivors, and Disability Insurance (OASID) and for Medicare's Hospital Insurance (HI) using data from the SSA. From 1960 to now, the sum of OASID and HI tax rates for each employee and employer varies from 3% to 7.65%.

4.2.7. **Initial Distribution**

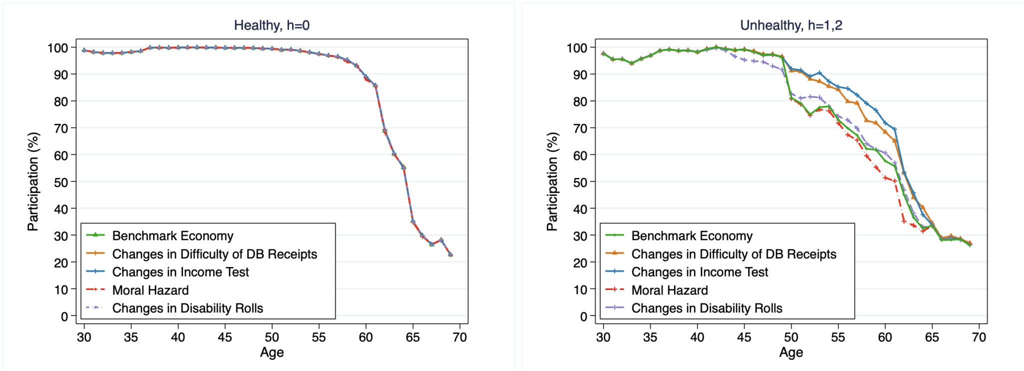
To compute the initial distribution of the relevant state variables at age 30, I take random draws from the empirical joint distribution of wages, health, and household assets for male household heads aged 28-32 from the PSID data for the 1930s cohort. I adjust the mean of log wages for good health, bad health, and disabled state to match the estimated wage profiles for each health status. For initial Social Security wealth $aime_{30}$, I assume that all individuals enter the labor market at age 25 and work 2,000 hours per year at the hourly wage rate of age 30 to impute for initial values of AIME, following the procedure used by French (2005). Table 10 in summarizes the initial distribution of assets, wages, and health status. It shows that individuals in good health have higher wages and assets than those in bad health and disability status.

Table 10: Summary Statistics for the Initial Conditions

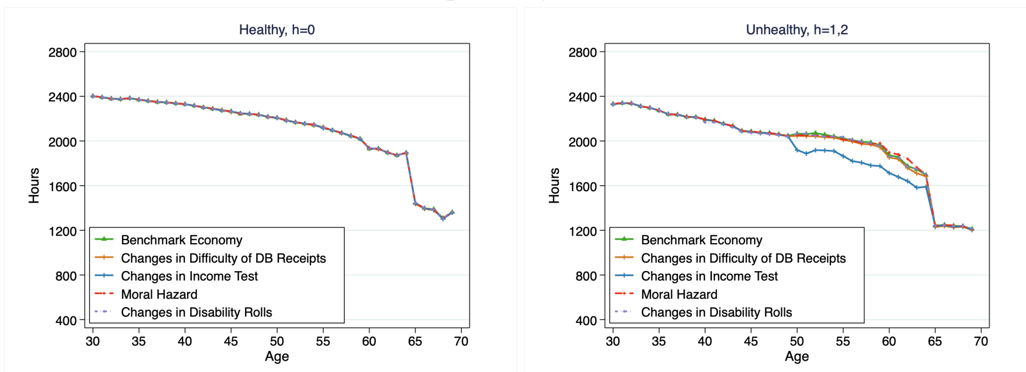
		Health Status		
	Overall	Good	Bad	Disabled
Assets (in 2016 dollars)				
Mean	42,164	42,611	36,020	13,507
Standard Deviation	56,935	57,457	46,480	15,600
Wages (in 2016 dollars)				
Mean	18.91	19.09	15.60	12.91
Standard Deviation	10.32	10.38	8.40	7.67
Percentage		95.28	4.11	0.61
Observations	2,479	2,362	102	15

Source: Panel Study of Income Dynamics, author's calculations.

5. Effects of Disability Benefits



(a) Participation by Health Status

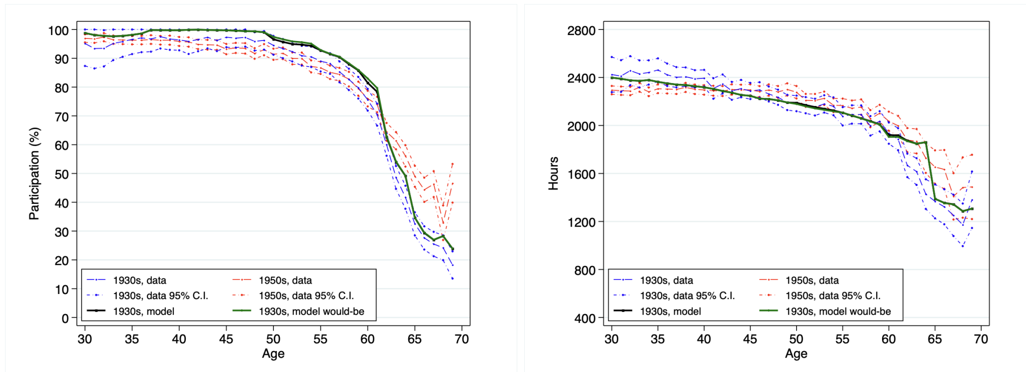


(b) Hours per Worker by Health Status

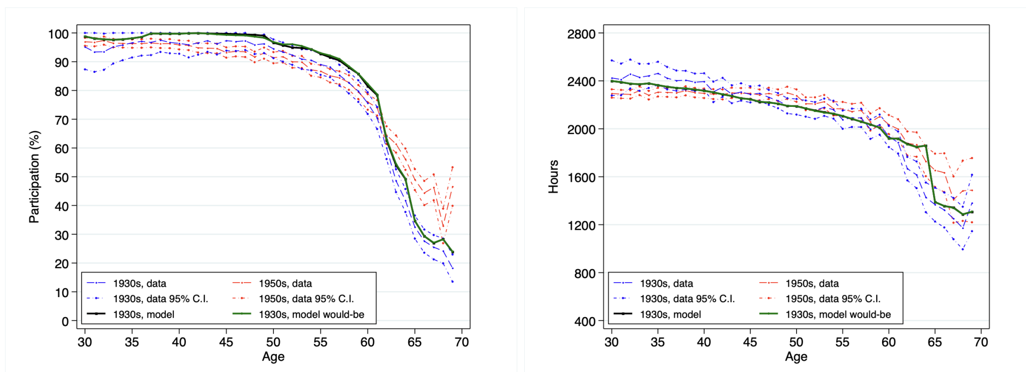
Fig. 10. Effects of Changing Disability Program Rules on Labor Supply

Notes: Panel a shows the simulated profiles of changing Disability Insurance (DI) rules on labor force participation by health status. Panel b shows simulated profiles of changing DI rules on hours worked conditional on participation by health status. Profiles for healthy people ($h = 0$) are on the left, whereas profiles for unhealthy people ($h = 1, 2$) are on the right. Experiments (from top to bottom): The benchmark economy; Doubling the DI receipts difficulty (altering π^{db} from 0.63 to 0.315); Doubling the income threshold for qualifying for DI benefits (changing y_{db} from 3600 to 7200); Allowing moral hazard for qualified non-disabled people ($db\mathbb{1}_{\{h\neq 0\}} > 0$, $\pi^{db}_{h=0} = 0.014$, $\pi^{db}_{h=1} = 0.16$); Changing Disability rolls (altering π^{db} from 0.63 for aged 50-65 to 0.58 for aged 50-65 and 0.33 for aged 40-50);

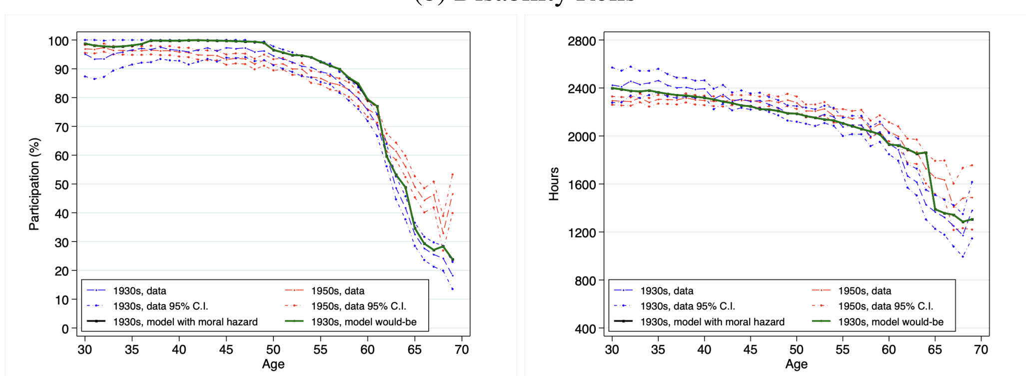
Data Source: Panel Study of Income Dynamics, author's calculations.



(a) Income Threshold



(b) Disability Rolls



(c) Moral Hazard

Fig. 11. Model v.s. Data Profiles: Effects of Changing Disability Benefits Parameters

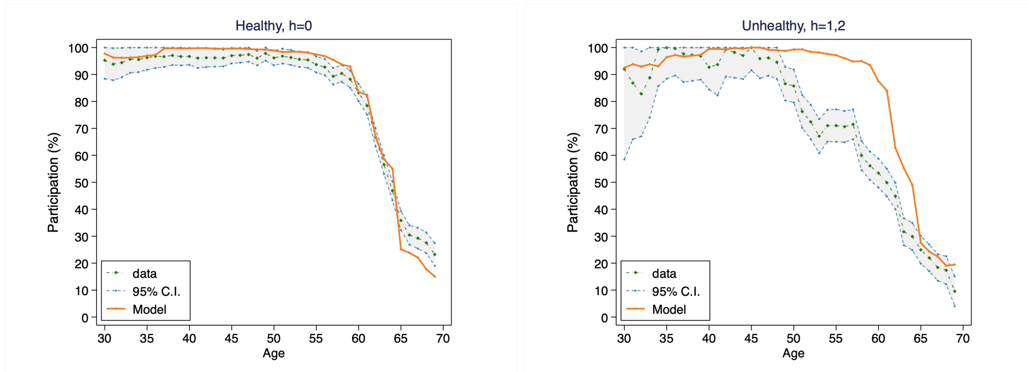
Notes: The effects of changing income threshold, disability rolls, and moral hazard on the labor force participation (left panels) and hours per worker (right panels) at the average level. In panel a and panel b, the black (green) lines represent the model-simulated profiles for the 1930s cohort before (after) implementing changed corresponding parameters. The blue (red) dashed lines represent the data profiles with 95% confidence intervals for the 1930s (1950s) cohort. In panel c, the black (green) lines represent the model-simulated profiles for the 1930s cohort after implementing moral hazard for the 1930s (1950s) cohort. The blue (red) dashed lines represent the data profiles with 95% confidence intervals for the 1930s (1950s) cohort.

Data Source: Panel Study of Income Dynamics, author's calculations.

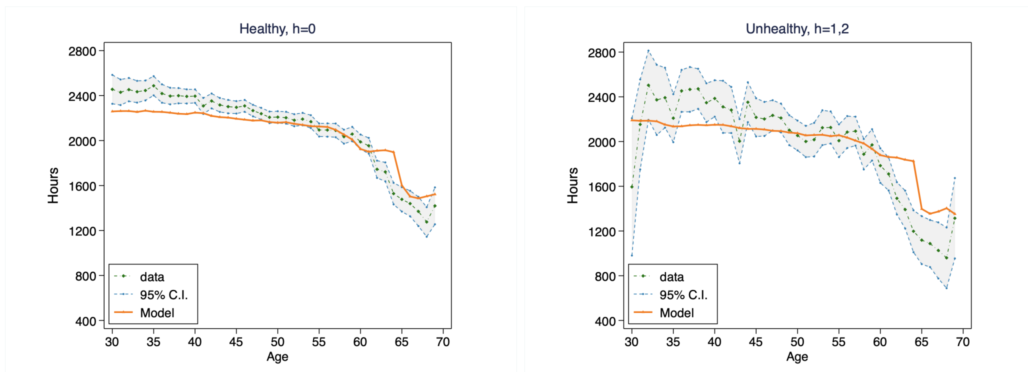
6. Model without Disability

Table 11: Comparition of Estimated Structural Parameters

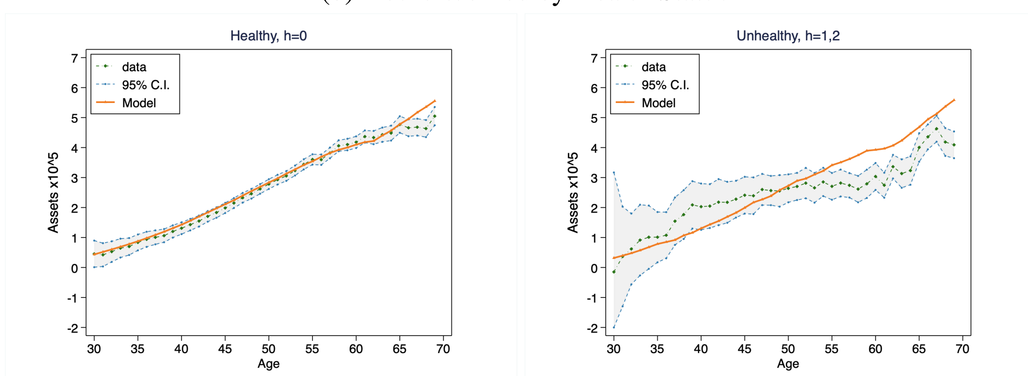
Parameter	Definition	Estimates With Disability	Estimates Without Disability
γ	Consumption weight	0.53	0.53
ν	CRRA for flow utility	4.75	2.74
β	Time discount factor	0.95	0.96
L	Leisure endowment	5268	5198.2
ϕ	Hours of leisure lost, unhealthy	105	106.35
$\theta_p^{h=0}$	Fixed cost of work, healthy	936	1023.1
$\theta_p^{h=1,2}$	Fixed cost of work, unhealthy	755	1023.1
θ_B	Bequest weight	0.039	0.040
κ	Curvature of the bequest	45k	9312
Labor supply elasticity, age 40, ($h = 0, h \neq 0$)		0.43, (0.42, 0.52)	0.48, (0.48, 0.50)
Labor supply elasticity, age 50, ($h = 0, h \neq 0$)		0.60, (0.49, 1.35)	0.60, (0.61, 0.57)
Labor supply elasticity, age 60, ($h = 0, h \neq 0$)		1.16, (1.00, 1.98)	1.23, (1.32, 1.03)
Labor supply elasticity, age 60, ($h = 0, h \neq 0$)		3.97, (4.03, 3.80)	5.68, (6.03, 5.01)



(a) Labor Force Participation by Health Status



(b) Hours Worked by Health Status



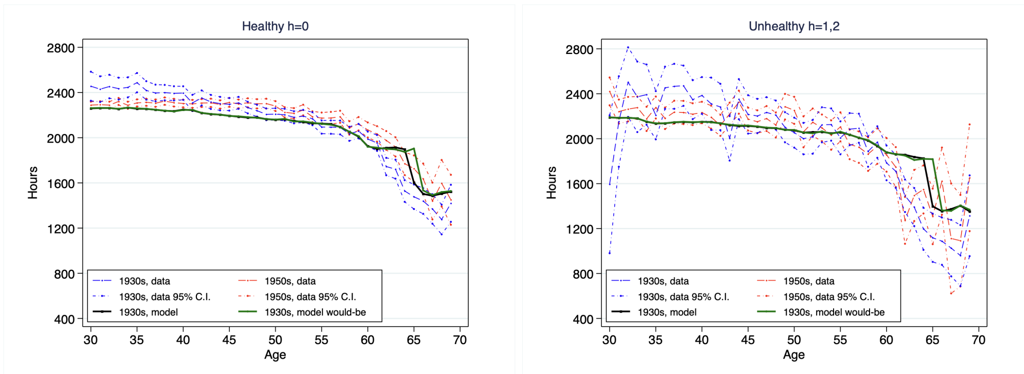
(c) (Non-Pension) Assets by Health Status

Fig. 12. Model v.s. Data Profiles: Targeted Moments

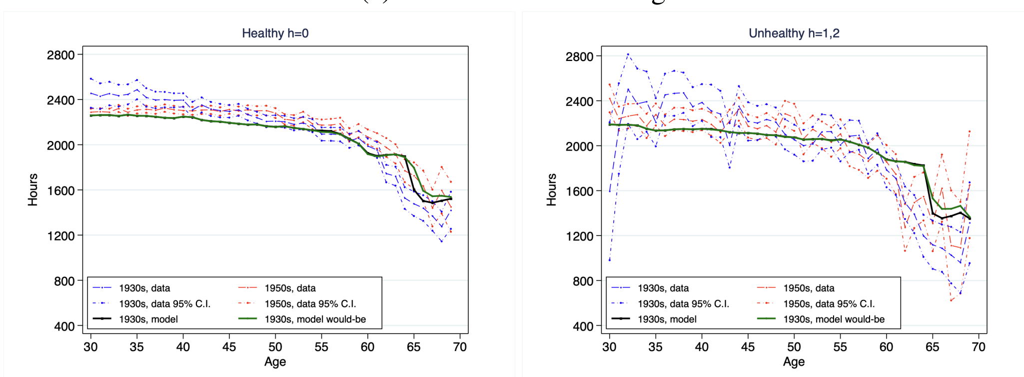
Notes: Panel a shows the model fit for labor force participation by health status. Panel b shows the model fit for hours worked conditional on participation by health status. Panel c shows the model fit for non-pension assets by health status. Profiles for healthy people ($h = 0$) are on the left, whereas profiles for unhealthy people ($h = 1, 2$) are on the right. Model profiles are represented by the orange lines. Data profiles with 95% confidence intervals are represented by the shaded area. Monetary values are expressed in 2016 dollars.

Data Source: Panel Study of Income Dynamics, author's calculations.

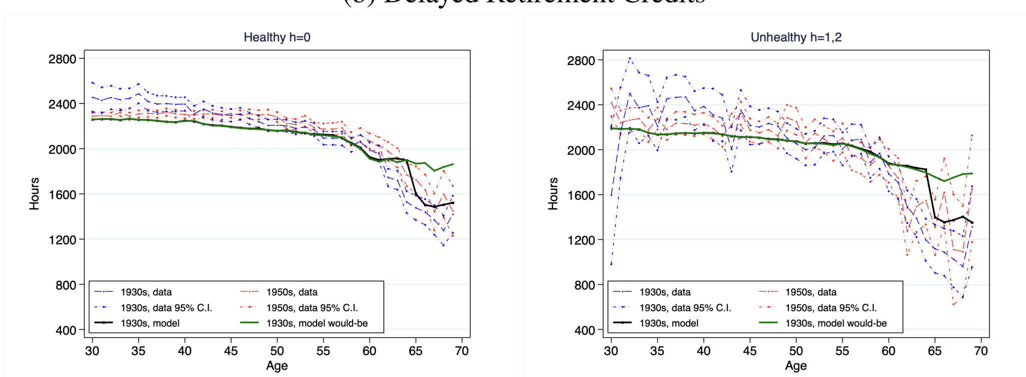
6.1. Effects of Social Security Reforms on Labor Supply



(a) Normal Retirement Age



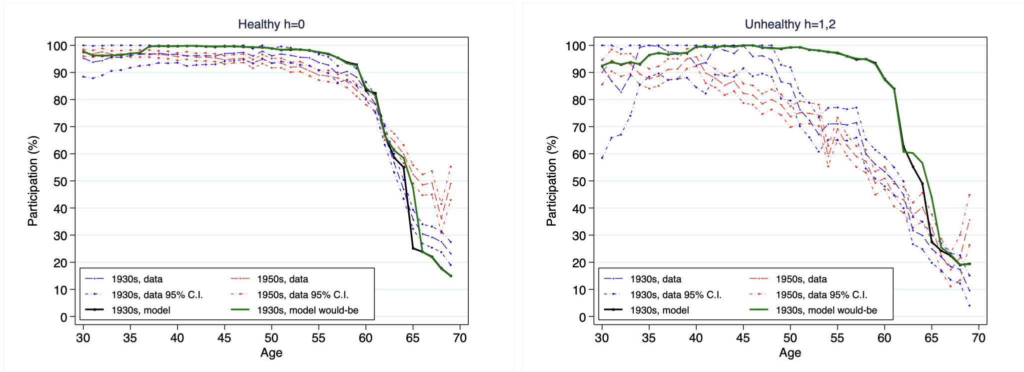
(b) Delayed Retirement Credits



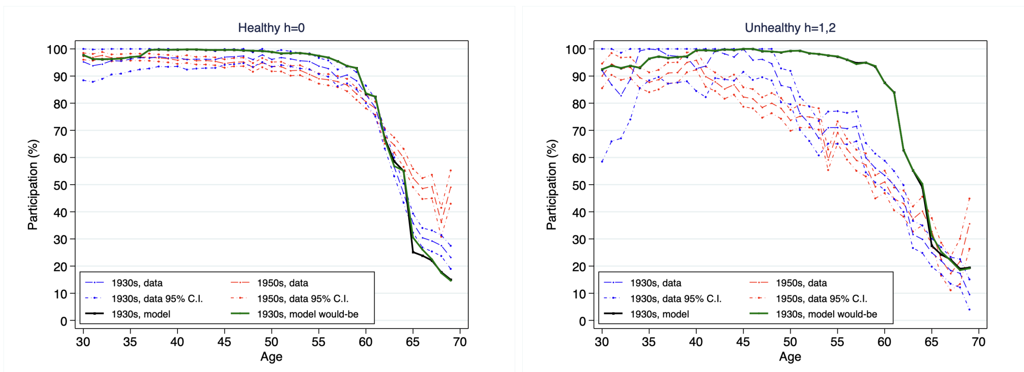
(c) Retirement Earnings Test

Fig. 13. Model v.s. Data Profiles: Effects of Changing Social Security Rules on Hours Worked by Health Status

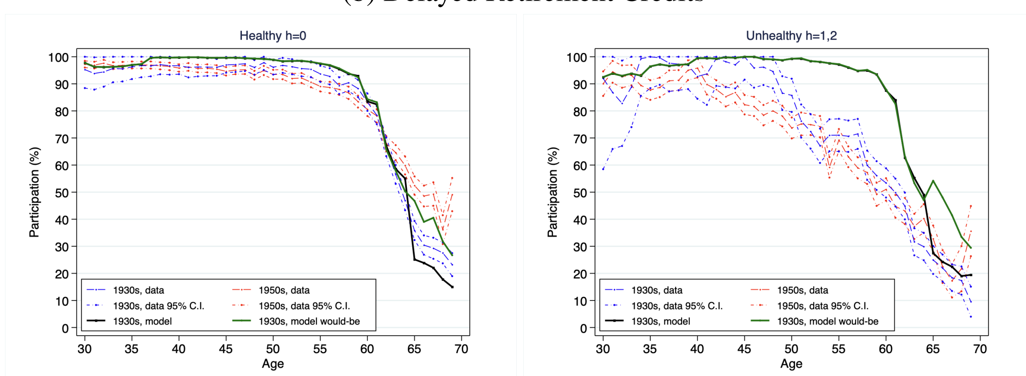
Notes: Effects of the corresponding policy changes on hours worked for healthy workers (left panels) and unhealthy workers (right panels). The black (green) lines represent the model-simulated profiles for the 1930s cohort before (after) implementing policy changes. The blue (red) dashed lines represent the data profiles with 95% confidence intervals for the 1930s (1950s) cohort.
Policy Experiments: increasing the NRA from 65 to 66 (panel a); increasing the DRC from 4.5% to 8% (panel b); removing the RET from 70 to 65 (panel c).
Data Source: Panel Study of Income Dynamics, author's calculations.



(a) Normal Retirement Age



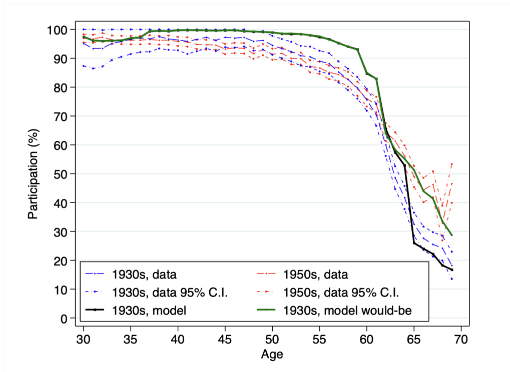
(b) Delayed Retirement Credits



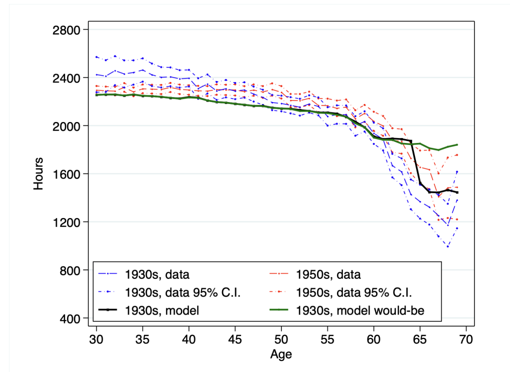
(c) Retirement Earnings Test

Fig. 14. Model v.s. Data Profiles: Effects of Changing Social Security Rules on Labor Force Participation by Health Status

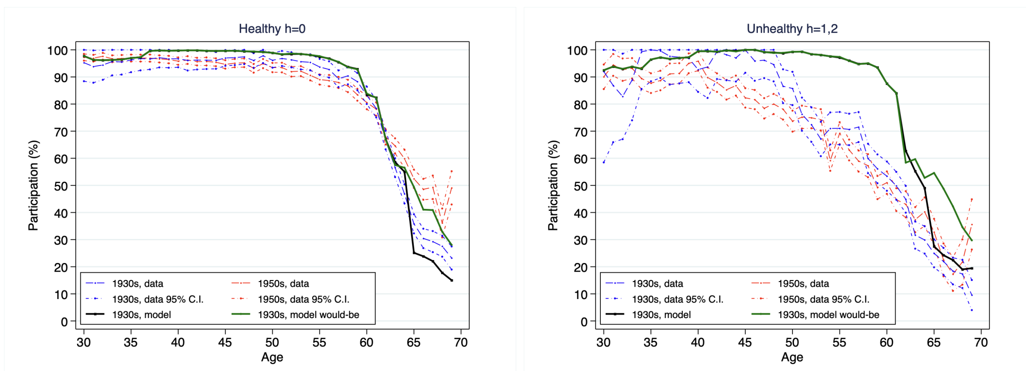
Notes: Effects of the corresponding policy changes on labor force participation for healthy workers (left panels) and unhealthy workers (right panels). The black (green) lines represent the model-simulated profiles for the 1930s cohort before (after) implementing policy changes. The blue (red) dashed lines represent the data profiles with 95% confidence intervals for the 1930s (1950s) cohort.
Policy Experiments: increasing the NRA from 65 to 66 (panel a); increasing the DRC from 4.5% to 8% (panel b); removing the RET from 70 to 65 (panel c).
Data Source: Panel Study of Income Dynamics, author's calculations.



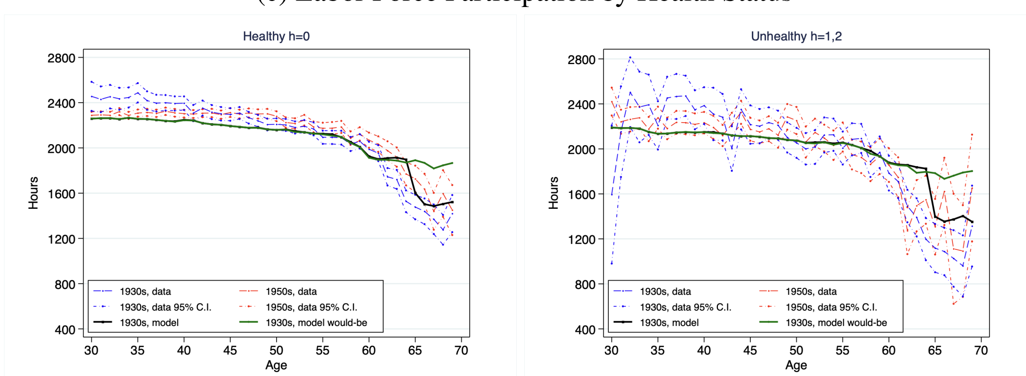
(a) Labor Force Participation



(b) Hours Worked by Workers



(c) Labor Force Participation by Health Status



(d) Hours Worked by Health Status

Fig. 15. Model v.s. Data Profiles: Effects of Changing Three Social Security Rules

Notes: Panel a and panel b show the effects on the labor behaviors at the average level. Panel c and panel d show the effects by health status. The black (green) lines represent the model-simulated profiles for the 1930s cohort before (after) implementing policy changes. The blue (red) dashed lines represent the data profiles with 95% confidence intervals for the 1930s (1950s) cohort.

Data Source: Panel Study of Income Dynamics, author's calculations.

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