A Appendix

A.1 The Choice Set of Household EPHI Plans

Table A1 and A2 show how the household EPHI eligibility, e_t, and household retirement status, L_t, affect the choice set of household EPHI plan, $\mathscr{J}_t$. The first column lists all possible household EPHI eligibilities, and the first row lists all possible household retirement statuses. Each cell represents the choice set of household EPHI plan decisions, $\mathscr{J}_t$, under a specific household EPHI eligibility and a specific household retirement status. Consider, for example, the first cell in Table A1. It shows a household in which both spouses' employers provide health insurance whether they are working or retired, and the insurance can cover the other spouse. When the household decides that both spouses retire, three household EPHI plan choices are available: (1) both spouses are covered by the husband's EPHI, (m,m); (2) both are covered by the wife's EPHI, (f,f); and (3) the husband is covered by his own EPHI and the wife is covered by her own EPHI, (m,f).[1] In this paper, I assume that a household makes the EPHI plan choice every period until both spouses are retired.[2]

A.2 Taxes

Individuals pay federal, state, and payroll taxes on income. I compute federal taxes using the Federal Income Tax tables for "Married Filing Jointly" in 1998.[3] I use the standard deduction,[4] and do not allow individuals to claim medical expenses as an itemized deduction. The state income tax rate varies across the U.S., and I use the average state tax rate to calculate state income taxes for each household. For a worker, payroll taxes are 7.65% up to $68,400, and are 1.45% thereafter.

In period t, a household's pre-tax income, Y_t, is

$$Y_t = rA_t + \sum_{i=m,f} w_{it}(1-L_{it}) + \sum_{i=m,f} b_{it}.$$

Post-tax income, y_t, is computed by applying the three taxes on pre-tax income, Y_t,

[1] A worker has to enroll in his own EPHI plan before he can add the other spouse into the plan. Thus, it is impossible that the husband is covered by the wife's EPHI and the wife is covered by the husband's EPHI. In other words, (f,m) is not a valid choice.

[2] In my sample, no household switches EPHI choices after both spouses retire. Therefore, I assume that a household stops making the EPHI plan choice after both spouses are retired.

[3] For widows or widowers, I compute federal taxes using the Federal Income Tax tables for "Single" in 1998.

[4] The standard deduction is $12,500 for a household, and is $6,250 for a widow or widower.

Table A1: The Choice Set of Household EPHI Plan Choices $\mathscr{J}_t$

	L_t=(1,1)	L_t=(1,0)	L_t=(0,1)	L_t=(0,0)
e_m=(1,1,1,1) e_f=(1,1,1,1)	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}
e_m=(1,1,1,1) e_f=(1,1,1,0)	$\mathscr{J}_t$={(m,m), (m,f)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}	$\mathscr{J}_t$={(m,m), (m,f)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}
e_m=(1,1,1,1) e_f=(1,1,0,0)	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m)} (f,f),(m,f)}	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}
e_m=(1,1,1,1) e_f=(1,0,1,0)	$\mathscr{J}_t$={(m,m), (m,f)}	$\mathscr{J}_t$={(m,m), (m,f)}	$\mathscr{J}_t$={(m,m), (m,f)}	$\mathscr{J}_t$={(m,m), (m,f)}
e_m=(1,1,1,1) e_f=(1,0,0,0)	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m), (m,f)}	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m), (m,f)}
e_m=(1,1,1,1) e_f=(0,0,0,0)	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m)}
e_m=(1,1,1,0) e_f=(1,1,1,1)	$\mathscr{J}_t$={(f,f), (m,f)}	$\mathscr{J}_t$={(f,f), (m,f)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}
e_m=(1,1,1,0) e_f=(1,1,1,0)	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(f,f), (m,f)}	$\mathscr{J}_t$={(m,m), (m,f)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}
e_m=(1,1,1,0) e_f=(1,1,0,0)	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(f,f), (m,f)}	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}
e_m=(1,1,1,0) e_f=(1,0,1,0)	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(m,m), (m,f)}	$\mathscr{J}_t$={(m,m), (m,f)}
e_m=(1,1,1,0) e_f=(1,0,0,0)	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m), (m,f)}
e_m=(1,1,1,0) e_f=(0,0,0,0)	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m)}
e_m=(1,1,0,0) e_f=(1,1,1,1)	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}
e_m=(1,1,0,0) e_f=(1,1,1,0)	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(m,m), (m,f)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}
e_m=(1,1,0,0) e_f=(1,1,0,0)	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m), (f,f),(m,f)}
e_m=(1,1,0,0) e_f=(1,0,1,0)	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(m,m), (m,f)}	$\mathscr{J}_t$={(m,m), (m,f)}
e_m=(1,1,0,0) e_f=(1,0,0,0)	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m), (m,f)}
e_m=(1,1,0,0) e_f=(0,0,0,0)	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(m,m)}	$\mathscr{J}_t$={(m,m)}
e_m=(1,0,1,0) e_f=(1,1,1,1)	$\mathscr{J}_t$={(f,f), (m,f)}	$\mathscr{J}_t$={(f,f), (m,f)}	$\mathscr{J}_t$={(f,f), (m,f)}	$\mathscr{J}_t$={(f,f), (m,f)}
e_m=(1,0,1,0) e_f=(1,1,1,0)	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(f,f), (m,f)}	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(f,f), (m,f)}
e_m=(1,0,1,0) e_f=(1,1,0,0)	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(f,f), (m,f)}	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(f,f), (m,f)}

Table A2: Table A1 Continued

	L_t=(1,1)	L_t=(1,0)	L_t=(0,1)	L_t=(0,0)
e_m=(1,0,1,0) e_f=(1,0,1,0)	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(m,f)}
e_m=(1,0,1,0) e_f=(1,0,0,0)	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(m,f)}
e_m=(1,0,1,0) e_f=(0,0,0,0)	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(m,0)}
e_m=(1,0,0,0) e_f=(1,1,1,1)	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(f,f), (m,f)}	$\mathscr{J}_t$={(f,f), (m,f)}
e_m=(1,0,0,0) e_f=(1,1,1,0)	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(f,f), (m,f)}
e_m=(1,0,0,0) e_f=(1,1,0,0)	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(f,f), (m,f)}
e_m=(1,0,0,0) e_f=(1,0,1,0)	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(m,f)}	$\mathscr{J}_t$={(m,f)}
e_m=(1,0,0,0) e_f=(1,0,0,0)	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(m,f)}
e_m=(1,0,0,0) e_f=(0,0,0,0)	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(m,0)}	$\mathscr{J}_t$={(m,0)}
e_m=(0,0,0,0) e_f=(1,1,1,1)	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(f,f)}
e_m=(0,0,0,0) e_f=(1,1,1,0)	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(f,f)}
e_m=(0,0,0,0) e_f=(1,1,0,0)	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(f,f)}	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(f,f)}
e_m=(0,0,0,0) e_f=(1,0,1,0)	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(0,f)}
e_m=(0,0,0,0) e_f=(1,0,0,0)	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(0,f)}	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(0,f)}
e_m=(0,0,0,0) e_f=(0,0,0,0)	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(0,0)}	$\mathscr{J}_t$={(0,0)}

$$y_t = \begin{cases} 0.9235Y_t & if\ \frac{Y_t}{2} \leqslant 12500, \\ 2(11543.75+0.7323(\frac{Y_t}{2}-12500)) & if\ 12500 < \frac{Y_t}{2} \leqslant 42350, \\ 2(33402.91+0.5665(\frac{Y_t}{2}-42350)) & if\ 42350 < \frac{Y_t}{2} \leqslant 102300, \\ 2(67363.67+0.5283(\frac{Y_t}{2}-102300)) & if\ 102300 < \frac{Y_t}{2} \leqslant 136800, \\ 2(85590.02+0.5903(\frac{Y_t}{2}-136800)) & if\ 136800 < \frac{Y_t}{2} \leqslant 155950, \\ 2(96894.27+0.5265(\frac{Y_t}{2}-155950)) & if\ 155950 < \frac{Y_t}{2} \leqslant 278450, \\ 2(161390.52+0.4806(\frac{Y_t}{2}-278450)) & if\ \frac{Y_t}{2} > 278450. \end{cases}$$

If one spouse dies, the widow or widower's pre-tax income is

$$Y_t = rA_t + w_{it}(1-L_{it}) + b_{it},$$

and his post-tax income is

$$y_t = \begin{cases} 0.9235Y_t & if\ \frac{Y_t}{2} \leqslant 6250, \\ 2(5771.87 + 0.7323(\frac{Y_t}{2} - 6250)) & if\ 6250 < \frac{Y_t}{2} \leqslant 21175, \\ 2(16701.45 + 0.5665(\frac{Y_t}{2} - 21175)) & if\ 21175 < \frac{Y_t}{2} \leqslant 51150, \\ 2(33682.29 + 0.5283(\frac{Y_t}{2} - 51150)) & if\ 51150 < \frac{Y_t}{2} \leqslant 68400, \\ 2(42795.47 + 0.5903(\frac{Y_t}{2} - 68400)) & if\ 68400 < \frac{Y_t}{2} \leqslant 77975, \\ 2(48447.59 + 0.5265(\frac{Y_t}{2} - 77975)) & if\ 77975 < \frac{Y_t}{2} \leqslant 139225, \\ 2(80695.71 + 0.4806(\frac{Y_t}{2} - 139225)) & if\ \frac{Y_t}{2} > 139225. \end{cases}$$

A.3 Social Security and Pension Benefits

In this subsection, I first introduce the formula that determines an individual's PIA. Then, I describe how I calculate Social Security benefits and pension benefits.

A.3.1 PIA Formula

A worker's PIA, Υ_{it}, is a monotone increasing function of his AIME, Δ_{it},

$$\Upsilon_{it} = \begin{cases} 0.9\Delta_{it} & if \quad \Delta_{it} < 5724, \\ 5151.6 + 0.32(\Delta_{it} - 5724) & if \quad 5724 \leq \Delta_{it} < 34500, \\ 14359.9 + 0.15(\Delta_{it} - 34500) & if \quad \Delta_{it} \geq 34500. \end{cases}$$

Note that the PIA and AIME in the function above are annualized.

A.3.2 Social Security Benefits

A worker can start his Social Security benefits as early as age 62. If he claims benefits based on his own earnings history, his benefits, s_{it}^O, are a function of his age this period, a_{it}, and his age and PIA at the time of claiming benefits, (a_i^c, Υ_i^c),

$$s_{it}^O(a_{it}, a_i^c, \Upsilon_i^c) = \begin{cases} 2\Upsilon_i^c 0.933^{(65-a_i^c)} & if\ 62 \leqslant a_i^c \leqslant 65\ \&\ a_i^c \leqslant a_{it}, \\ 2\Upsilon_i^c 1.055^{min\{(a_i^c-65),5\}} & if\ a_i^c > 65\ \&\ a_i^c \leqslant a_{it}, \\ 0 & otherwise. \end{cases}$$

Note that $a_i^c \leqslant a_{it}$ means spouse i has already claimed benefits before or at period t, and $a_i^c > a_{it}$ means spouse i has not claimed benefits before or at period t. In addition, each period is two years. Thus, the benefits that spouse i receives during period t equal two times his annual benefits.

If a worker's spouse is alive ($S_{-i,t} = 1$), the worker can claim spousal benefits as early as age 62. If he claims spousal benefits at his normal retirement age (65) or older, the spousal benefits equal one half of his spouse's benefits. If he claims benefits before age 65, the benefits are reduced by 6.67% for every year before age 65. His spousal benefits, s_{it}^S, are a function of his age this period, a_{it}, his age at the time of claiming benefits, a_i^c, and his spouse's benefits, $s_{-i,t}^O(a_{-i,t}, a_{-i}^c, \Upsilon_{-i}^c)$,

$$s_{it}^S(a_{it}, a_i^c; s_{-i,t}^O) = \begin{cases} \frac{1}{2} s_{-i,t}^O(a_{-i}^c, \Upsilon_{-i}^c, a_{-i,t}) 0.933^{max\{(65-a_i^c),0\}} & if\ a_i^c \geqslant 62\ \&\ a_i^c \leqslant a_{it}, \\ 0 & otherwise. \end{cases}$$

If a worker's spouse is dead ($S_{-i,t} = 0$), the worker can claim survivor benefits. His survivor benefits, s_{it}^W, are calculated based on the deceased spouse's basic benefits. If the deceased spouse started collecting benefits before his death ($a_{-i}^c < a_{-i}^D$), his basic benefits equal the benefits he receives. If the deceased spouse did not start collecting benefits before his death ($a_{-i}^c \geqslant a_{-i}^D$), his basic benefits are calculated as if he claimed benefits at the time of his death, or at age 62 if he died before 62. The PIA used in the calculation is his PIA at the time of his death. Thus, the deceased spouse's basic benefits, s_{-i}^D, are a function of his age and PIA at the time of death, $(a_{-i}^D, \Upsilon_{-i}^D)$, and his age and PIA at the time of claiming benefits, $(a_{-i}^c, \Upsilon_{-i}^c)$,

$$s_{-i}^D(a_{-i}^D, \Upsilon_{-i}^D, a_{-i}^c, \Upsilon_{-i}^c) = \begin{cases} 2\Upsilon_{-i}^c 0.933^{(65-a_{-i}^c)} & if\ 62 \leqslant a_{-i}^c \leqslant 65\ \&\ a_{-i}^c < a_{-i}^D, \\ 2\Upsilon_{-i}^c 1.055^{min\{(a_{-i}^c-65),5\}} & if\ a_{-i}^c > 65\ \&\ a_{-i}^c < a_{-i}^D, \\ 2\Upsilon_{-i}^D 0.933^{min\{(65-a_{-i}^D),3\}} & if\ a_{-i}^D \leqslant 65\ \&\ a_{-i}^c \geqslant a_{-i}^D, \\ 2\Upsilon_{-i}^D 1.055^{min\{(a_{-i}^D-65),5\}} & if\ a_{-i}^D > 65\ \&\ a_{-i}^c \geqslant a_{-i}^D. \end{cases}$$

A survivor can claim survivor benefits as early as age 60. The full retirement age for a survivor is age 66. If the survivor claims survivor benefits at his full retirement age (66) or older, the survivor benefits equal the deceased spouse's basic benefits. If he claims benefits before age 66, the benefits are reduced by 6% for every year before age 66. If a survivor is getting benefits (either his own or spousal benefits) when the other spouse dies, he can switch to survivor benefits if they are higher than the benefits he is receiving now. Thus, the worker's survivor benefits, s_{it}^W, are a function of his age this period, a_{it}, his age at the time of claiming survivor benefits, a_i^{cW}, and the deceased spouse's basic benefits, $s_{-i}^D(a_{-i}^D, \Upsilon_{-i}^D, a_{-i}^c, \Upsilon_{-i}^c)$,

$$s_{it}^W(a_{it}, a_i^{cW}; s_{-i}^D) = \begin{cases} s_{-i}^D(a_{-i}^D, \Upsilon_{-i}^D, a_{-i}^c, \Upsilon_{-i}^c) 0.94^{max\{(66-a_i^c),0\}} & if\ a_i^{cW} \geqslant 60\ \&\ a_i^{cW} \leqslant a_{it}, \\ 0 & otherwise. \end{cases}$$

In summary, the Social Security benefits a worker receives, s_{it}, depend on his own benefits, $s_{it}^O(a_{it}, a_i^c, \Upsilon_i^c)$, his spouse's survival status, $S_{-i,t}$, his spousal benefits, $s_{it}^S(a_{it}, a_i^c; s_{-i,t}^O)$, and his survivor benefits, $s_{it}^W(a_{it}, a_i^{cW}; s_{-i}^D)$,

$$s_{it} = s(s_{it}^O, S_{-i,t}, s_{it}^S, s_{it}^W) = \begin{cases} max\{s_{it}^O(a_i^c, \Upsilon_i^c, a_{it}), s_{it}^S(a_{it}, a_i^c; s_{-i,t}^O)\} & if\ S_{-i,t} = 1, \\ max\{s_{it}^O(a_i^c, \Upsilon_i^c, a_{it}), s_{it}^W(a_{it}, a_i^{cW}; s_{-i}^D)\} & if\ S_{-i,t} = 0. \end{cases}$$

A.3.3 Pension Benefits

I model the pension benefits for DC and DB plans differently. If spouse i has a DC plan, I assume that he withdraws the pension wealth when he retires, or at the early withdrawal age if he retires earlier.[5] His pension wealth in period t, b^w_{it}, depends on pension wealth in the last period, $b^w_{i,t-1}$, and the pension accrual this period, b^A_{it},

$$b^w_{it} = (1+r)b^w_{i,t-1} + b^A_{it},$$

where r is the constant asset return rate,[6] and b^A_{it} is a function of his labor income, $w_{it}(1-L_{it})$, his contribution rate, r^o_{it}, and his employer's contribution rate, r^e_{it},

$$b^A_{it} = w_{it}(1-L_{it})(r^o_{it} + r^e_{it}).$$

Spouse i's DC pension benefits in period t, b^{DC}_{it}, are a function of his pension wealth this period, b^w_{it}, his age this period, a_{it}, and his age at the time of his retirement, a^r_i,

$$b^{DC}_{it}(b^w_{it}, a_{it}, a^r_i) = \begin{cases} b^w_{it} & if\ a_{it} = a^r_i, \\ 0 & otherwise. \end{cases}$$

Computing the pension benefits for DB plan recipients requires detailed data on DB plan characteristics, including normal and early retirement ages, job tenure, pensionable salary, and the pension accrual rate which varies with job tenure. This information is often missing.[7] Even if it were in the data, a model that took into account all of these characteristics would be computationally burdensome.[8] To overcome this data problem and simplify the model, following French and Jones (2011), I model a worker's DB pension benefits, b^{DB}_{it}, as a function of his age this period, a_{it}, and his age, PIA, and EPHI eligibility type at the time of his retirement, $(a^r_i, \Upsilon^r_i, e^r_i)$,

$$b^{DB}_{it}(a_{it}, \Upsilon^r_i, e^r_i; \gamma^{a^r_i}) =$$
$$\begin{cases} 2(\sum_{k=\{R,T,N\}} \gamma^{a^r_i}_{1,k} 1[e^r_i = k] + \gamma^{a^r_i}_2 \Upsilon^r_i + \gamma^{a^r_i}_3 max\{0, \Upsilon^r_i - 9{,}999.6\} + \gamma^{a^r_i}_4 max\{0, \Upsilon^r_i - 14{,}359.9\}) & if\ a_{it} \geqslant a^r_i, \\ 0 & otherwise, \end{cases}$$

[5] Most DC plan recipients withdraw their pension wealth when they retire, and treat their pension wealth as household wealth.

[6] With a constant asset return rate, my model ignores an important feature of DC pension plans: the employees incur all of the risk associated with the random asset return rate. Yet, the effects on retirement of ignoring the randomness in asset return rates are very limited (explained in subsection 3.3).

[7] The HRS data matches with a data on pensions from a survey of the employers of HRS sample members. The data on pensions provides crucial information to calculate DB plan benefits. However, some HRS respondents do not have matched pension data, and this data can be used only on a computer that is not connected to the internet. I cannot use this data because, to run parallel computing for my code, I need to use the High-Performance Computing system at University of Virginia, and this requires internet access.

[8] In the literature on retirement, papers that address the difficulty in modeling the DB pension benefits use different simplification methods. Some papers exclude people who are covered by a DB plan (Van der Klaauw and Wolpin (2008) or by any pension plan (Benitez-Silva et al. (1999, 2004). Other papers use data on pension plan characteristics to calculate DB plan benefits, and reduce the computational burden by simplifying other parts of the model. For example, Gustman and Steinmeier (2008) simplify the model by taking the spousal labor market decision as exogenous; and Fields and Mitchell (1984) simplify the model by ignoring the variation in individuals' earnings and years of service.

where k denotes the category of EPHI eligibility type. Different types of EPHI eligibility can be divided into three categories: (1) $k = R$ (retiree insurance) if e_i^r equals $(1,1,1,1)$, $(1,1,1,0)$, or $(1,0,1,0)$; (2) $k = T$ (tied insurance) if e_i^r equals $(1,1,0,0)$, or $(1,0,0,0)$; and (3) $k = N$ (no insurance) if e_i^r equals $(0,0,0,0)$. The vector of parameters, $\gamma^{a_i^r} = (\gamma_{1,k}^{a_i^r}, \gamma_2^{a_i^r}, \gamma_3^{a_i^r}, \gamma_4^{a_i^r})$, is the same across spouses but varies with retirement age, a_i^r. Table A3 lists the value of $\gamma^{a_i^r}$ for different retirement ages.

Table A3: Value of γ by Retirement Age

Retirement Age	$\gamma_{1,no}^a$	$\gamma_{1,retiree}^a$	$\gamma_{1,tied}^a$	γ_2^a	γ_3^a	γ_4^a
59	1695	8446	5009	-0.1955	1.421	0.8186
60	1929	8854	5111	-0.1955	1.533	0.3831
61	2146	9222	5184	-0.1955	1.637	-0.023
62	2345	9551	5227	-0.1955	1.735	-0.399
63	2528	9840	5242	-0.1955	1.826	-0.747
64	2693	10090	5228	-0.1955	1.910	-1.065
65	2841	10300	5184	-0.1955	1.987	-1.354
66	2972	10470	5112	-0.1955	2.057	-1.613
67	3085	10600	5010	-0.1955	2.120	-1.843
68	3182	10690	4879	-0.1955	2.176	-2.043
69	3261	10740	4719	-0.1955	2.225	-2.214
70	3323	10760	4530	-0.1955	2.268	-2.356
71	3368	10730	4312	-0.1955	2.303	-2.468
72	3396	10660	4065	-0.1955	2.331	-2.551
73	3406	10550	3789	-0.1955	2.353	-2.605

Source: French and Jones (2011).

In summary, spouse i's pension benefits, b_{it}, are

$$b_{it} = b_{it}^{DC} 1_{[DC]} + b_{it}^{DB} 1_{[DB]},$$

where $1_{[DC]}$ is a variable indicating whether spouse i has a DB plan, and $1_{[DB]}$ is a variables indicating whether he has a DC plan.

A.4 Remaining Parts of The Model

A.4.1 Household Health Transitions

In a household, the two spouses' health transitions may be interdependent because they experience similar events that can affect health.[9] I use a bivariate probit framework to model the household health transitions.[10] I model health transitions as a second channel

[9]As Wilson (2002) points out, the health status of the two spouses in a household often are interdependent due to marriage sorting, similar lifestyles, or shared family income and health insurance coverage.

[10]Previous papers (e.g., Blau (1998) and French and Jones (2004)) that study the retirement behavior of married couples ignore the possible correlation between the husband's and wife's health transitions and calculate them separately.

through which health insurance can affect retirement decisions.[11] Health insurance (especially private health insurance) can affect health, and health is a factor that determines spouses' preference for leisure (equation (3.2)).[12] Let an indicator variable, H_{it}, denote whether spouse i has good health in period t. The latent variable, H^*_{it}, represents the true (continuous) health status of spouse i in period t. H^*_{it} is modeled as a function of health insurance coverage, $I_{i,t-1}$, health status, $H_{i,t-1}$,[13] and demographic information, $X_{i,t-1}$, in the last period, and an error term, u^H_{it},

$$H^*_{it} = H(I_{i,t-1}, H_{i,t-1}, X_{i,t-1}) + u^H_{it},$$

$$\begin{pmatrix} u^H_{mt} \\ u^H_{ft} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_H \\ \rho_H & 1 \end{pmatrix}\right].$$

A.4.2 Household Survival Rates

Similar to the way that I model household health transitions, I use a bivariate probit framework to model household survival rates.[14] Let an indicator variable, S_{it}, denote whether spouse i is alive at period t. The latent variable, S^*_{it}, measures the underlying continuous propensity for spouse i to survive at period t. S^*_{it} is modeled as a function of demographics, $X_{i,t-1}$, and health status, $H_{i,t-1}$, in the last period, and an error term, u^S_{it},[15]

$$S^*_{it} = S(X_{i,t-1}, H_{i,t-1}) + u^S_{it},$$

$$\begin{pmatrix} u^S_{mt} \\ u^S_{ft} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_S \\ \rho_S & 1 \end{pmatrix}\right].$$

The two error terms, u^H_{it} and u^S_{it}, denote spouse i's idiosyncratic health shock and mortality shock, respectively. One spouse's health shock, mortality shock, and medical expense-related shocks, (ϑ_{it}, u_{it}), might be correlated. Limitations in my data prevent me from modeling the possible correlation between medical expense-related shocks and the

[11] Recall that the first channel (described in subsection 3.4) is that health insurance can affect retirement decisions through spouses' out-of-pocket medical expenditures, which are part of the household budget constraint.

[12] While Finkelstein et al. (2013) find no significant effects of Medicaid coverage on health, Dor et al. (2006), Levy and Meltzer (2008), and Zimmer (2012) find positive effects of health insurance (especially private health insurance) on health.

[13] It is more realistic to model the health transition, the utility flow, and total medical expenses as functions of the true continuous health status, H^*_{it}. However, it is difficult to incorporate H^*_{it} in the model because: (1) H^*_{it} is not observed; and (2) health status becomes a continuous state variable. In the future, I can extend my model using the technique developed in Brien et al. (2006), which shows how to use a modified GHK algorithm (Geweke (1989), Hajivassiliou (1990), and Keane (1994)) to solve a dynamic structural model that includes an unobserved continuous state variable.

[14] In the literature on married couples' retirement (e.g., Blau and Gilleskie (2006) and Gustman and Steinmeier (2004)), the husband's and wife's survival rates are calculated separately.

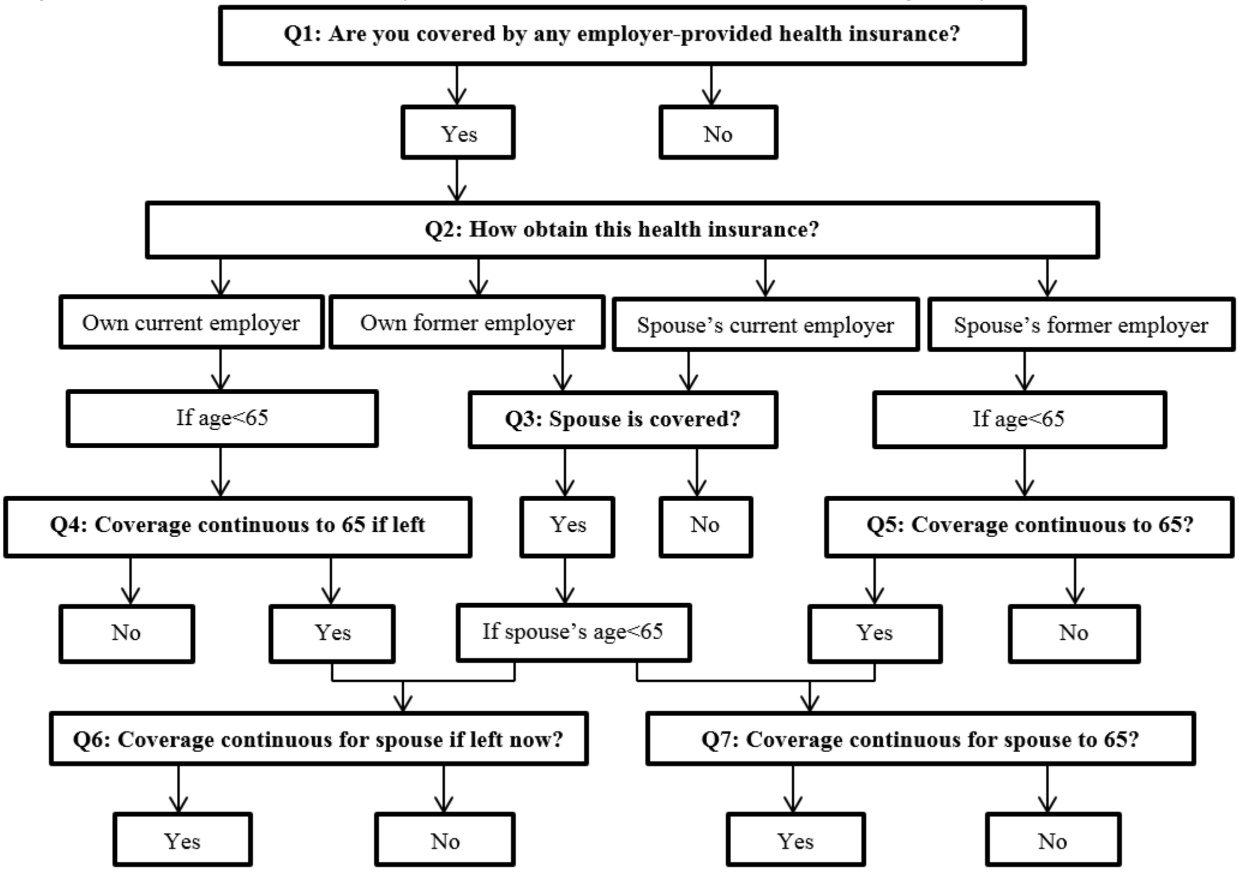
[15] Casanova (2010) assumes that the survival rate is a function of age and gender. French and Jones (2004) model the survival rate as a function of previous health status and age.

other two shocks.[16] And I assume that a spouse's health shock is independent from his life shock. Ignoring the correlation between these two shocks may cause biased estimates.[17]

A.5 Employer-Provided Health Insurance Eligibility

In the HRS, the only people who are selected to be surveyed about their EPHI eligibility are those covered by their own EPHI plan. Consequently, there is no information about the EPHI eligibility of those who are covered by their spouse's employer. Figure A1 shows how the HRS surveys households about their health insurance eligibility.

Figure A1: Flowchart of Survey Questions about Health Insurance Eligibility in the HRS



To impute the EPHI eligibility for those who are not surveyed about their EPHI eligibility, I establish a multivariate probit model of the observed EPHI eligibility and the

[16]The HRS data has no information on total medical expenses, and I use a different data set to estimate medical expense-related equations, separately from estimating health transitions and survival rates (explained in data section 4.1).

[17]If one spouse's health shock and life shock are positively correlated, ignoring this correlation might underpredict the probability of being alive in the next period. Then, the model might overpredict the household savings. The overprediction of household savings may cause a downward bias in the estimate of risk aversion parameter. In the health insurance literature, some papers (e.g., Blau and Gilleskie (2008) model the possible correlation between one's health and life shocks, while others (e.g., Rust and Phelan (1997) ignore this possible correlation.

selection of reporting EPHI eligibility (equations (4.1)-(4.5)). The error terms in the five equations are assumed to be multivariate normally distributed,

$$\begin{pmatrix} \omega_{it}^{w1} \\ \omega_{it}^{w2} \\ \omega_{it}^{r1} \\ \omega_{it}^{r2} \\ \omega_{it}^{s} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} & \rho_{15} \\ \rho_{12} & 1 & \rho_{23} & \rho_{24} & \rho_{25} \\ \rho_{13} & \rho_{23} & 1 & \rho_{34} & \rho_{35} \\ \rho_{14} & \rho_{24} & \rho_{34} & 1 & \rho_{45} \\ \rho_{15} & \rho_{25} & \rho_{35} & \rho_{45} & 1 \end{pmatrix} \right].$$

I use married couples in the HRS to estimate the imputation model. In this sample, each spouse's likelihood contribution is the probability of having the EPHI coverage outcome observed in the data. A coverage outcome includes two pieces of information: (1) whether a spouse reports his EPHI eligibility; and (2) his EPHI eligibility type if he reports. Table A4 defines the seven EPHI coverage outcomes observed in the data, using the five binary variables, $(e_{it}^{w1}, e_{it}^{w2}, e_{it}^{r1}, e_{it}^{r2}, e_{it}^{s})$.

Table A4: EPHI Coverage Outcome

Outcome	e^{w1}	e^{w2}	e^{r1}	e^{r2}	e^{s}
1	1	1	1	1	1
2	1	1	1	0	1
3	1	1	0	0	1
4	1	0	1	0	1
5	1	0	0	0	1
6	0	0	0	0	1
7					0

I calculate each spouse's likelihood contribution using equations (4.1)-(4.5). Let $P1_{it}$, $P2_{it}$, $P3_{it}$, $P4_{it}$, $P5_{it}$, $P6_{it}$, and $P7_{it}$ represent the probability of observing outcomes 1-7 for spouse i in period t, respectively,

$$\begin{aligned} P1_{it} &= Pr[e_{it}^{w1}=1, e_{it}^{w2}|_{[e_{it}^{w1}=1]}=1, e_{it}^{r1}|_{[e_{it}^{w1}=1]}=1, e_{it}^{r2}|_{[e_{it}^{r1}=1,e_{it}^{w2}=1]}=1, e_{it}^{s}=1] \\ &= \int_{D1}\int_{D2}\int_{D3}\int_{D4}\int_{D5} dG(\omega_{it}^{w1}, \omega_{it}^{w2}, \omega_{it}^{r1}, \omega_{it}^{r2}, \omega_{it}^{s}), \end{aligned} \tag{A1}$$

$$\begin{aligned} P2_{it} &= Pr[e_{it}^{w1}=1, e_{it}^{w2}|_{[e_{it}^{w1}=1]}=1, e_{it}^{r1}|_{[e_{it}^{w1}=1]}=1, e_{it}^{r2}|_{[e_{it}^{r1}=1,e_{it}^{w2}=1]}=0, e_{it}^{s}=1] \\ &= \int_{D1}\int_{D2}\int_{D3}\int^{D4}\int_{D5} dG(\omega_{it}^{w1}, \omega_{it}^{w2}, \omega_{it}^{r1}, \omega_{it}^{r2}, \omega_{it}^{s}), \end{aligned} \tag{A2}$$

$$\begin{aligned} P3_{it} &= Pr[e_{it}^{w1}=1, e_{it}^{w2}|_{[e_{it}^{w1}=1]}=1, e_{it}^{r1}|_{[e_{it}^{w1}=1]}=0, e_{it}^{s}=1] \\ &= \int_{D1}\int_{D2}\int^{D3}\int_{D5} dG_{1,2,3,5}(\omega_{it}^{w1}, \omega_{it}^{w2}, \omega_{it}^{r1}, \omega_{it}^{s}), \end{aligned} \tag{A3}$$

$$\begin{aligned} P4_{it} &= Pr[e_{it}^{w1}=1, e_{it}^{w2}|_{[e_{it}^{w1}=1]}=0, e_{it}^{r1}|_{[e_{it}^{w1}=1]}=1, e_{it}^{s}=1] \\ &= \int_{D1}\int^{D2}\int_{D3}\int_{D5} dG_{1,2,3,5}(\omega_{it}^{w1}, \omega_{it}^{w2}, \omega_{it}^{r1}, \omega_{it}^{s}), \end{aligned} \tag{A4}$$

$$\begin{aligned} P5_{it} &= Pr[e_{it}^{w1}=1, e_{it}^{w2}|_{[e_{it}^{w1}=1]}=0, e_{it}^{r1}|_{[e_{it}^{w1}=1]}=0, e_{it}^{s}=1] \\ &= \int_{D1}\int^{D2}\int^{D3}\int_{D5} dG_{1,2,3,5}(\omega_{it}^{w1}, \omega_{it}^{w2}, \omega_{it}^{r1}, \omega_{it}^{s}), \end{aligned} \tag{A5}$$

$$
\begin{aligned}
P6_{it} &= Pr[e_{it}^{w1} = 0, e_{it}^{s} = 1] \\
&= \int^{D1} \int_{D5} dG_{1,5}(\omega_{it}^{w1}, \omega_{it}^{s}),
\end{aligned} \tag{A6}
$$

$$
\begin{aligned}
P7_{it} &= Pr[e_{it}^{s} = 0] \\
&= \int^{D5} dG_5(\omega_{it}^{s}),
\end{aligned} \tag{A7}
$$

where $D1 = -(\varsigma_{w1}^1 X_{it}^d + \varsigma_{w1}^2 X_{it}^E)$, $D2 = -(\varsigma_{w2}^1 X_{it}^d + \varsigma_{w2}^2 X_{it}^E)$, $D3 = -(\varsigma_{r1}^1 X_{it}^d + \varsigma_{r1}^2 X_{it}^E)$, $D4 = -(\varsigma_{r2}^1 X_{it}^d + \varsigma_{r2}^2 X_{it}^E)$, $D5 = -(\varsigma_s^1 X_{it}^d + \varsigma_s^2 X_{it}^E + \varsigma_s^3 X_{-i,t}^E)$, and $G(\cdot)$ is the joint distribution function of the five error terms. The term $G(\cdot)$ with subscript represents the joint distribution function of a subset of the five error terms. For example, the term $G_{1,2,3,5}(\cdot)$ represent the joint distribution function of the 1st, 2nd, 3rd, and 5th elements of the five error terms.

Spouse i's likelihood contribution in period t, P_{it}, is

$$
\begin{aligned}
P_{it} = &\; P1_{it}^{1[Outcome\,1]} \cdot P2_{it}^{1[Outcome\,2]} \cdot P3_{it}^{1[Outcome\,3]} \cdot P4_{it}^{1[Outcome\,4]} \\
&\cdot P5_{it}^{1[Outcome\,5]} \cdot P6_{it}^{1[Outcome\,6]} \cdot P7_{it}^{1[Outcome\,7]},
\end{aligned}
$$

where $1_{[Outcome\,k]}$ is a variable indicating whether spouse i has outcome $k = \{1, 2, ..., 7\}$ in period t.

The likelihood function is

$$
L(\varsigma, \rho) = \prod_{i=1}^{N} \prod_{t=1}^{T} P_{it}.
$$

Equations (A1)-(A6) show that calculating the likelihood contribution requires an integration over the joint distribution of multiple error terms. Because evaluation of the multidimensional integrals is not possible analytically or numerically, I use a GHK simulator (Geweke (1989), Hajivassiliou (1990), Keane (1994)) to simulate the likelihood contribution. Parameter estimates of the EPHI eligibility imputation model maximize the likelihood function.

Table A5 lists the estimates of parameters associated with the explanatory variables in the imputation model, ς. These estimates represent the correlation between the explanatory variables and the dependent variables. Individuals who work for bigger firms, have a higher hourly wage, work longer hours per year, have longer tenure, or are eligible for pension benefits, are more likely to be eligible for employer-provided working and retiree insurance. They are also more likely to report their EPHI eligibility. Compared with wives, husbands are more likely to be eligible for employer-provided working and retiree insurance and to report their EPHI eligibility. Workers in good health are more likely to be eligible for employer-provided insurance (especially for the retiree insurance) and to report their EPHI eligibility. There are two possible reasons that cause the positive correlation between health and being eligible for EPHI plans. First, individuals who have insurance coverage might visit doctors more often and choose more health care treatments, and thus, have better health. Second, individuals who care about health are more likely to have better health, and they are more likely to choose a job that provides insurance coverage.

Table A5: EPHI Eligibility Imputation Model Estimates

Variable	e^{w1}		$e^{w2}\|_{[e^{w1}=1]}$		$e^{r1}\|_{[e^{w1}=1]}$		$e^{r2}\|_{[e^{r1}=1;e^{w2}=1]}$		e^{s}	
	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.
Constant	0.65**	0.27	2.12***	0.43	1.26***	0.21	1.53***	0.44	-0.23	0.23
Race										
White (omitted)										
Black	-0.07	0.13	-0.09	0.17	-0.41***	0.08	-0.10	0.13	-0.02	0.09
Other	-0.32	0.21	-0.52**	0.22	0.04	0.12	0.03	0.24	0.08	0.18
Hispanic	-0.06	0.17	0.13	0.23	-0.27***	0.10	-0.16	0.19	-0.13	0.14
Firmsize										
[1,24] (omitted)										
[25,99]	0.05	0.09	0.19	0.16	0.02	0.07	-0.04	0.13	0.06	0.07
[100,499]	0.14	0.10	0.15	0.15	0.06	0.07	-0.15	0.13	0.16**	0.08
[500,+∞)	0.29**	0.12	0.12	0.17	0.03	0.07	0.001	0.14	0.22***	0.09
Good Health	0.11	0.13	0.26	0.17	0.23***	0.08	0.13	0.15	-0.11	0.10
Log(hourly wage)	0.42***	0.07	0.16	0.14	0.26***	0.05	0.41***	0.12	0.03	0.06
Log(annual hours)	0.11*	0.06	-0.08	0.11	0.46***	0.06	0.35***	0.13	0.36***	0.05
Tenure	0.18**	0.07	-0.13	0.14	0.02	0.06	0.04	0.11	0.16**	0.07
Pension	0.58***	0.12	-0.11	0.19	-0.17**	0.08	-0.002	0.16	0.50***	0.08
Tenure*Pension	0.02	0.09	0.21	0.16	0.19***	0.06	0.08	0.11	-0.01	0.08
Region										
Northeast (omitted)										
Midwest	-0.13	0.13	-0.13	0.19	0.04	0.08	-0.10	0.15	-0.16	0.10
South	-0.17	0.12	-0.02	0.18	-0.07	0.07	-0.01	0.15	-0.06	0.09
West	0.14	0.12	-0.05	0.19	0.10	0.07	-0.07	0.14	0.05	0.09
Education										
No degree (omitted)										
High school	0.13	0.14	0.07	0.22	0.07	0.09	0.30**	0.15	0.08	0.10
College+	0.01	0.16	0.02	0.25	0.08	0.10	0.29	0.18	0.02	0.12
Female	-0.21**	0.09	-0.15	0.16	-0.19***	0.05	-0.44***	0.11	-0.43***	0.08
Spouse Self-employed									0.08	0.09
Spouse Education										
No degree (omitted)										
High school									-0.01	0.08
College+									-0.13	0.09
Spouse Full-Time									-0.17**	0.07
Spouse Tenure									-0.01	0.04
Spouse Tenure*Pension									-0.07	0.04
Sample Size: N=4,354										

Source: Health and Retirement Study;

Est. is short for Estimates, and S.E. is short for standard error;

*,**,*** represent the 10, 5, and 1 percentage significance level, respectively.

Table A6 lists the estimates of parameters in the covariance matrix of the five error terms, ρ. Individuals who experience shocks that increase the probability of being eligible for employer-provided working insurance also tend to experience shocks that increase the probability of being eligible for employer-provided retiree insurance and the probability of reporting their EPHI eligibility. Individuals experience shocks that increase the probability of being eligible for retiree insurance that cover themselves or their spouse also tend to experience shocks that increase the probability of reporting their EPHI eligibility.

Table A6: Covariance Matrix Estimates

Parameter	Estimate	Std. Err.
ρ_{12}	0.23	0.48
ρ_{13}	0.92***	0.37
ρ_{14}	0.09	0.33
ρ_{15}	1.61***	0.59
ρ_{23}	0.06	0.15
ρ_{24}	0.58	0.46
ρ_{25}	0.04	0.19
ρ_{34}	0.01	0.46
ρ_{35}	0.66***	0.14
ρ_{45}	0.67***	0.18

Source: Health and Retirement Study;
*,**,*** represent the 10, 5, and 1 percentage significance level, respectively.

A.6 Employer-Provided Health Insurance Plan Characteristics

Using the cell averages of EPHI plan characteristics to impute individual plan characteristics creates a measurement error problem in my model. Tables A7 lists the 2002 EPHI plan characteristics in the private sector by industry type and firm size, and Table A8 lists the 2002 EPHI plan characteristics in the public sector. The numbers in the parentheses are standard deviations associated with these averages. The high standard deviations show that the plan characteristics within each cell are spread out over a wide range of values. Thus, the observed cell averages of plan characteristics (also called the observed data) and the true individual plan characteristics (also called the error-free data) may be significantly different.

In my model, the measurement errors cause two problems. First, measurement error may cause the estimates of the structural model to be inconsistent and biased. As is well known (see Carroll et al. (2006) and Wooldridge (2010)), in linear regression, the effect of measurement error is to bias the slope estimate in the direction of 0 (also called attenuation bias). In my model, the effects of measurement error on model estimates are more complex than the attenuation bias because my model is nonlinear. In my structural model, the value function is a nonlinear function of parameters and plan characteristics, and the likelihood function is a nonlinear function of value functions.[18] This means that the

[18]The likelihood function is described in estimation section 5.2.

Table A7: EPHI Characteristics in Private Sector (Year 2002)

Cells		EPHI Characteristics									
				Family Coverage				Single Coverage			
		Co-insurance Rate		Premium		Deductible		Premium		Deductible	
Industry	Firm Size	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Agric.,fish.,forest.	<100	22.2%	(3.2%)	1,182	(983)	1,699	(418)	435	(266)	743	(287)
	≥100	16.7%	(7.4%)	867	(894)	929	(399)	397	(284)	436	(229)
Mining and manufact.	<100	16.8%	(2.9%)	1,239	(309)	1,469	(402)	468	(133)	611	(97)
	≥100	17.5%	(0.9%)	921	(359)	778	(45)	485	(53)	375	(38)
Construction	<100	17.3%	(1.8%)	1,391	(361)	1,231	(140)	526	(105)	595	(77)
	≥100	16.7%	(2.3%)	1,586	(1,114)	1,195	(361)	540	(180)	513	(119)
Utilities and transp.	<100	16.9%	(4.5%)	1,151	(867)	1,075	(409)	508	(306)	610	(202)
	≥100	17.2%	(2.7%)	916	(510)	746	(198)	537	(117)	345	(72)
Wholesale trade	<100	22.0%	(6.7%)	1,643	(808)	1,533	(274)	428	(171)	697	(108)
	≥100	15.9%	(2.7%)	1,063	(687)	850	(129)	500	(59)	413	(37)
Fin. svs. and real estate	<100	17.1%	(2.9%)	1,580	(455)	1,350	(188)	356	(94)	602	(106)
	≥100	18.3%	(3.3%)	1,281	(380)	900	(127)	606	(63)	374	(37)
Retail trade	<100	19.6%	(1.3%)	1,582	(307)	1,386	(279)	602	(124)	608	(77)
	≥100	17.2%	(1.3%)	1,417	(453)	953	(138)	695	(43)	392	(33)
Professioal services	<100	18.3%	(1.8%)	1,341	(284)	1,353	(162)	404	(81)	582	(56)
	≥100	16.5%	(1.7%)	1,228	(454)	851	(154)	580	(67)	381	(51)
Other services	<100	19.0%	(1.6%)	1,330	(388)	1,361	(461)	566	(89)	560	(38)
	≥100	17.6%	(1.8%)	1,429	(402)	948	(134)	702	(71)	418	(45)

Source: Medical Expenditure Panel Survey, 2002

Table A8: EPHI Characteristics in Public Sector (Year 2002)

		Family Coverage				Single Coverage			
Co-insurance Rate		Premium		Deductible		Premium		Deductible	
Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
18.4%	(0.8%)	1,137	(77)	707	(50)	325	(44)	346	(21)

Source: Medical Expenditure Panel Survey, 2002

likelihood function is a nonlinear function of parameters and plan characteristics. Because the parameter estimates are the values that maximize the likelihood function, the parameter estimates can be expressed as

$$\hat{\theta} = f(X_1, Z_2) \tag{A8}$$

where X_1 is a vector of variables without measurement error, and Z_2 is a vector of observed plan characteristics. Let X_2 be a vector of plan characteristics in the error-free data, then Z_2 can be expressed as

$$Z_2 = X_2 + e \tag{A9}$$

where e represents the measurement error in plan characteristics. A second-order Taylor series expansion of $f(X_1,Z_2)$ around Z_2 at X_2 is

$$f(X_1,Z_2) \approx f(X_1,X_2) + \frac{\partial f(X_1,Z_2)}{\partial Z_2}(Z_2 - X_2) + \frac{1}{2}(Z_2 - X_2)' \frac{\partial^2 f(X_1,Z_2)}{\partial Z_2 \partial Z_2'}(Z_2 - X_2). \quad \text{(A10)}$$

Assuming that $\hat{\theta}^c = f(X_1,X_2)$ is a consistent estimate, then equation (A10) can be rewritten as

$$\hat{\theta} \approx \hat{\theta}^c + \frac{\partial f(X_1,Z_2)}{\partial Z_2} e + \frac{1}{2} e' \frac{\partial^2 f(X_1,Z_2)}{\partial Z_2 \partial Z_2'} e. \quad \text{(A11)}$$

Because the observed plan characteristics are the averages of the true plan characteristics, $E(e) = 0$. Thus, $plim\, \frac{\partial f(X_1,Z_2)}{\partial Z_2} e = 0$ if e is uncorrelated with X_1 and X_2. Equation (A11) shows that $plim\, \hat{\theta} = \hat{\theta}^c$ if the term $e' \frac{\partial^2 f(X_1,Z_2)}{\partial Z_2 \partial Z_2'} e$ equals zero. This term equals zero only if $\frac{\partial^2 f(X_1,Z_2)}{\partial Z_2 \partial Z_2'} = 0$. However, the term $\frac{\partial^2 f(X_1,Z_2)}{\partial Z_2 \partial Z_2'}$ is unlikely to equal zero because the function $f(\cdot)$ is unlikely to be linear in Z_2. This means that the measurement errors in plan characteristics cause inconsistent estimates.

The second problem caused by the measurement errors in my model is that the observed data exhibit relationships not present in the error-free data. In the error-free data, different plan characteristics are correlated. For example, a plan with a high premium usually has a low deductible, whereas a plan with a low premium usually has a high deductible. The relationships between different plan characteristics are nonlinear. Assuming that the insurance market is competitive, and an insurance company adapts plan characteristics to gain zero profit, then the relationships between different plan characteristics can be expressed as

$$\Gamma = (1 - \Lambda)(m(\Gamma, \Lambda, \Xi) - \Xi). \quad \text{(A12)}$$

Variables Γ, Λ, and Ξ represent the premium, the co-insurance rate, and the deductible, respectively, and $m(\cdot)$ represents the total medical expenses, which are a function of plan characteristics. The derivative of the premium with respect to the deductible is

$$\frac{\partial \Gamma}{\partial \Xi} = (1 - \Lambda)\left(\frac{\partial m(\Gamma, \Lambda, \Xi)}{\partial \Xi} - 1\right). \quad \text{(A13)}$$

Equation (A13) shows that, if the total medical expenses are nonlinear in the deductible, then the premium is nonlinear in the deductible. Next, I use a simple example to show that the total medical expenses are nonlinear in the deductible. I assume that individuals choose their total medical expenses, m, and consumption, C, to maximize their utility. An individual's optimization problem is

$$max\, U(m(\Gamma, \Lambda, \Xi), C) \quad \text{(A14)}$$

$$s.t. \begin{cases} y \geqslant m + C & if\ m \leqslant \Xi, \\ y \geqslant \Xi + \Lambda(m - \Xi) + C & if\ m \geqslant \Xi, \end{cases}$$

where y represents income. The First Order Condition (FOC) is

$$U_1(m,C) = \begin{cases} U_2(m,C) & if\ m \leqslant \Xi, \\ \Lambda U_2(m,C) & if\ m \geqslant \Xi. \end{cases} \tag{A15}$$

Equation (A15) shows that the utility function, $U(\cdot)$, is nondifferentiable in total medical expenses. This nondifferentiability implies that m might be nondifferentiable in Ξ. This equation also shows that the relationship between m and C depends on $U_1(m,C)$ and $U_2(m,C)$, and thus, the relationship is unlikely to be linear. In summary, the total medical expenses, m, are likely to be nonlinear and nondifferentiable in Ξ. Therefore, as equation (A10) shows, the premium, Γ, is also likely to be nonlinear and nondifferentiable in the deductible, Ξ. Let

$$\Gamma = g(\Xi) \tag{A16}$$

represent the relationship between the premium and the deductible. The nonlinear relationship between the premium and the deductible means that $g(\cdot)$ is a nonlinear function. Let Γ^* and Ξ^* represent the observed premium and deductible. Because the plan characteristics in the observed data are the averages of the true plan characteristics, Ξ^* and Γ^* can be expressed as

$$\begin{aligned} \Xi^* &= \textstyle\int \Xi dF_{\Xi}(\Xi), \\ \Gamma^* &= \textstyle\int g(\Xi) dF_{\Xi}(\Xi). \end{aligned} \tag{A17}$$

where $F_{\Xi}(\Xi)$ is the distribution of the deductible in the error-free data. The nonlinearity in $g(\cdot)$ implies that

$$\int g(\Xi) dF_{\Xi}(\Xi) \neq g(\int \Xi dF_{\Xi}(\Xi)). \tag{A18}$$

Equation (A15) implies that

$$\Gamma^* \neq g(\Xi^*). \tag{A19}$$

Equations (A13) and (A16) show that the relationships between the true plan characteristics are different from the relationships between the observed plan characteristics.[19]

I do not address these measurement error problems in this paper, but future analysis of these problems would be worthwhile.

[19]Carroll et al. (2006) conclude that one of the potential effects of measurement error is that the observed data exhibit relationships not present in the error-free data.

A.7 Wage Imputation Model Estimates

I use a wage equation to impute annual wage for spouses whose wage cannot be observed in the HRS. I model the log real annual wage in period t as

$$ln(w_{it}) = \beta^w X_{it}^w + u_{it} \tag{A20}$$

where X_{it}^w is a vector of explanatory variables (including age, gender, education, and annual working hours), and $u_{it} \sim N(0, \sigma_u^2)$ is an error term. Simultaneously estimating this wage equation and my structural model is computationally burdensome. This is because including the wage equation increases the number of parameters, and the computational time increases more than linearly in the number of parameters.

Due to this computational burden, I estimate the wage equation separately from my structural model. One resulting problem is that the error term in the wage equation, u_{it}, might be correlated with the error terms (e.g., the idiosyncratic shock ι_{dt}) in my structural model that affect individuals' retirement decisions. Ignoring this correlation causes inconsistent estimates. To capture the correlation between the error that affects the log wage and the error that affects the labor supply, I use a probit framework to model the probability of working. Let an indicator variable, D_{it}, denote whether spouse i is working in period t. The latent variable, D_{it}^*, is modeled as

$$D_{it}^* = \gamma^D X_{it}^D + \varepsilon_{it} \tag{A21}$$

where X_{it}^D is a vector of explanatory variables (including age, race, gender, and marital status) and $\varepsilon_{it} \sim N(0,1)$. The wage imputation model consists of equations (A20) and (A21). The exclusion restriction is that marital status is assumed to affect only the probability of working (equation (A21)) and not affect the real wage (equation (A20)).

I use the two-step Heckman selection method to estimate the wage imputation model. The Heckman method assumes that

$$\begin{pmatrix} u_{it} \\ \varepsilon_{it} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_u^2 & \rho_u\sigma_u \\ \rho_u\sigma_u & 1 \end{pmatrix}\right]. \tag{A22}$$

Under this assumption, the log real wage conditional on working is

$$ln(w_{it})\,|_{D_{it}=1} = \beta^w X_{it}^w + \rho_u\sigma_u\lambda(\gamma^D X_{it}^D) + \nu_{it} \tag{A23}$$

where $\lambda(\gamma^D X_{it}^D)$ is the inverse Mills ratio evaluated at $\gamma^D X_{it}^D$ and ν_{it} is

$$\begin{aligned} \nu_{it} &= u_{it} - E[u_{it}|D_{it}=1] \\ &= u_{it} - \rho_u\sigma_u\lambda(\gamma^D X_{it}^D). \end{aligned}$$

Following Heckman (1979), in the first step, I use a probit regression to estimate γ^D in equation (A21). In the second step, I compute $\lambda(\hat{\gamma^D X_{it}^D})$ and I use a least squares regression to estimate equation (A20). Although including the probit equation reduces the asymptotic bias of the estimate of β^w, the two-step Heckman estimates are still inconsistent because the probit equation differs from my structural model of individuals' labor supply (or retirement) behavior.

I use individuals in the HRS to estimate the wage imputation model. The sample size to estimate the first-stage probit regression is 163,538 person-periods, and the sample size to estimate the second-stage regression is 33,721 person-periods. Table A9 lists the estimates of these two stages. Using the resulting estimates, I compute the expectation of wage conditional on working, which I use as my annual wage data.

Table A9: Annual Wage Imputation Model Estimates

	Probit (1st Stage)		Wage (2nd Stage)	
Variable	Est.	S.E.	Est.	S.E.
Age	0.388***	0.101	0.939***	0.049
Age^2	-0.032***	0.008	-0.094***	0.004
Education				
No degree (omitted)				
High school degree	0.742***	0.035	0.254***	0.011
College degree+	1.421***	0.045	0.739***	0.013
Race				
White (omitted)				
Black	-0.150***	0.041	-0.059***	0.011
Other	-0.280***	0.067	-0.044**	0.017
Male	0.345***	0.043	0.451***	0.008
Married	-0.308***	0.027		
Married*Male	0.646***	0.045		
Experience			0.346***	0.011
Inverse Mills ratio			0.003	0.006
Constant	2.944***	0.319	1.745***	0.149
Sample Size	N=163,538		N=33,721	

Source: Health and Retirement Study;
Est. is short for Estimate, and S.E. is short for standard error;
Age equals real age divided by 10; Experience equals the log of working years;
*,**,*** represent the 10, 5, and 1 percentage significance level, respectively.

The coefficients of age, education, race, gender, and marital status are statistically significant. Before age 60, aging significantly increases the probability of working, while after age 60, aging significantly decreases the probability of working. Before age 53, aging significantly increases annual wage, while after age 53, aging significantly decreases annual wage. Having more education significantly increases annual wage and the probability of working. Whites and males are more likely to choose to work and have higher wages than non-whites and females, respectively. Being married significantly increases the probability of working for males and significantly decreases the probability of working for females.

Having more working experience significantly increases annual wage.

A.8 AIME and Earnings History

In this subsection, I first describe the function that use a worker's current AIME to update his AIME in the next year. Then, I present the estimates of the modified AR(1) process used to derive each spouse's past earnings history.

A.8.1 AIME Updating Function

I can calculate each spouse's AIME in the first wave (year 1992) using the labor income history up to 1992. To calculate the AIME for future years, following French and Jones (2011), I assume that spouse i's annualized AIME in the next year is a function of his annualized AIME, Δ_{it}, labor income, $w_{it}L_{it}$, and age, a_{it}, in the current year,

$$\begin{aligned}\Delta_{i,t+1} &= (1+g1_{[a_{it}\leq 60]}L_{it})\Delta_{it}\\ &+ \frac{1}{35}max\{0, w_{it}L_{it} - \alpha^{a_{it}}(1+g1\{a_{it}\leq 60\})\Delta_{it}\},\end{aligned}$$

where g denotes the average real wage growth rate, set to 0.016. The parameter $\alpha^{a_{it}}$ is the same across people but varies with age. Table A10 lists the value of $\alpha^{a_{it}}$ for different ages.

Table A10: Value of $\alpha^{a_{it}}$ by Age

Age	$\alpha^{a_{it}}$
56	0.107
57	0.213
58	0.320
59	0.427
60	0.534
61	0.570
62	0.589
63	0.600
64	0.608
65	0.614
66	0.616
67	0.617
68	0.618
69	0.618
70	0.619
71	0.619

Source: French and Jones (2011).

A.8.2 Earnings History

To calculate the AIME in 1992, I need a worker's earnings history up to 1992. Due to the HRS data usage restriction of individuals' earnings history,[20] I impute the earnings history prior to 1992 for each spouse in my sample. I construct a worker's earnings history in two steps. In the first step, the log real labor income in period t is modeled as[21]

$$ln(w_{it}) = \rho^L ln(w_{i,t-1}) + \theta^L X_{it}^L + \varepsilon_{it}^L \tag{A24}$$

where X_{it}^L is a vector of explanatory variables (including education, race, and age) and ε_{it}^L is white noise.[22] To estimate equation (A24), I use the Panel Study of Income Dynamics (PSID), which is a longitudinal household survey that began in 1968. The PSID collects data about employment and income for individuals in a nationally representative sample of households. I include husbands and wives who were between the ages of 20 and 40 in 1968, and I track their earnings history until 1988. I use this sample to estimate equation (A24) for husbands and wives separately.[23]

In the second step, given the estimates of equation (A24) and each spouse's annual labor income in 1992, I derive a spouse's earnings history backwards from 1992 to the year when he was 20 years old.[24] With the constructed earnings histories in hand, I compute the annualized AIME in 1992 for each spouse in my sample.[25]

Table A11 shows the estimates of this modified AR(1) process (equation (A24)). Labor incomes are highly persistent, and the level of persistence is around 0.7. In addition, age, education, and race have significant effects on predicting labor income. Before age 60, aging significantly increases the husbands' labor income; while after age 60, aging significantly decreases the husbands' labor income. Age has similar effects on predicting the wives' labor income; the age cutoff for the wives is 50. Having more education significantly increases labor income. Whites have higher labor incomes than non-whites.

In the literature on labor income processes, there are two leading views about the nature of the income process. As summarized in Guvenen (2009), the first view (the "Heterogeneous Income Profile" (HIP) model) is that individuals are subject to shocks with

[20]For an explanation of the data usage restriction, see data section 4.1.

[21]Real labor income equals nominal labor income divided by the Consumer Price Index (CPI). The reference base for the CPI is 1992.

[22]Most literature about the labor income process models labor income as a function of both explanatory variables and an income shock that follows an AR(1) process. See Guvenen (2009) for a summary.

[23]I cannot observe how much labor income non-working people would have earned. Thus, to estimate the modified AR(1) process, I include only the labor income of those who are working. However, this introduces a selection problem, which I ignore here.

[24]To derive a spouse's earnings history using equation (A24), I need to know the variables in X_{it}^L for years prior to 1992. The only variable in X_{it}^L that changes over time is age, which can be easily calculated for these years.

[25]If a spouse is older than 55 in 1992, then the AIME as of 1992 is the average monthly labor income during his 35 highest earnings years. If one spouse is younger than 55 in 1992, then his earnings history is less than 35 years, and his AIME is the sum of his labor income over the history divided by 35×12.

Table A11: Modified AR(1) Process Estimates

	Husband		Wife	
Variable	Est.	S.E.	Est.	S.E.
Labor Income next period	0.706***	0.003	0.679***	0.007
Age	0.024***	0.001	0.009***	0.002
Age^2	-0.0002***	0.00001	-0.00009***	0.00002
Education				
No degree (omitted)				
High school degree	0.060***	0.004	0.077***	0.009
College degree+	0.127***	0.005	0.174***	0.015
Race				
White (omitted)				
Black	-0.068***	0.004	-0.046***	0.009
Other	-0.022**	0.009	-0.054*	0.031
Constant	0.96***	0.025	1.213***	0.057
Sample Size	N=51,491		N=10,473	

Source: Panel Study of Income Dynamics;
Est. is short for Estimate, and S.E. is short for standard error;
*,**,*** represent the 10, 5, and 1 percentage significance level, respectively.

modest persistence, but face life-cycle profiles that are individual-specific. The second view (the "Restricted Income Profile" (RIP) model) is that individuals are subject to extremely persistent shocks, but face similar life-cycle income profiles. The RIP models get higher estimates of the level of persistence than the HIP models.[26] Because I do not include the individual-specific effect in equation (A24), I may overestimate the level of persistence of a worker's income and underestimate the consistent difference between two workers' labor incomes over time. However, for each spouse in each year, the imputed labor income using equation (A24) is still a mostly accurate prediction of the real labor income. This is because the individual-specific effect on labor income is absorbed in the estimate of ρ^L.

Table A12 compares the sample statistics of husbands' annualized AIME[27] in 1992 using my imputed earnings histories and those calculated by French and Jones (2011), who use the restricted SSER file. Compared to the annualized AIME calculated using the SSER file, the annualized AIME that I calculate for husbands has similar sample means and has smaller standard deviations.[28] The smaller standard deviations might be because I ignore the individual-specific effect in equation (A24).[29] Yet, it is still reasonable to use equation

[26]In HIP models, the estimated level of persistence in income shocks ranges from 0.5 to 0.7 (Lillard and Weiss (1979), Baker (1997), and Haider (2001)); in RIP models, the estimated level of persistence is close to 1 (MaCurdy (1982), Abowd and Card (1989), and Topel and Ward (1992)).

[27]Annualized AIME equals AIME times 12 months.

[28]The only exception is that, for husbands in the none category (who have no insurance), I calculated a larger sample mean of AIME than French and Jones (2011). This might be because, in my sample, many husbands who have no EPHI are self-employed, and self-employed workers have higher labor income than salary workers (Hochguertel (2015).

[29]For husbands in my sample, 27.6% of the standard deviation of the AIME is due to the error, and 72.4%

(A24) because the purpose of the process is to impute annual labor income prior to 1992 but not to explain the nature of the income process.

Table A12: Sample Statistics for Initial Annualized AIME

EPHI Eligibility Category	Imputed Earnings History		SSER File	
	Mean	Std. Dev.	Mean	Std. Dev.
Retiree	24.8	(5.0)	24.9	(9.1)
Tied	24.6	(4.5)	24.9	(8.6)
None	21.9	(4.3)	16.0	(9.0)

Note: Numbers are measured in thousands of dollars

A.9 Bargaining Power

I describe how to use the method developed by Friedberg and Webb (2006) to predict the husband's bargaining power relative to that of his wife. Let γ_n be the true bargaining power in household n and assume that it is a function of household observables X_n^γ. Let R_{ni} represents spouse i's response to the survey question, and let R_{ni}^* be the underlying continuous measure of R_{ni}, which depends on the true bargaining power γ_n and some reporting bias $\beta_i^\gamma X_n^\gamma$,

$$\begin{aligned} \gamma_n &= \alpha^\gamma X_n^\gamma + u_n^\gamma, \\ R_{ni}^* &= \gamma_n + \beta_i^\gamma X_n^\gamma + u_{ni}^\gamma = (\alpha^\gamma + \beta_i^\gamma) X_n^\gamma + \tilde{u}_{ni} \; i \in \{m, f\}. \end{aligned}$$

Based on the answer to the survey question, R_{ni}, is defined as below

$$R_{ni} = \begin{cases} 1 & if\ husband\ has\ final\ say \\ 0 & if\ about\ equal \\ -1 & if\ wife\ has\ final\ say. \end{cases}$$

Since R_{ni}^* is the underlying continuous measure of R_{ni}, the definition of R_{ni} can be rewritten as

$$R_{ni} = \begin{cases} 1 & if\ R_{ni}^* > \mu_1 \\ 0 & if\ \mu_0 < R_{ni}^* \leq \mu_1 \\ -1 & if\ R_{ni}^* \leq \mu_0. \end{cases}$$

Assume that $\tilde{u}_{ni} = (u_{ni}^\gamma + u_i^\gamma) \sim N(0, \sigma_\gamma^2)$, and $cor(\tilde{u}_{nm}, \tilde{u}_{nf}) = \rho_\gamma$. The parameters $(\alpha^\gamma + \beta_i^\gamma), \sigma_\gamma, \rho_\gamma, \mu_0, \mu_1$ are identified by estimating the bivariate ordered probit model. Then, α^γ can be estimated after imposing the restriction $\beta_m^\gamma + \beta_f^\gamma = 0$. With the estimated α^γ, I can predict the value of the bargaining power $\hat{\gamma}_n = \hat{\alpha}^\gamma X_n^\gamma$.

is due to the variation in X^L.

For each household in my sample, I impute the husband's bargaining power relative to that of his wife using the explanatory variables and parameter estimates provided by Friedberg and Webb (2006).

A.10 Computation of Optimal Consumption

Given any d_t, optimal household consumption, denoted as $C^*(d_t)$, satisfies the First Order Condition (FOC) of equation (5.2),

$$\frac{\partial U(d_t, C_t; z_t)}{\partial C_t} + \beta \frac{\partial E_m\{E[V(z_{t+1})|z_t, d_t, C_t, m_t]\}}{\partial A_{t+1}} \frac{\partial A_{t+1}(C_t)}{\partial C_t} = 0. \tag{A25}$$

The functional form of household utility flow (equations (3.1)-(3.2)) implies that $\frac{\partial U(d_t, C_t; z_t)}{\partial C_t} = \frac{1}{C_t^{\alpha}}$. Similarly, the budget constraint (equation (3.4) implies that $\frac{\partial A_{t+1}(C_t)}{\partial C_t} = -1$. Thus, the FOC can be rewritten as

$$C_t = \left\{ \beta \frac{\partial E_m\{E[V(z_{t+1})|z_t, d_t, C_t, m_t]\}}{\partial A_{t+1}} \right\}^{-(1/\alpha)}. \tag{A26}$$

Computing the term $\frac{\partial E_m\{E[V(z_{t+1})|z_t, d_t, C_t, m_t]\}}{\partial A_{t+1}}$ analytically is computationally burdensome. My approach is to use several linear splines to approximate $E_m\{E[V(z_{t+1})|z_t, d_t, C_t, m_t]\}$. Then, instead of computing $\frac{\partial E_m\{E[V(z_{t+1})|z_t, d_t, C_t, m_t]\}}{\partial A_{t+1}}$ at every point of A_{t+1}, I compute the slope of each linear spline.

I first discretize the household assets using five points $(A^1, A^2, A^3, A^4, A^5)$.[30] Then, I calculate $E_m\{E[V(z_{t+1})|z_t, d_t, C_t, m_t]\}$ at these five points. Let

$$D^q(d_t) = E_m\{E[V(z_{t+1}(A^q))|z_t, d_t, C_t, m_t]\} \quad q = \{1, 2, 3, 4, 5\} \tag{A27}$$

denote the value of $E_m\{E[V(z_{t+1})|z_t, d_t, C_t, m_t]\}$ when $A_{t+1} = A^q$. Therefore, the slope of the linear spline that connects D^q and D^{q+1} is

$$S^q(d_t) = \frac{D^{q+1}(d_t) - D^q(d_t)}{A^{q+1} - A^q} \quad q = \{1, 2, 3, 4\}. \tag{A28}$$

For each $S^q(d_t)$, there exist corresponding assets, denoted as $A_{t+1}(d_t, q)$. If $A_{t+1}(d_t, q)$ is located inside of $[A^q, A^{q+1}]$, I replace the term $\frac{\partial E_m\{E[V(z_{t+1})|z_t, d_t, C_t, m_t]\}}{\partial A_{t+1}}$ in the FOC (equation (A26)) with $S^q(d_t)$. The optimal household consumption for the q^{th} spline, conditional on d_t, is

$$C(d_t, q) = \{\beta S^q(d_t)\}^{-(1/\alpha)}. \tag{A29}$$

[30] These five points are defined by the mean, m_A, and the standard deviation, std_A, of the distribution of the household assets observed in the first wave: $A^1 = m_A - 2std_A$, $A^2 = m_A - std_A$, $A^3 = m_A$, $A^4 = m_A + std_A$, and $A^5 = m_A + 2std_A$.

If $A_{t+1}(d_t,q)$ is located outside of $[A^q, A^{q+1}]$, I update $A_{t+1}(d_t,q)$ with A^q or A^{q+1}, whichever is closer to $A_{t+1}(d_t,q)$. Given the updated $A_{t+1}(d_t,q)$, I then update $C(d_t,q)$ in equation (A29) with the amount of consumption that satisfies the household budget constraint.[31] I derive $C(d_t,q)$ for each of the four splines, and the optimal household consumption, conditional on d_t, is

$$C^*(d_t) = \underset{C_t \in \{C(d_t,q), q=1,\dots,4\}}{argmax} \{v(d_t, C_t; z_t)\}. \tag{A30}$$

A.11 Identification of First Stage Parameters

A.11.1 Medical Expenditure Function Parameters

Recall that two independent processes are modeled to determine each spouse's total medical expenditures: (1) whether he has positive medical expenses; and (2) the amount of total medical expenses conditional on having positive medical expenses. I use a Bivariate Probit framework to model the first process. Let P_{it} be a binary variable indicating whether spouse i has positive total medical expenses in period t. As described in model section 3.4.2 (equation (3.8)), the latent variable, P^*_{it}, is modeled as

$$P^*_{it} = \xi^i_1 I_{it} + \xi^i_2 H_{it} + \xi^i_3 L_{it} + \xi^i_4 X_{it} + \vartheta_{it}, \tag{A31}$$

$$\begin{pmatrix} \vartheta_{mt} \\ \vartheta_{ft} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_\vartheta \\ \rho_\vartheta & 1 \end{pmatrix}\right].$$

The parameters associated with the explanatory variables, ξ^i, are identified by the co-variation in whether spouse i has positive medical expenses and the explanatory variables, $(I_{it}, H_{it}, L_{it}, X_{it})$. The correlation between the two spouses' error terms, ρ_ϑ, is identified by the co-variation in the residuals of the two spouses' probits.

In the second process, the log of positive total medical expenditures, $ln(m^P_{it})$, is modeled as a function of the four components used in the first process, $\overrightarrow{X_{it}} = (I_{it}, H_{it}, L_{it}, X_{it})$, and an idiosyncratic shock, u_{it}. Additionally, I assume that the vector of explanatory variables, $\overrightarrow{X_{it}}$, can affect both the mean, $\mu(\cdot)$, and the variance, $\sigma(\cdot)$, of $ln(m^P_{it})$. Thus, $ln(m^P_{it})$ is modeled as (equation (3.9))

$$ln(m^P_{it}) = \mu(\overrightarrow{X_{it}}) + \sigma(\overrightarrow{X_{it}}) u_{it}, \tag{A32}$$

$$\begin{pmatrix} u_{mt} \\ u_{ft} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_u \\ \rho_u & 1 \end{pmatrix}\right],$$

[31] Although the introduction of the spline function simplifies the computation of the optimal consumption, it creates kink points in the value function. See section 5.2.4 for a discussion about the estimation problem caused by these kinks.

where

$$\mu(\overrightarrow{X_{it}}) = \chi_1^i I_{it} + \chi_2^i H_{it} + \chi_3^i L_{it} + \chi_4^i X_{it}, \tag{A33}$$

$$\sigma(\overrightarrow{X_{it}}) = \pi_1^i I_{it} + \pi_2^i H_{it} + \pi_3^i L_{it} + \pi_4^i X_{it}. \tag{A34}$$

The parameters that affect the mean of the log of total medical expenditures, χ^i, are identified by the co-variation in the log of total medical expenditures and the explanatory variables. The parameters that affect the volatility of the log of total medical expenditures, π^i, are identified by the co-variation in the two spouses' squared residuals of the log of total medical expenditures and the explanatory variables. With the estimated parameters $\widehat{\pi^i}$ and the vector of observed explanatory variables $\overrightarrow{X_{it}}$, I can calculate each spouse's preference for medical expenditure shocks, $\sigma(\widehat{\pi^i}\overrightarrow{X_{it}})$.[32] The co-variation in the two spouses' residuals divided by $\sigma(\widehat{\pi^i}\overrightarrow{X_{it}})$ identifies the correlation between the two spouses' error terms, ρ_u.

A.11.2 Health Transitions and Survival Rates Parameters

In the household health transitions function, H_{it} is a binary variable that indicates whether spouse i is in good health in period t. As described in model section 3.6.1, the latent variable, H_{it}^*, is modeled as

$$H_{it}^* = \kappa_1^i I_{i,t-1} + \kappa_2^i H_{i,t-1} + \kappa_3^i X_{i,t-1} + u_{it}^H, \tag{A35}$$

$$\begin{pmatrix} u_{mt}^H \\ u_{ft}^H \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_H \\ \rho_H & 1 \end{pmatrix}\right].$$

The parameters associated with the explanatory variables, κ^i, are identified by the co-variation in the health status in this period, H_{it}, and the explanatory variables in the last period, $(I_{i,t-1}, H_{i,t-1}, X_{i,t-1})$. The correlation between the two spouses' health shocks, ρ_H, is identified by the co-variation in the residuals of the two probits.

In the household survival rates function, S_{it} is a binary variable that indicates whether spouse i is alive in period t. As described in model section 3.6.2, the latent variable, S_{it}^*, is modeled as

$$S_{it}^* = \zeta_1^i H_{i,t-1} + \zeta_2^i X_{i,t-1} + u_{it}^S, \tag{A36}$$

$$\begin{pmatrix} u_{mt}^S \\ u_{ft}^S \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_S \\ \rho_S & 1 \end{pmatrix}\right].$$

The parameters associated with the explanatory variables, ζ^i, are identified by the co-variation in the survival status in this period and the explanatory variables in the last period, $(H_{i,t-1}, X_{i,t-1})$. The correlation between the two spouses' life shocks, ρ_S, is identified by the co-variation in the residuals of the two probits.

[32] $\sigma(\overrightarrow{X}\pi)$ shows that spouses who have different values of explanatory variables, $\overrightarrow{X}$, react to the medical expenditure shock differently.

A.12 First Stage Parameter Estimates

I first present parameter estimates that affect the distribution of total medical expenses (see A.12.1). Then, I list parameter estimates that determine health transitions (see A.12.2). Lastly, I discuss parameter estimates that determine survival rates (see A.12.3).

A.12.1 Total Medical Expenditure Parameter Estimates

As described in model section 3.4.2, I assume that each spouse's total medical expenses are generated by two separate processes: (1) whether each spouse has zero or positive total medical expenses (equation (3.8)); and (2) the amount of total medical expenditures conditional on having positive total medical expenditures (equation (3.9)). Tables A13 and A14 present estimates of parameters in the first and the second processes, respectively. In Table A13, the binary $(0/1)$ dependent variable equals 1 if a spouse has zero total medical expenses. In Table A14, the dependent variable is the log of positive total medical expenses, which is modeled as the sum of a mean function and a standard deviation function (equations (A32)-(A34)). The sign of parameters are as expected, and most of the estimates are statistically significant. To put the size of the estimates into perspective, I compute the AME (average marginal effect) for each of the variables.

The effects of health status, health insurance coverage, and employment status are of particular interest. The estimates of the "Good Health" parameters indicate that being in good health increases the probability of having zero total medical expenses. It also decreases the mean and the variance of the distribution of the log positive medical expenses. The AMEs of the "Good Health" variable show that, on average, being in good health increases the probability of having zero medical expenses by 10.1 and 6.7 percentage points for husbands and wives, respectively. Additionally, it decreases the expectation of positive total medical expenses by $\$6,494.7$ and $\$5,063.6$ for husbands and wives, respectively.[33]

The estimates of health insurance coverage parameters imply that spouses who have insurance coverage (either public or private) are more likely to have positive medical expenses than those who have no insurance. The distribution of the log of positive total medical expenses for those who have insurance has larger mean and variance than that for those who have no insurance. For example, the AMEs of the "Private HI" variable show that, on average, compared to having no health insurance coverage, having private coverage decreases the probability of having zero medical expenses by 8.5 and 5.3 percentage points for husbands and wives, respectively. It also increases the expectation of positive total medical expenses by $\$1,708.6$ and $\$1,307.1$ for husbands and wives, respectively.

The estimates of the "Full-time Work" parameters indicate that, on average, full-time workers are more likely to have zero total medical expenses than retirees. The distri-

[33] Positive total medical expenses are the amount of total medical expenses conditional on having positive medical expenses.

Table A13: Parameter Estimates For The Probability Of Having Zero Total Medical Expenses

	Husband's Equation			Wife's Equation		
Variable	Estimate	S/E	AME	Estimate	S/E	AME
Age/10 Slope			-0.004			-0.001
Age≤64	-0.50***	0.03		-0.45***	0.03	
Age≥65	-0.03	0.05		0.11	0.09	
Hispanic	0.35***	0.04	0.058	0.29***	0.05	0.032
Good Health	0.67***	0.05	0.101	0.71***	0.07	0.067
Full-time Work	0.26***	0.05	0.062	0.22***	0.07	0.046
Family Assets$*10^{-6}$	-3.29***	0.36	-0.566	-2.37***	0.45	-0.241
Race (White is omitted)						
Black	0.32***	0.05	0.051	0.21***	0.06	0.024
Other	0.01	0.03	0.001	0.02	0.04	0.002
Education (less than high school is omitted)						
High school	-0.19***	0.04	-0.027	-0.13***	0.05	-0.014
College and above	-0.37***	0.05	-0.057	-0.33***	0.06	-0.033
Health Insurance (having no insurance coverage is omitted)						
Public HI	-0.12**	0.06	-0.048	0.03	0.07	-0.015
Private HI	-0.46***	0.04	-0.085	-0.48***	0.05	-0.053
Constant	1.35***	0.17		0.51***	0.19	
Correlation Coefficient	0.37***	0.02				

Note: 1) *, **, and *** represent 10, 5 and 1 percent significance, respectively;
2) the columns labelled AME list average marginal effects of variables on the probability of having zero total medical expenses;
3) the AME of the "Age/10 Slope" is the AME of increasing age by 1 year;
4) the AME of the "Family Assets" is the AME of increasing assets by 1%.

bution of the log of positive total medical expenses for full-time workers has smaller mean and variance than the distribution for retirees. The AMEs of the "Full-time Work" variable show that, on average, working full-time increases the probability of having zero total medical expenses by 6.2 and 4.6 percentage points for husbands and wives, respectively. It also decreases the expectation of total medical expenses by $1,947.6 and $1,599.2 for husband and wives, respectively.

A.12.2 Health Transitions Parameter Estimates

Recall that I use a bivariate probit framework to model health status in the next period as a function of current health insurance coverage, health status, age, race, and education degree. Table A15 presents the estimates of parameters that affect health transitions and the AME for each of the variables. Note that I include health status this period as a factor that affects health status next period. Thus, health transition is the probability of being in good health next period conditional on health status this period. The effects of current health status and health insurance coverage are of particular interest. The AMEs of the

Table A14: Parameter Estimates For Positive Total Medical Expenses

	Mean Function(μ)		S.D. Function(σ)		AME
Variable	Estimate	S/E	Estimate	S/E	
Husband's Equation					
Age/10 Slope					60.8
Age≤64	0.37***	0.02	-0.20***	0.02	
Age≥65	0.06	0.04	0.04*	0.02	
Hispanic	-0.22***	0.05	-0.06*	0.03	-1,522.3
Good Health	-0.97***	0.04	-0.02	0.02	-6,494.7
Full-time Work	-0.25***	0.04	-0.07***	0.02	-1,947.6
Family Assets*10^{-6}	0.84***	0.32	-0.15	0.19	3,367.2
Race (White is omitted)					
Black	-0.18***	0.05	-0.002	0.03	-813.8
Other	0.30	0.03	0.01	0.02	1,803.7
Education (less than high school is omitted)					
High school	0.31***	0.04	-0.10***	0.03	816.4
College and above	0.40***	0.04	-0.18***	0.03	644.4
Health Insurance (having no insurance coverage is omitted)					
Public HI	0.38***	0.04	0.14***	0.03	2198.1
Private HI	0.48***	0.04	-0.006	0.02	1708.6
Constant	5.09***	0.15	2.72***	0.11	
Wife's Equation					
Age/10 Slope					38.9
Age≤64	0.22***	0.02	-0.24***	0.02	
Age≥65	0.04	0.04	0.08***	0.03	
Hispanic	-0.28***	0.04	0.004	0.03	-1,061.1
Good Health	-0.86***	0.03	-0.04*	0.02	-5,063.6
Full-time Work	-0.36***	0.04	0.002	0.02	-1,599.2
Family Assets*10^{-6}	1.7***	0.26	-1.04***	0.13	1,142.9
Race (White is omitted)					
Black	-0.22***	0.05	0.10***	0.03	-270.9
Other	0.37***	0.02	0.03*	0.01	1,813.7
Education (less than high school is omitted)					
High school	0.26***	0.04	0.02	0.02	1,160.1
College and above	0.25***	0.04	-0.03	0.02	809.2
Health Insurance (having no insurance coverage is omitted)					
Public HI	0.30***	0.04	0.17***	0.02	1,867.3
Private HI	0.59***	0.04	-0.12***	0.02	1,307.1
Constant	5.98***	0.13	2.76***	0.10	
Correlation Coefficient	0.13***	0.01			

Note: 1) *, **, and *** represent 10, 5 and 1 percent significance, respectively;

2) the column labelled AME lists average marginal effects of variables on the expected positive total medical expenses, which equal $exp\{\mu + 0.5\sigma^2\}$.

3) the AME of the "Age/10 Slope" is the AME of increasing age by 1 year;

4) the AME of the "Family Assets" is the AME of increasing assets by 1%.

"Good Health" variable show that, on average, improving health status from bad to good increases the probability of being in good health next period by 34.1 and 33.1 percentage points for husbands and wives, respectively. Compared to people who lack health insurance coverage, especially for those under age 65, being covered by public health insurance, on average, decreases the probability of being in good health next period by 14.6 and 11.9 percentage points for husbands and wives, respectively. This might be because people who are under age 65 and have access to public health insurance usually have poor health, and their poor health either due to disability or lack of medical treatment (as a result of low income). By contrast, compared to people who have no health insurance, being covered by private health insurance increases the probability of being in good health next period by 1.8 and 2.5 percentage points for husbands and wives, respectively. This might be because people who have private health insurance usually work full-time and have a better financial situation, which makes them more likely to receive better health care, and thus makes them more likely to be in good health next period.

Table A15: Health Transitions Parameter Estimates

	Husband's Equation			Wife's Equation		
Variable	Estimate	S/E	AME	Estimate	S/E	AME
Age			0.004			0.004
Age/10	0.19**	0.09		0.23***	0.08	
$(Age/10)^2$	-0.03***	0.01		0.006	0.09	
Hispanic	-0.23***	0.03	-0.052	-0.33***	0.03	-0.064
Good Health	1.47***	0.02	0.341	1.64***	0.02	0.331
Race (White is omitted)						
Black	-0.18***	0.03	-0.042	-0.22***	0.03	-0.046
Other	-0.16***	0.03	-0.036	-0.10***	0.03	-0.019
Education (less than high school is omitted)						
High school	0.25***	0.02	0.065	0.33***	0.02	0.078
College and above	0.52***	0.03	0.127	0.59***	0.03	0.129
Health Insurance (having no insurance coverage is omitted)						
Public HI_65	-0.05*	0.03	-0.010	-0.004	0.03	-0.0002
Public HI_64	-0.62***	0.04	-0.146	-0.59***	0.05	-0.119
Private HI	0.08***	0.02	0.018	0.12***	0.02	0.025
Constant	-0.74**	0.33		-1.04***	0.25	
Correlation Coefficient	0.13***	0.01				

Note: 1) *, **, and *** represent 10, 5 and 1 percent significance, respectively;
2) indicator variable Public HI_65 equals 1 if one has public insurance and age≥65;
3) indicator variable Public HI_64 equals 1 if one has public insurance and age≤64;
4) the columns labelled AME list average marginal effects of variables on the probability of being in good health the next period.

A.12.3 Survival Rates Parameter Estimates

I also use a bivariate probit framework to model survival rates in the next period as a function of current health status, age, race, and education degree. Table A16 lists the estimated parameters that affect survival rates and the AME for each of the variables. For example, the estimates of the "Good Health" parameters indicate that spouses who have good health this period are more likely to survive in the next period. The AMEs of the "Good Health" variable show that, on average, improving health status from bad to good increases the probability of being alive in the next period by 7.0 and 3.8 percentage points for husbands and wives, respectively.

Table A16: Survival Rates Parameter Estimates

	Husband's Equation			Wife's Equation		
Variable	Estimate	S/E	AME	Estimate	S/E	AME
Age			0.003			0.002
Age/10	0.29**	0.12		0.51***	0.13	
$(\text{Age}/10)^2$	-0.05***	0.01	-0.005	-0.06	0.01	-0.003
Hispanic	0.21***	0.04	0.020	0.29***	0.06	0.015
Good Health	0.74***	0.02	0.070	0.74***	0.03	0.038
Race (White is omitted)						
Black	-0.04	0.03	-0.003	-0.07*	0.04	-0.004
Other	-0.001	0.05	-0.0007	-0.11*	0.06	-0.006
Education (less than high school is omitted)						
High school	0.005	0.02	0.0005	0.003	0.03	0.0002
College and above	0.11***	0.03	0.010	0.12**	0.05	0.006
Constant	1.58**	0.44		0.99**	0.43	
Correlation Coefficient	0.11***	0.02				

Note: 1) *, **, and *** represent 10, 5 and 1 percent significance, respectively;
2) the columns labelled AME list average marginal effects of variables on the probability of being alive in the next period.

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