

## Medicaid Insurance in Old Age

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December 2012

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## **Acknowledgements**

This work was supported by a grant from the Social Security Administration through the Michigan Retirement Research Center (Grant # 5 RRC08098401-04-00). The findings and conclusions expressed are solely those of the author and do not represent the views of the Social Security Administration, any agency of the Federal government, or the Michigan Retirement Research Center.

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# Medicaid Insurance in Old Age

## Abstract

Medicaid was primarily designed to protect and insure the poor. However, the poor tend to live much shorter lifespans and thus incur much lower medical expenses before death. In this paper we assess the insurance and redistributive properties of Medicaid, taking these dimensions of heterogeneity into account, for single retirees.

The Medicaid reciprocity rate for those at the bottom income quintile stays around 60%-70% throughout their retirement. In contrast, Medicaid reciprocity by higher-income retirees is much lower but increases by age, especially after age 90.

Our preliminary results show that the annuity value of Medicaid payments is a hump-shaped function of permanent income. People in the middle of the income distribution receive more than those at the top or the bottom. Once one takes into account that the rich live longer, Medicaid is even less redistributive: in terms of present discounted value, the richest people receive almost as much as the poorest ones, and the middle income people still benefit the most.

Accounting for risk makes Medicaid less redistributive further still. Compensating differential calculations show that Medicaid insurance is valued most highly by the most rich, who have the most to lose.

## Authors' Acknowledgements

For useful comments and suggestions we thank Norma Coe, Amy Finkelstein, Karl Scholz, and Gianluca Violante. Jones gratefully acknowledges financial support from the Social Security Administration through the Michigan Retirement Research Center (MRRC grants UM10-16 and UM12-12). The views expressed in this paper are those of the authors and not necessarily those of the Federal Reserve Bank of Chicago, the Social Security Administration or the MRRC. Jones gratefully acknowledges the hospitality of the Federal Reserve Bank of Chicago.

# 1 Introduction

In the United States, a key public health insurance program for the elderly poor is Medicaid, a means-tested program that covers any medical expenses not picked up by other insurance programs. While Medicaid is often perceived as supporting only the lifetime poor, a significant portion of Medicaid spending for the elderly aids middle income people who have been wiped out financially by expensive medical conditions. While poor people tend to live shorter lives and to die before incurring large medical expenses, richer people are more likely to live long and face expensive medical conditions, such as nursing home stays, when very old. For example, extended stays in a nursing home are generally not covered by other public or private insurance, even though nursing home care costs \$60,000 to \$75,000 a year (in 2005). Medicaid ends up financing 70% of nursing home residents (Kaiser Foundation [34]).

In this paper we analyze the insurance and redistributive properties of Medicaid during old age. Using the Asset and Health Dynamics of the Oldest Old (AHEAD) dataset, we find that the average Medicaid reciprocity rate for old people in the bottom quintile of the permanent income distribution is just under 70% and stays more or less constant throughout retirement. Medicaid reciprocity by higher-income retirees is significantly lower, but increases with age. Most notably, this increase tends to happen at more advanced ages for people in the highest permanent income quintiles, reflecting the fact that survivors with higher lifetime resources run out of savings (and thus qualify for Medicaid) later on in life.

To understand these mechanisms, we construct and estimate a life-cycle model of consumption and endogenous medical expenditure that accounts for Medicare, Supplemental Social Insurance (SSI) and Medicaid. Agents in the model face uncertainty about their health, lifespan, and medical needs (including nursing home stays). This uncertainty is partially offset by the insurance provided by the government and private institutions. Agents choose whether they want to apply for Medicaid if they are eligible, how much to save, and how to split their consumption between medical and non-medical goods.<sup>1</sup> We model two pathways to Medicaid, and allow the pathways to differ in generosity.

To appropriately evaluate redistribution, we allow for heterogeneity in wealth, permanent income (PI), health, gender, life expectancy, and medical needs. We also require our model to fit well across the entire income distribution, rather than simply explain mean or median behavior. Our model closely matches the life-cycle profiles of assets, out-of-pocket medical spending, and Medicaid reciprocity rates for elderly singles in different cohorts and permanent income groups.

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<sup>1</sup>Three recent papers contain life-cycle models where the choice of medical expenditures also affects health outcomes. In addition to having different emphases, these papers model Medicaid in ways different from ours. Feng [13] models Medicaid as an insurance policy with no premiums and extremely low—possibly zero—co-payment rates. Fonseca et al. [17] assume that the consumption floor is invariant to medical needs (private conversation with Pierre-Carl Michaud). Ozkan [35] assumes that indigent individuals receive curative, but not preventative, care.

We use our estimated model to compute how Medicaid payments vary by age, gender, permanent income, and health status. We find that the current Medicaid system provides different kinds of insurance to households with different resources. Households in the lower permanent income quintiles are much more likely to receive Medicaid transfers, but the transfers that they receive are on average relatively small. Households in the higher permanent income quintiles are much less likely to receive any Medicaid pay-outs, but when they do, these pay-outs are very big and correspond to severe and expensive medical conditions. Therefore, Medicaid is an effective insurance device for the poorest, but also offers valuable insurance to the rich by insuring them against catastrophic medical conditions.

We also compute the value of Medicaid insurance in old age. Although there is a large literature on the health effects of public insurance programs, and a smaller literature on the private markets that public insurance displaces, little is known about the insurance properties of public insurance.

Summing over agents' lives, our preliminary results show that at age 74 the expected annuity value of Medicaid payments is a hump-shaped function of permanent income. People in the middle of the income distribution receive more than those at the top or the bottom. Once one takes into account that the rich live longer, Medicaid is even less redistributive: in terms of present discounted value, the richest people receive almost as much as the poorest ones, and the middle income people still benefit the most. Accounting for risk makes Medicaid less redistributive further still. Compensating differential calculations show that Medicaid insurance is valued most highly by the most rich, who have the most to lose.

## 2 Brief literature review

This paper is related to several previous papers on savings, health risks, and social insurance. Hurd [22] and Hurd, McFadden, Merrill [23] highlight the importance of accounting for the link between wealth and mortality risk when estimating life-cycle models. Kotlikoff [28] stresses the importance of modeling health expenditures to understand precautionary savings.

Hubbard et al. [20] and Palumbo [37] solve dynamic programming models of savings with medical expense risk and find that medical expenses have relatively small effects. The key reason why these papers underestimate medical spending risk is that the data sets available at that time had poor measures of medical spending and, in particular, were missing late-in-life medical spending and had poor measures of nursing home costs. As a result, they underestimate the extent to which medical expenses rise with age and income.

Hubbard et al. [21] and Scholz et al. [42] argue that means-tested social insurance programs (in the form of a minimum consumption floor) provide strong incentives for low-income individuals not to save. Kopecky and Koreshkova [27] find that old-age medical expenses, and the coverage of these expenses provided by Medicaid, have

large effects on aggregate capital accumulation. Brown and Finkelstein [5] develop a dynamic model of optimal savings and long-term care purchase decisions. They conclude that Medicaid could explain the lack of private long-term care insurance for about two-thirds of the wealth distribution. Consistent with this evidence, Brown et al. [6] exploit cross-state variation in Medicaid rules and also find significant crowding out.

Marshall, McGarry, and Skinner [30] consider whether out-of-pocket medical expenditures are a risk to financial security, particularly at older ages, by studying health care spending near the end of life. They conclude that such expenses are large and represent a substantial fraction of liquid wealth for decedents. Poterba, Venti, and Wise [39] document important correlations between poor health and asset accumulation.

Koijen, Van Nieuwerburgh, and Yogo [25] develop risk measures for health and longevity insurance and compare the risk exposure of each household in the Health and Retirement Study with the model predicted optimal risk exposure.

This paper also contributes to the literature on the redistribution generated by various government programs. Although there is a lot of research about the amount of redistribution provided by Social Security and a smaller amount of research about Medicare, to the best of our knowledge this is the first paper to examine the amount of transfers provided to different income groups by Medicaid in old age. Furthermore, we are the first to assess individuals' valuation of the insurance provided by Medicaid.<sup>2</sup>

## 3 Institutional background and data highlights

### 3.1 Institutional background

In the United States, there are two major public insurance programs helping the elderly with their medical expenses. The first is Medicare, a federal program that provides health insurance to almost every person over the age of 65. The second is Medicaid, a means-tested program that is run jointly by the federal and state governments.

An important characteristic of Medicaid is that it is the payer of “last resort”: Medicaid contributes only after Medicare and private insurance pay their share, and the individual spends down his assets to a “disregard” amount. Because Medicaid restricts benefits to those with assets below the disregard, it discourages saving through an additional channel not present in non-means-tested insurance, which reduces savings only by reducing risks. One area where Medicaid is particularly important is long-term care. Medicare reimburses only a limited amount of long-term care costs,

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<sup>2</sup>Unlike Social Security, unemployment benefits, and disability insurance, Medicaid is not financed using a specific tax, but by general government revenue, making it difficult to determine how redistributive “Medicaid taxes” are. For this reason, we focus on the redistribution generated by Medicaid benefits.

and most elderly people do not have private long-term care insurance. As a result, Medicaid covers almost all nursing home costs of poor old recipients; in fact, Medicaid now assists 70 percent of nursing home residents.<sup>3</sup>

Medicaid-eligible individuals can be divided into two main groups. The first group comprises the *categorically needy*, whose income and assets fall below certain thresholds. People who receive SSI typically qualify under the categorically needy provision. The second group comprises the *medically needy*, who are individuals whose income is not particularly low, but who face such high medical expenditures that their resources become small in comparison.

The categorically needy provision thus affects the saving of people who have been poor throughout most of their lives, but has no impact on the saving of middle- and upper-income people. The medically needy provision, instead, provides insurance to people with higher income and assets who are still at risk of being impoverished by expensive medical conditions.

## 3.2 The AHEAD dataset

We use data from the Assets and Health Dynamics of the Oldest Old (AHEAD) data set. The AHEAD is a survey of individuals who were non-institutionalized and aged 70 or older in 1994. It is part of the Health and Retirement Survey (HRS) conducted by the University of Michigan. We consider only single (i.e., never married, divorced, or widowed) retired individuals. A total of 3,872 singles were interviewed for the AHEAD survey in late 1993-early 1994, which we refer to as 1994. These individuals were interviewed again in 1996, 1998, 2000, 2002, 2004, and 2006. This leaves us with 3,259 individuals, of whom 592 are men and 2,667 are women. Of these 3,259 individuals, 884 are still alive in 2006. We do not use 1994 assets or medical expenses. Assets in 1994 were underreported (Rohwedder et al. [41]) and medical expenses appear to be underreported as well.

A key advantage of the AHEAD relative to other datasets is that it provides panel data on health status, including nursing home stays. We assign individuals a health status of “good” if self-reported health is excellent, very good or good and are assigned a health status of “bad” if self-reported health is fair or poor. We assign individuals to the nursing home state if they were in a nursing home at least 120 days since the last interview or if they spent at least 60 days in a nursing home before the next scheduled interview and died before that scheduled interview.

We break the data into 5 cohorts. The first cohort consists of individuals that were ages 72-76 in 1996; the second cohort contains ages 77-81; the third ages 82-86; the fourth ages 87-91; and the final cohort, for sample size reasons, contains ages 92-102.<sup>4</sup> We use data for 6 different years; 1996, 1998, 2000, 2002, 2004, and

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<sup>3</sup>Statistics from the Kaiser Foundation [34].

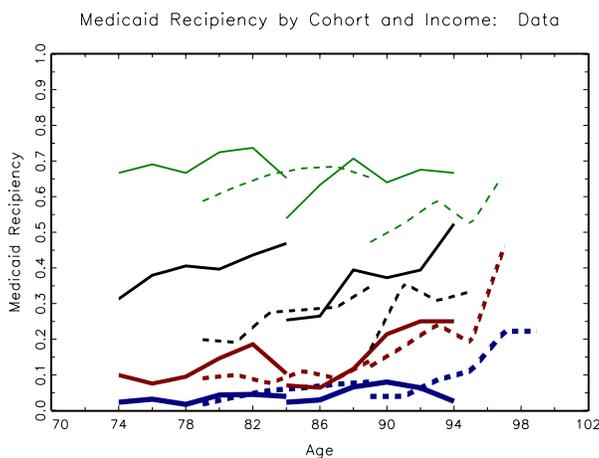
<sup>4</sup>Even with the longer interval, the final cohort contains relatively few observations, yielding short and erratic profiles. In the interest of clarity, we therefore exclude this cohort from our graphs,

2006. We calculate summary statistics (e.g., medians), cohort-by-cohort, for surviving individuals in each calendar year—we use an unbalanced panel. We then construct life-cycle profiles by ordering the summary statistics by cohort and age at each year of observation. Moving from the left-hand-side to the right-hand-side of our graphs, we thus show data for four cohorts, with each cohort’s data starting out at the cohort’s average age in 1996. Our graphs omit profiles for the oldest cohort because sample size for this cohort is tiny.

Since we want to understand the role of income, we further stratify the data by post-retirement permanent income (PI). Hence, for each cohort our graphs usually display several horizontal lines showing, for example, average Medicaid status in each PI group in each calendar year. These lines also identify the moment conditions we use when estimating the model.

We measure post-retirement PI as the individual’s average non-asset income over all periods during which he or she is observed. Non-asset income includes the value of Social Security benefits, defined benefit pension benefits, veterans benefits and annuities. Since we model social insurance explicitly, we do not include SSI transfers. Because there is a roughly monotonic relationship between lifetime earnings and the income variables that we use, our measure of post-retirement PI is also a good measure of lifetime permanent income.

### 3.3 Medicaid Reciprocity



**Figure 1:** Medicaid reciprocity rates by age, cohort, and permanent income. Thicker lines refer to higher PI groups.

AHEAD respondents are asked whether they are currently covered by Medicaid. Figure 1 plots the fraction of the sample receiving Medicaid by age, birth cohort  


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 although we use many of the observations when estimating the model.

and income quintile for all the individuals alive at each moment in time. There are four lines representing PI groupings within each cohort. We split the data into PI quintiles, but then merge the top two quintiles together because at younger ages no one in the top PI quintile is on Medicaid.

The members of the first cohort appear in our sample at an average age of 74 in 1996. We then observe them in 1998, when they are on average 76 years old, and then again every two years until 2006. The other cohorts start from older initial ages and are also followed for ten years. The graph reports the Medicaid reciprocity rate for each cohort and PI grouping for six data points over time.

Unsurprisingly, Medicaid usage is inversely related to permanent income: the top line shows the fraction of Medicaid recipients in the bottom 20% of the permanent income distribution, while the bottom line shows median assets in the top 40%. For example, the top left line shows that for the bottom PI quintile of the cohort aged 74 in 1996, about 70% of the sample receives Medicaid in 1996; this fraction stays rather stable over time. This suggests that the poorest people are qualifying for Medicaid under the categorically needy provision, where eligibility depends on income and assets, but not the amount of the medical expenses.

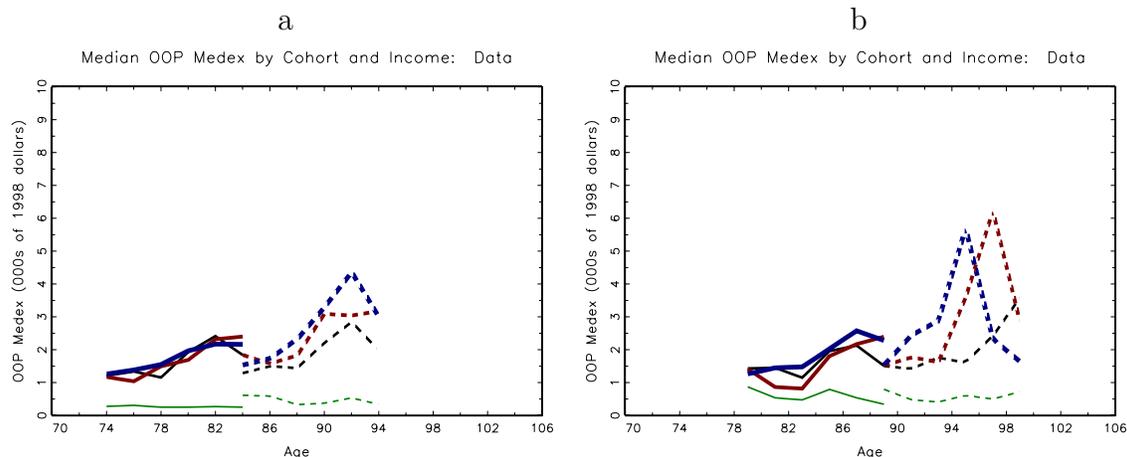
The Medicaid reciprocity rate tends to rise with age most quickly for people in the middle and highest PI groups. For example, Medicaid reciprocity in the oldest cohort and top two permanent income quintiles rises from about 4% at age 89 to over 20% at age 96. Even people with relatively large resources can be hit by medical shocks severe enough to exhaust their assets and qualify them for Medicaid under the medically needy provision.

### 3.4 Medical expense profiles

In all waves, AHEAD respondents are asked about what medical expenses they paid out of pocket. Out-of-pocket medical expenses are the sum of what the individual spends out of pocket on insurance premia, drug costs, and costs for hospital, nursing home care, doctor visits, dental visits, and outpatient care. It includes medical expenses during the last year of life. It does not include expenses covered by insurance, either public or private.

French and Jones [18] show that the medical expense data in the AHEAD line up with the aggregate statistics. For our sample, mean medical expenses are \$3,712 with a standard deviation of \$13,429 in 1998 dollars. Although this figure is large, it is not surprising, because Medicare did not cover prescription drugs for most of the sample period, requires co-pays for services, and caps the number of reimbursed nursing home and hospital nights.

Figures 2 and 3 display the median and 90th percentile of the out-of-pocket medical expense distribution, respectively. The bottom two quintiles of permanent income are merged as there is very little variation in out-of-pocket medical expenses in the lowest quintile until very late in life: at younger ages, most of the expenses in the



**Figure 2:** Median out-of-pocket medical expenditures by age, cohort, and permanent income.

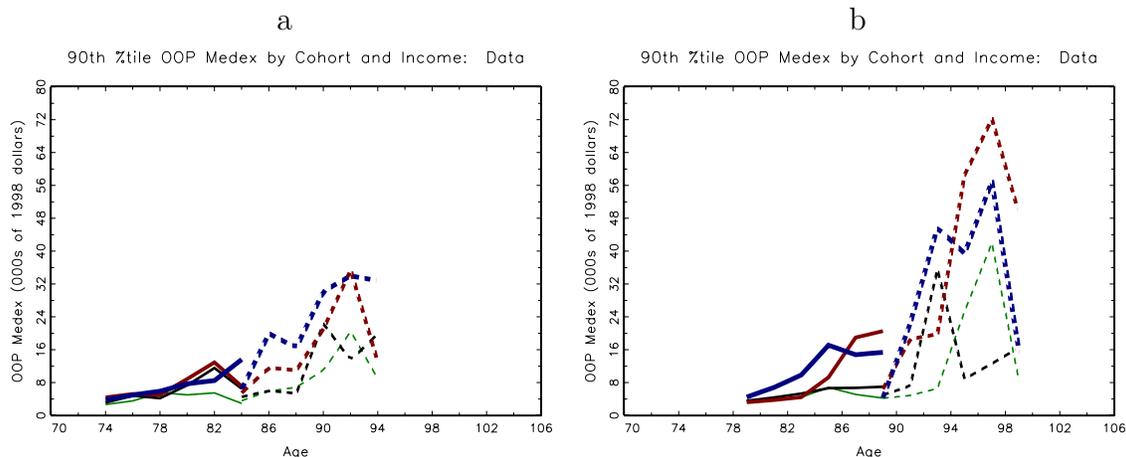
bottom quintile are bottom-coded at \$250. The graphs highlight the large increase in out-of-pocket medical expenses as people reach very advanced ages and show that this increase is especially pronounced for people in the highest PI quintiles.

### 3.5 Net worth profiles

Our measure of net worth (or assets) is the sum of all assets less mortgages and other debts. The AHEAD has information on the value of housing and real estate, autos, liquid assets (which include money market accounts, savings accounts, T-bills, etc.), IRAs, Keoghs, stocks, the value of a farm or business, mutual funds, bonds, and “other” assets.

Figure 4 reports median assets by cohort, age, and PI quintile. However, the fifth, bottom line is hard to distinguish from the horizontal axis because households in this PI quintile hold few assets. Unsurprisingly, assets turn out to be monotonically increasing in income, so that the bottom line shows median assets in the lowest PI quintile, while the top line shows median assets in the top quintile. For example, the top left line shows that for the top PI quintile of the cohort age 74 in 1996, median assets started at \$170,000 and then stayed rather stable over time: \$150,000 at age 76, \$160,000 at age 78, \$180,000 at ages 80 and 82, and \$190,000 at age 84.

For all PI quintiles in these cohorts, the assets of surviving individuals neither rise rapidly nor decline rapidly with age. If anything, those with high income tend to have their assets increase as they age, whereas those with low income tend to have their assets decrease. The slow rate at which the elderly deplete their wealth has been a long-standing puzzle (see for example, Mirer [31]). However, as De Nardi, French, and Jones [11] show, the risk of medical spending rising with age and income goes a long way toward explaining this puzzle.



**Figure 3:** 90th percentile out-of-pocket medical expenditures by age, cohort, and permanent income.

## 4 The model

We focus on single people, male or female, who have already retired. This allows us to abstract from labor supply decisions and from complications arising from changes in family size.

### 4.1 Preferences

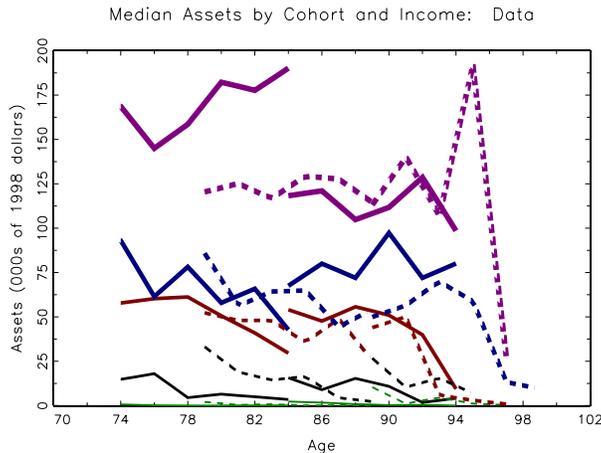
Individuals in this model receive utility from the consumption of both non-medical and medical goods. Each period, their flow utility is given by

$$u(c_t, m_t, \mu(\cdot)) = \frac{1}{1-\nu} c_t^{1-\nu} + \mu(h_t, \zeta_t, \xi_t, t) \frac{1}{1-\omega} m_t^{1-\omega}, \quad (1)$$

where  $t$  is age,  $c_t$  is consumption of non-medical goods,  $m_t$  is total consumption of medical goods, and  $\mu(\cdot)$  is the medical needs shifter, which affects the marginal utility of consuming medical goods and services. The consumption of both goods is expressed in dollar values. The intertemporal elasticities for the two goods,  $1/\nu$  and  $1/\omega$ , can differ.

We assume that  $\mu(\cdot)$  shifts with medical needs, such as dementia, arthritis, or a broken bone. These shocks affect the utility of consuming medical goods and services, including nursing home care. Formally, we model  $\mu(\cdot)$  as a function of age, the discrete-valued health status indicator  $h_t$ , and the medical needs shocks  $\zeta_t$  and  $\xi_t$ . Individuals optimally choose how much to spend in response to these shocks.

A complementary approach is that of Grossman [19], in which medical expenses represent investments in health capital, which in turn decreases mortality (e.g., Yogo [43]) or improves health. While a few studies find that medical expenditures have significant effects on health and/or survival (Card et al. [8]; Doyle [10], Finkelstein et



**Figure 4:** Median assets by age, cohort, and permanent income. Thicker lines refer to higher PI groups.

al. [15]), most others find small effects (Brook et al. [3]; Fisher et al. [16]; Finkelstein and McKnight [14]; Khwaja [24]); see De Nardi et al. [11] for a discussion. These findings suggest that the effects of medical expenditures on the health outcomes are, at a minimum, extremely difficult to identify. Identification problems include reverse causality (sick people have higher health expenditures) and lack of insurance variation (most elderly individuals receive Medicare or Medicaid). Given that older people have already shaped their health and lifestyle, we view our assumption that their health and mortality depend on their lifetime earnings, but is exogenous to their current decisions, to be a reasonable simplification.

## 4.2 Insurance Mechanisms

We model two important types of health insurance. The first one pays a proportional share of total medical expenses and can be thought of as a combination of Medicare and private insurance. Let  $q(h_t)$  denote the individual’s co-insurance (co-pay) rate, i.e., the share of medical expenses not paid by Medicare or private insurance. We allow the co-pay rate to depend on whether a person is in a nursing home ( $h_t = 1$ ) or not. Because nursing home stays are virtually uninsured by Medicare and private insurance, people residing in nursing homes face much higher co-pay rates. However, co-pay rates do not vary much across other medical conditions.

The second type of health insurance that we model is Medicaid, which is means-tested. To link Medicaid transfers to medical needs,  $\mu(h_t, \zeta_t, \xi_t, t)$ , we assume that each period Medicaid guarantees a minimum level of flow utility  $u_i$ , which differs between categorically needy ( $i = c$ ) and medically needy ( $i = m$ ) recipients. More precisely, once the Medicaid transfer is made, an individual with the state vector

$(h_t, \zeta_t, \xi_t, t)$  can afford a consumption-medical goods pair  $(c_t, m_t)$  such that

$$\underline{u}_i = \frac{1}{1-\nu} c_t^{1-\nu} + \mu(h_t, \zeta_t, \xi_t, t) \frac{1}{1-\omega} m_t^{1-\omega}. \quad (2)$$

To implement our utility floor, for every value of the state vector, we find the expenditure level  $\underline{x}_i = c_t + m_t q(h_t)$  needed to achieve the utility level  $\underline{u}_i$  (equation (2)), assuming that individuals make intratemporally optimal decisions. This yields the minimum expenditure  $\underline{x}_c(\cdot)$  or  $\underline{x}_m(\cdot)$ , which correspond to the categorically and medically needy utility floors. The actual amount that Medicaid transfers,  $b_c(a_t, y_t, h_t, \zeta_t, \xi_t, t)$  or  $b_m(a_t, y_t, h_t, \zeta_t, \xi_t, t)$ , is then given by  $\underline{x}_c(\cdot)$  or  $\underline{x}_m(\cdot)$  less the individual's total financial resources (assets,  $a_t$ , and non-asset income,  $y_t$ ).

### 4.3 Uncertainty and Non-Asset Income

The individual faces several sources of risk, which we treat as exogenous: health status risk, survival risk, and medical needs risk. At the beginning of each period, the individual's health status, and medical needs shocks are realized and need-based transfers are given. The individual then chooses consumption, medical expenditure, and saves. Finally, the survival shock hits.

We parameterize the preference shifter for medical goods and services (the needs shock) as

$$\log(\mu(\cdot)) = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \alpha_3 t^3 + \alpha_4 h_t + \alpha_5 h_t \times t \quad (3)$$

$$+ \sigma(h, t) \times \psi_t, \quad (4)$$

$$\sigma(h, t)^2 = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_4 h_t + \beta_5 h_t \times t \quad (5)$$

$$\psi_t = \zeta_t + \xi_t, \quad \xi_t \sim N(0, \sigma_\xi^2), \quad (6)$$

$$\zeta_t = \rho_m \zeta_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma_\epsilon^2), \quad (7)$$

$$\sigma_\xi^2 + \frac{\sigma_\epsilon^2}{1 - \rho_m^2} \equiv 1, \quad (8)$$

where  $\xi_t$  and  $\epsilon_t$  are serially and mutually independent. We thus allow the need for medical services to have temporary ( $\xi_t$ ) and persistent ( $\zeta_t$ ) shocks. It is worth stressing that we not allow any component of  $\mu(\cdot)$  to depend on permanent income; income affects medical expenditures solely through the budget constraint.

Health status can take on three values: good (3), bad (2), and in a nursing home (1). We allow the transition probabilities for health to depend on previous health, sex ( $g$ ), permanent income ( $I$ ), and age. The elements of the health status transition matrix are

$$\pi_{j,k,g,I,t} = \Pr(h_{t+1} = k | h_t = j, g, I, t), \quad j, k \in \{1, 2, 3\}. \quad (9)$$

Mortality also depends on health, sex, permanent income and age. Let  $s_{g,h,I,t}$  denote the probability that an individual of sex  $g$  is alive at age  $t+1$ , conditional on being alive at age  $t$ , having time- $t$  health status  $h$ , and enjoying permanent income  $I$ .

Non-asset income  $y_t$ , is a deterministic function of sex, permanent income, and age:

$$y_t = y(g, I, t). \quad (10)$$

#### 4.4 The Individual's Problem

Consider a single person seeking to maximize his or her expected lifetime utility at age  $t$ ,  $t = t_{r+1}, \dots, T$ , where  $t_r$  is the retirement age.

To be categorically needy, this person's income and assets need to be below  $\underline{Y}$  and  $A_d$ , respectively. Besides being the maximum amount of income (excluding disregards) that one can have and still qualify for SSI/Medicaid,  $\underline{Y}$  is also the maximum SSI benefit that one can receive.

Note that Medicaid and SSI apply to income *gross* of taxes. Let  $a_t$  denote assets and  $r$  the real interest rate. The SSI benefit equals  $\underline{Y} - \max\{y_t + ra_t - y_d, 0\}$ , where  $y_d$  is the income disregard.

If a person is categorically needy and applies for SSI and Medicaid, he receives the SSI transfer and Medicaid goods and services as dictated by his medical needs shock and utility floor. The combined SSI/Medicaid transfer for the categorically needy is thus given by:

$$b_c(a_t, y_t, \mu(\cdot)) = \underline{Y} - \max\{y_t + ra_t - y_d, 0\} + \max\{0, \underline{x}_c - \max\{a_t + \underline{Y} - A_d, 0\}\}, \quad (11)$$

Under this formulation, agents with assets in excess of the disregard  $A_d$  can spend down their wealth and qualify for Medicaid.

If the person's total income is above  $\underline{Y}$  and or assets are above  $A_d$ , she is not eligible for SSI. If the person applies for Medicaid, transfers are given by

$$b_m(a_t, y_t, \mu(\cdot)) = \max\{0, \underline{x}_m(\cdot) - \max\{a_t + ra_t + y_t - A_d, 0\}\}, \quad (12)$$

where we assume that the asset disregard  $A_d$  is the same as under the categorically needy pathway.

Each period eligible individuals choose whether to receive Medicaid or not. We will use the indicator function  $I_M$  to denote this choice, with  $I_M = 1$  if the person applies for Medicaid and  $I_M = 0$  if the person does not apply.

When the person dies, any remaining assets are left to his or her heirs. We denote with  $e$  the estate net of taxes. Estates are linked to assets by

$$e_t = e(a_t) = a_t - \max\{0, \tau \cdot (a_t - \tilde{x})\}.$$

The parameter  $\tau$  denotes the tax rate on estates in excess of  $\tilde{x}$ , the estate exemption level. The utility the household derives from leaving the estate  $e$  is

$$\phi(e) = \theta \frac{(e + k)^{(1-\nu)}}{1 - \nu},$$

where  $\theta$  is the intensity of the bequest motive, while  $k$  determines the curvature of the bequest function and hence the extent to which bequests are luxury goods.

Using  $\beta$  to denote the discount factor, we can then write the individual's value function as:

$$V_t(a_t, g, h_t, I, \zeta_t, \xi_t) = \max_{c_t, m_t, a_{t+1}, I_M} \left\{ u(c_t, m_t, \mu(\cdot)) \right. \\ \left. + \beta s_{g,h,I,t} E_t \left( V_{t+1}(a_{t+1}, g, h_{t+1}, I, \zeta_{t+1}, \xi_{t+1}) \right) \right. \\ \left. + \beta (1 - s_{g,h,I,t}) \theta \frac{(e(a_{t+1}) + k)^{(1-\nu)}}{1-\nu} \right\}, \quad (13)$$

subject to the law of motion for the shocks and the following constraints. If  $I_M = 0$ , i.e., the person does not apply for SSI and Medicaid.

$$a_{t+1} = a_t + y_n(ra_t + y_t) - c_t - q(h_t)m_t \geq 0, \quad (14)$$

where the function  $y_n(\cdot)$  converts pre-tax to post-tax income. If  $I_M = 1$ , i.e., the person applies for SSI and Medicaid, we have

$$a_{t+1} = b_i(\cdot) + a_t + y_n(ra_t + y_t) - c_t - q(h_t)m_t \geq 0, \quad (15)$$

$$a_{t+1} \leq \min\{A_d, a_t\}, \quad (16)$$

where  $b_i(\cdot) = b_c(\cdot)$  if  $y_t + ra_t - y_d \leq \underline{Y}$  and  $b_i(\cdot) = b_m(\cdot)$  otherwise. Equations (14) and (15) both prevent the individual from borrowing against future income.

To express the dynamic programming problem as a function of  $c_t$  only, we can derive  $m_t$  as a function of  $c_t$  by using the optimality condition implied by the intratemporal allocation decision. Suppose that at time  $t$  the individual decides to spend the total  $x_t$  on consumption and out-of-pocket payments for medical goods. The optimal intratemporal allocation then solves:

$$\mathcal{L} = \frac{1}{1-\nu} c_t^{1-\nu} + \mu(\cdot) \frac{1}{1-\omega} m_t^{1-\omega} + \lambda_t (x_t - m_t q(h_t) - c_t),$$

where  $\lambda_t$  is the multiplier on the intratemporal budget constraint. The first-order conditions for this problem reduce to

$$m_t = \left( \frac{\mu(\cdot)}{q(h_t)} \right)^{1/\omega} c_t^{\nu/\omega}. \quad (17)$$

This expression can be used to eliminate  $m_t$  from the dynamic programming problem in equation (13).

## 5 Estimation procedure

We adopt a two-step strategy to estimate the model. In the first step, we estimate or calibrate those parameters that can be cleanly identified outside our model. For example, we estimate mortality rates from raw demographic data. In the second step, we estimate the rest of the model’s parameters ( $\nu, \omega, \beta, \underline{u}_c, \underline{u}_m$ , and the parameters of  $\ln \mu(\cdot)$ ) with the method of simulated moments (MSM), taking as given the parameters that were estimated in the first step. In particular, we find the parameter values that allow simulated life-cycle decision profiles to “best match” (as measured by a GMM criterion function) the profiles from the data. The moment conditions that comprise our estimator are:

1. To better evaluate the effects of Medicaid insurance, we match the fraction of people on Medicaid by PI quintile, cohort and age (with the top two permanent income quintiles merged together).
2. Because the effects of Medicaid depend directly on an individual’s asset holdings, we match median asset holdings by birth-year cohort, permanent income, and calendar year. We sort individuals into PI quintiles, and the 5 birth-year cohorts described in section 3. We then compare data and model-generated cell medians in 5 different years (1998, 2000, 2002, 2004, and 2006).<sup>5</sup>
3. We match the median and 90th percentile of the out-of-pocket medical expense distribution in each year-cohort-PI cell (the bottom two quintiles are merged). Because the AHEAD’s medical expense data are reported net of any Medicaid payments, we deduct government transfers from the model-generated expenses before making any comparisons.
4. To capture the dynamics of medical expenses, we match the first and second autocorrelations for medical expenses in each year-cohort-PI cell.

The mechanics of our MSM approach are as follows. We compute life-cycle histories for a large number of artificial individuals. Each of these individuals is endowed with a value of the state vector  $(t, a_t, g, h_t, I)$  drawn from the data distribution for 1996, and each is assigned the entire health and mortality history realized by the person in the AHEAD data with the same initial conditions. The simulated medical needs shocks  $\zeta$  and  $\xi$  are Monte Carlo draws from discretized versions of our estimated shock processes.

We discretize the asset grid and, using value function iteration, we solve the model numerically. This yields a set of decision rules, which, in combination with the simulated endowments and shocks, allows us to simulate each individual’s net worth, medical expenditures, health, and mortality. We then compute asset, medical expense

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<sup>5</sup>Simulated agents are endowed with asset levels drawn from the 1996 data distribution. Cells with less than 10 observations are excluded from the moment conditions.

and Medicaid profiles from the artificial histories in the same way as we compute them from the real data. We use these profiles to construct moment conditions, and evaluate the match using our GMM criterion. We search over the parameter space for the values that minimize the criterion. Appendix A contains a detailed description of our moment conditions, the weighting matrix in our GMM criterion function, and the asymptotic distribution of our parameter estimates.

## 6 First-step estimation results

In this section, we briefly discuss the life-cycle profiles of the stochastic variables used in our dynamic programming model. The process for income is estimated using the procedure in De Nardi et al. [11], and is described in more detail there. The procedure for estimating demographic transition probabilities and and co-pay rates are new.

### 6.1 Income profiles

We model non-asset income as a function of age, sex, health status, and the individual’s PI ranking. Figure 5 presents average income profiles, conditional on permanent income quintile, computed by simulating our model. In this simulation we do not let people die, and we simulate each person’s financial and medical history up through the oldest surviving age allowed in the model. Since we rule out attrition, this picture shows how income evolves over time for the same sample of elderly people. Figure 5 shows that average annual income ranges from about \$4,000 per year in the bottom PI quintile to about \$20,000 in the top quintile; median wealth holdings for the two groups are zero and just under \$200,000, respectively.

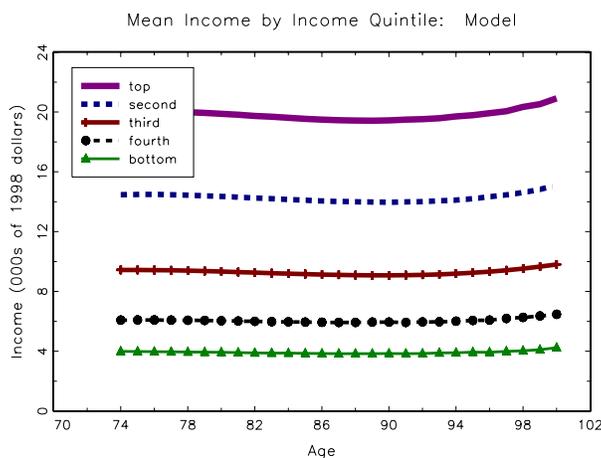


Figure 5: Average income, by permanent income quintile.

## 6.2 Mortality and health status

We estimate health transitions and mortality rates simultaneously by fitting the transitions observed in the HRS to a multinomial logit model. We allow the transition probabilities to depend on age, sex, current health status, and permanent income. We estimate annual transition rates: combining annual transition probabilities in consecutive years yields two-year transition rates we can fit to the AHEAD data. Appendix B gives details on the procedure.

Using the estimated transition probabilities, we simulate demographic histories, beginning at age 70, for different gender-PI-health combinations. Table 1 shows life expectancies. We find that rich people, women, and healthy people live much longer than their poor, male, and sick counterparts. For example, a male at the 10th permanent income percentile in a nursing home expects to live only 3.5 more years, while a female at the 90th percentile in good health expects to live 16.1 more years.

Income Percentile	Nursing Home	Males		Females			All <sup>†</sup>
		Bad Health	Good Health	Nursing Home	Bad Health	Good Health	
10	3.53	5.86	7.22	6.02	9.99	11.97	10.38
30	3.61	6.40	8.14	6.41	10.92	13.04	11.36
50	3.77	7.05	9.11	6.85	11.94	14.18	12.36
70	3.98	7.81	10.10	7.38	12.96	15.20	13.40
90	4.26	8.61	11.01	8.05	13.97	16.14	14.31
By gender: <sup>‡</sup>							
Men							9.41
Women							13.54
By health status: <sup>◊</sup>							
Bad Health							10.56
Good Health							13.93

Notes: Life expectancies calculated through simulations using estimated health transition and survivor functions. <sup>†</sup> Using gender and health distributions for entire population; <sup>‡</sup> Using health and permanent income distributions for each gender; <sup>◊</sup> Using gender and permanent income distributions for each health status group.

**Table 1:** Life expectancy in years, conditional on reaching age 70.

Another important saving determinant is the risk of requiring nursing home care. Table 2 shows the probability at age 70 of ever entering a nursing home. The calcu-

lations show that 30.1% of women will ultimately enter a nursing home, as opposed to 17.9% for men. These numbers are lower than those from the Robinson model described in Brown and Finkelstein [4], which show 27% of 65-year-old men and 44% of 65-year-old women require nursing home care. One reason we find lower numbers is that the Robinson model is based on older data, and nursing home utilization has declined in recent years (Alexih [1]).

Income Percentile	<u>Males</u>		<u>Females</u>		All <sup>†</sup>
	Bad Health	Good Health	Bad Health	Good Health	
10	15.9	17.6	26.6	28.8	26.0
30	15.8	17.8	27.3	29.6	26.4
50	15.7	18.1	27.8	30.6	27.1
70	16.1	19.0	29.0	32.0	27.9
90	16.4	18.8	30.2	33.2	29.4
By gender: <sup>‡</sup>					
	Men				17.9
	Women				30.1
By health status: <sup>◊</sup>					
	Bad Health				25.4
	Good Health				29.0

Notes: Entry probabilities calculated through simulations using estimated health transition and survivor functions; <sup>†</sup> Using gender and health distributions for entire population; <sup>‡</sup> Using health and permanent income distributions for each gender; <sup>◊</sup> Using gender and permanent income distributions for each health status group.

**Table 2:** Probability of ever entering a nursing home, people alive at age 70.

### 6.3 Co-pay rates

The co-pay rate  $q_t = q(h_t)$  is the share of total billable medical spending not paid by Medicare or private insurers. Thus, it is the share paid out-of-pocket or by Medicaid. We allow it to differ depending on whether the person is in a nursing home or not:  $q_t = q(h_t)$ .

There are two problems with inferring co-pay rates using out-of-pocket medical expenses and total billable medical expenses from the AHEAD data. First, total

medical expense information are largely imputed in this data set. Second, since we explicitly model Medicaid, we have to make sure that Medicaid payments are included in our measure of total medical expenses. Unfortunately, the AHEAD data provide no information on Medicaid payments.

For these reasons, to estimate co-pay rates for people not in a nursing home, we use data from the 2005 panel of the Medical Expense Panel Survey (MEPS), which is a representative sample of the non-institutionalized population. MEPS provides high quality information on total billable medical expenses as well as the payor of those expenses, including Medicaid. It does so by collecting medical expenses data from health care providers as well as from individuals.

The co-pay rate for people not in a nursing home averages 29% in MEPS and does not vary much with demographics. We compute these numbers by applying the same data filters to MEPS that we used for the AHEAD data. Next, we estimate  $q(h_t)$  by taking the ratio of mean out-of-pocket spending plus Medicaid payments to mean total medical expenses.

To estimate the co-pay rate for those in nursing homes we use data from the 2006 Medicare Current Beneficiary Survey (MCBS), which is a representative sample of Medicare enrollees aged 65+. These data reveal that the co-pay rate for those in nursing homes is 92%. For every dollar spent on nursing homes, 47 cents come from Medicaid and 45 cents are from out of pocket, with only 8 cents coming from Medicare or other sources. In our model, we round this number to 90%.

## 7 Second step results and model fit

### 7.1 Parameter values

Our parameter estimates are still preliminary, and we are exploring different specifications. Table 3 shows results for a specification that provides a good fit to the data.

Our estimate of  $\beta$ , the discount factor is 1.16. This number has to be multiplied by the survival probability to obtain the effective discount factor. As Table 1 shows, the survival probability for our sample of older individuals is low, implying an effective discount factor much lower than  $\beta$ .

The estimate of  $\nu$ , the coefficient of relative risk aversion for “regular” consumption, is 3.0, while the estimate of  $\omega$ , the coefficient of relative risk aversion for medical goods, is 3.35; the demand for medical goods is less elastic than the demand for consumption.

The utility floors correspond to the utility levels a person gets when the medical needs shifter  $\mu$  equals 0 (no medical needs) and the person consumes \$2,400 for the categorically needy and \$5,600 for the medically needy. It should be noted that the medically needy are also guaranteed a minimum income level of \$6,000, so that their total consumption when healthy is \$6,000 a year. However, when there are large

$\nu$ : RRA, consumption	2.99 (0.033)
$\omega$ : RRA, medical expenditures	3.35 (0.041)
$\beta$ : discount factor	1.156 (0.013)
$\underline{u}_c$ : utility floor, <sup>†</sup> categorically needy	2,433 (130)
$\underline{u}_c$ : utility floor, <sup>†</sup> medically needy	5,577 (140)
$\theta$ : bequest intensity	NA (NA)
$k$ : bequest curvature (in 000s)	NA (NA)

<sup>†</sup> The estimated utility floor is indexed by the consumption level that provides the floor when  $\mu = 0$ .

**Table 3:** Estimated preference parameters. Standard errors are in parentheses below estimated parameters. NA refers to parameters fixed for a given estimation .

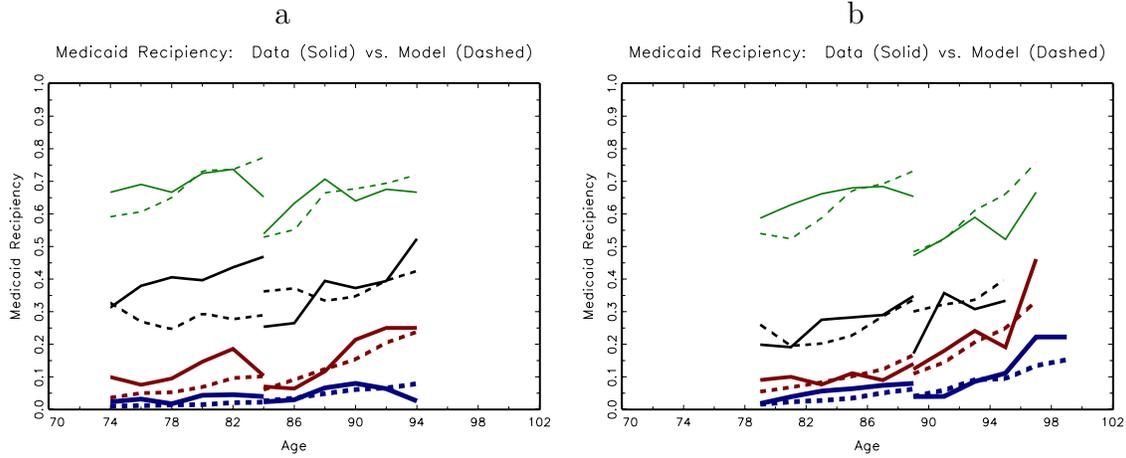
medical needs, transfers are determined by the utility floor, and the medically needy are more insured than the categorically needy.

We also estimate the coefficients for the mean of the logged medical needs shifter  $\mu(h_t, \psi_t, t)$ , the volatility scaler  $\sigma(h_t, t)$  and the process for the shocks  $\zeta_t$  and  $\xi_t$ . As we show in the graphs that follow, the estimates for these parameters (available from the authors on request) imply that the demand for medical services rises rapidly with age.

We now turn to discussing how well the model fits the some key aspects of the data and also look at some additional model implications.

## 7.2 Medicaid reciprocity

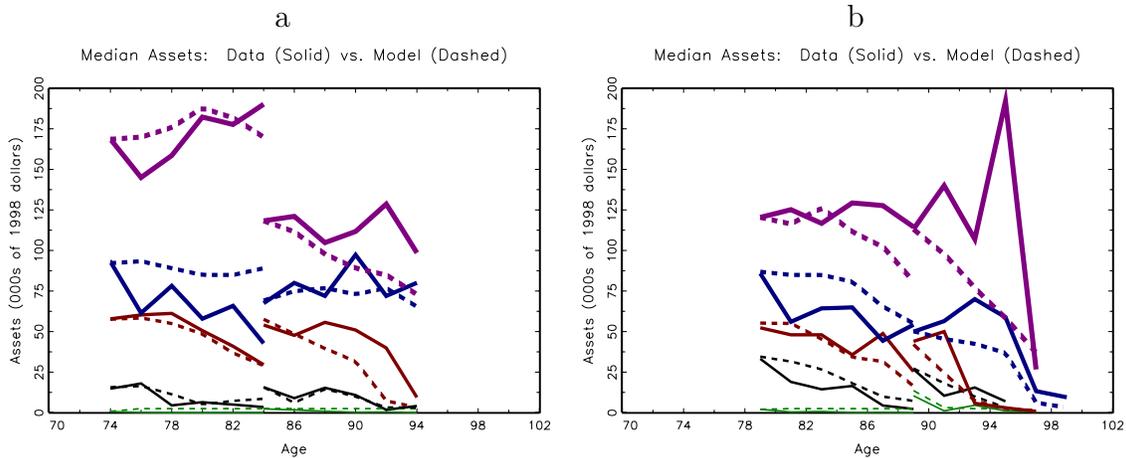
Figure 6 compares the Medicaid reciprocity profiles generated by the model (dashed line) to those in the data (solid line) for the members of two birth-year cohorts. In panel a, the lines at the far left of the graph are for the youngest cohort, whose members in 1996 were aged 72-76, with an average age of 74. The second set of lines are for the cohort aged 82-86 in 1996. Panel b displays the two other cohorts, starting



**Figure 6:** Medicaid reciprocity by cohort and PI quintile: data (solid lines) and model (dashed lines).

respectively at age 79 and 89. The graphs show that the model matches well both the usage levels and their rise by age and permanent income.

### 7.3 Net worth profiles



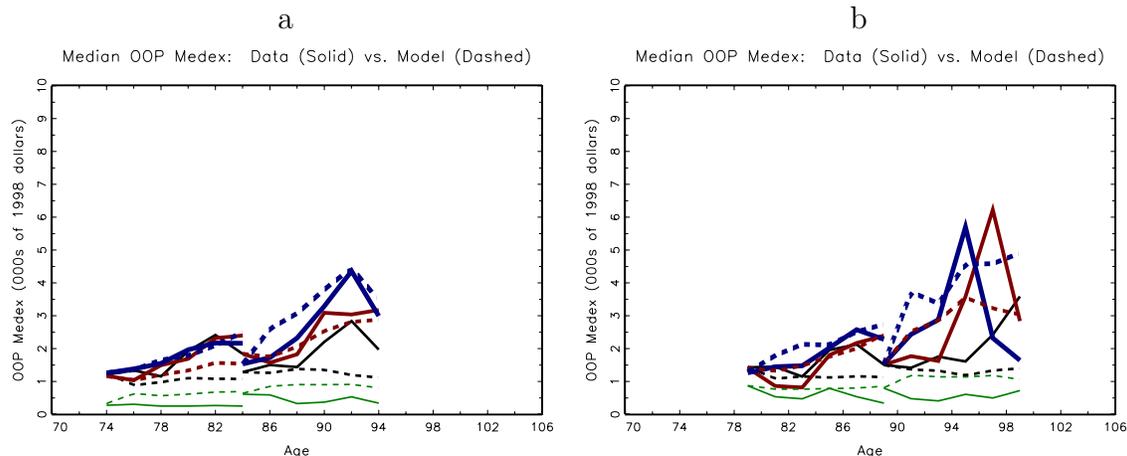
**Figure 7:** Median net worth by cohort and PI quintile: data (solid lines) and model (dashed lines).

Figure 7 plots median net worth by age, cohort, and permanent income. Here too the model does well, matching the observation that the savings patterns differ by permanent income and that higher PI people don't run down their assets until well past age 90.

## 7.4 Medical expenses

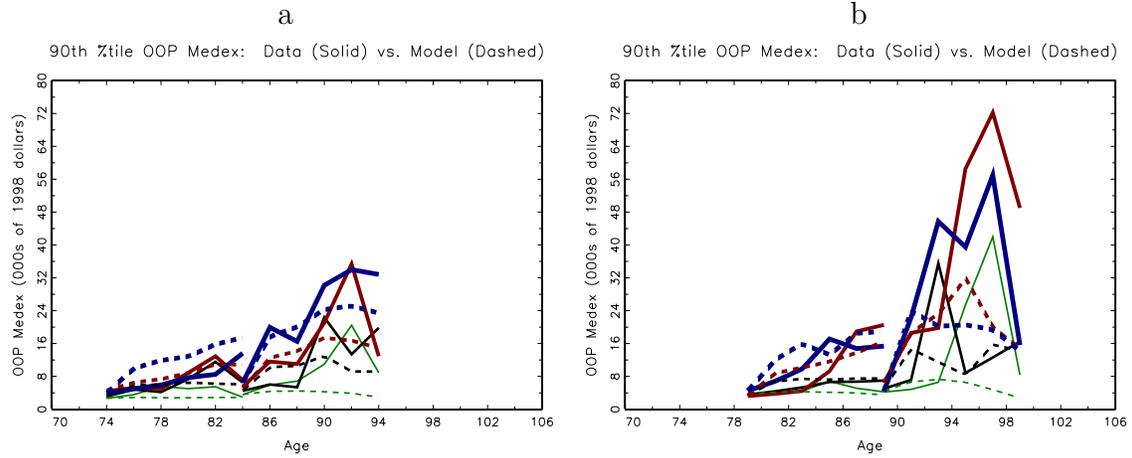
Figure 8 displays median out-of-pocket medical expenses (that is, net of Medicaid payments and private and public insurance co-pays) paid by people in the model and in the data. Permanent income has a large effect on out-of-pocket medical expenses, especially at older ages. Median medical expenses are less than \$2,000 a year at age 75. By age 100, they stay flat for those in the bottom quintile of the income distribution but rise to over \$6,000 for those at the top of the income distribution. The model does a reasonable job of matching the key patterns in the data.

Figure 9 compares the 90th percentile of out-of-pocket medical expenses generated by the model to those found in the data and thus provides a better idea of the tail risk by age and permanent income. Here the model reproduces medical expenses of \$5,000 or less at age 74, staying flat over time for the lower PI people, but understates the medical of the high PI people in their late nineties.

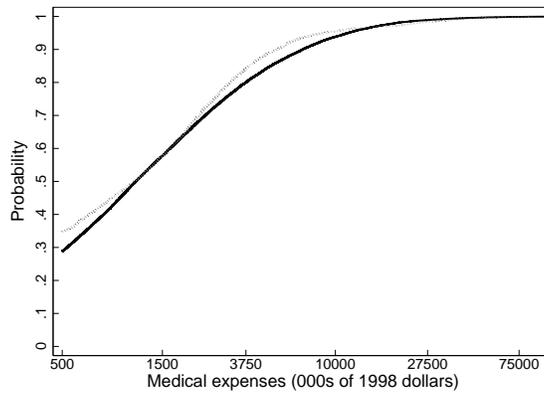


**Figure 8:** Median out-of-pocket medical expenses by cohort and PI quintile: data (solid lines) and model (dashed lines).

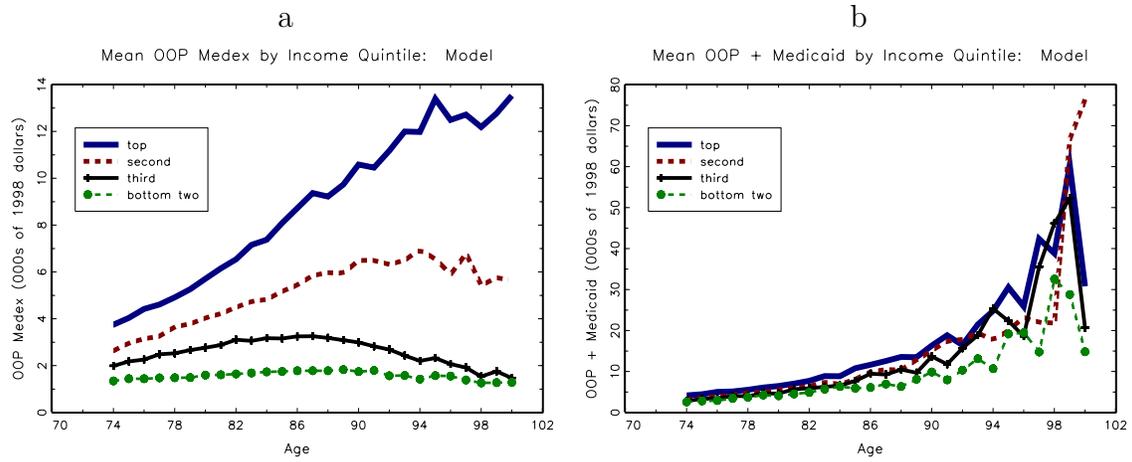
Turning to cross-sectional distributions, Figure 10 compares the cumulative distribution function (CDF) of out-of-pocket medical expenditures found in the AHEAD data with that produced by the model. The model CDF fits the data well.



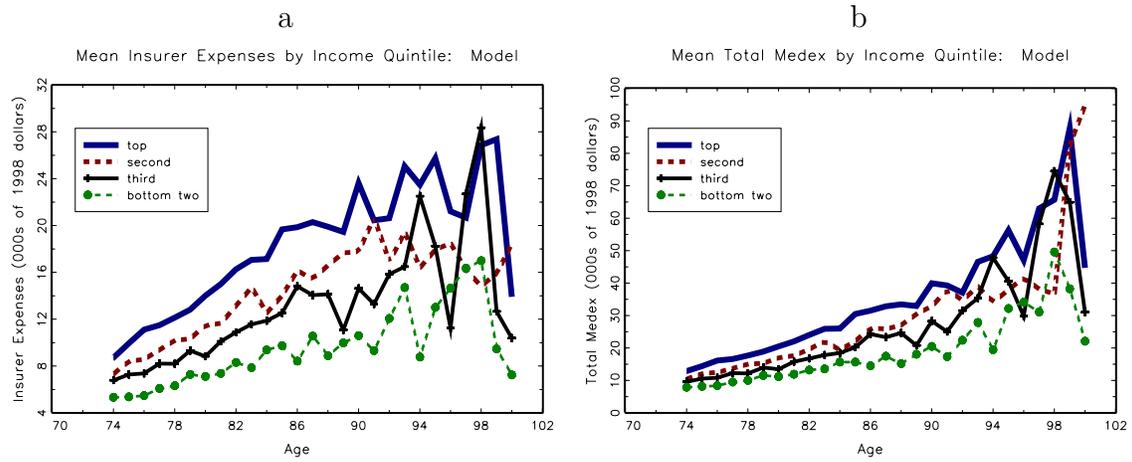
**Figure 9:** Ninetieth percentile of out-of-pocket medical expenses by cohort and PI quintile: data (solid lines) and model (dashed lines).



**Figure 10:** Cumulative distribution function of out-of-pocket medical expenses: data (solid line) and model (lighter line).



**Figure 11:** Average medical expenses by age and permanent income. Panel a: paid out-of-pocket. Panel b: paid out-of-pocket or by Medicaid.



**Figure 12:** Average medical expenses by age and permanent income. Panel a: paid by insurers. Panel b: total.

Figure 11 presents profiles that arise when the youngest cohort is simulated from ages 74 to (potentially) 100. Panel a shows average out-of-pocket medical expenses, which follow a pattern similar to that in Figures 8 and 9. Panel b of Figure 11 shows the sum of medical expenses paid out-of-pocket and the expenses paid by Medicaid, the latter measured as the increase in  $q(h_t)m_t$  generated by government transfers. These sums also increase rapidly with age, going from around \$3,500 at age 74 to \$50,000 at age 99. Medicaid allows poorer people to consume proportionally much more medical goods and services than they pay for. As a result, the expense sum shown in panel b rises more slowly with income than the out-of-pocket expenditures shown in panel a.

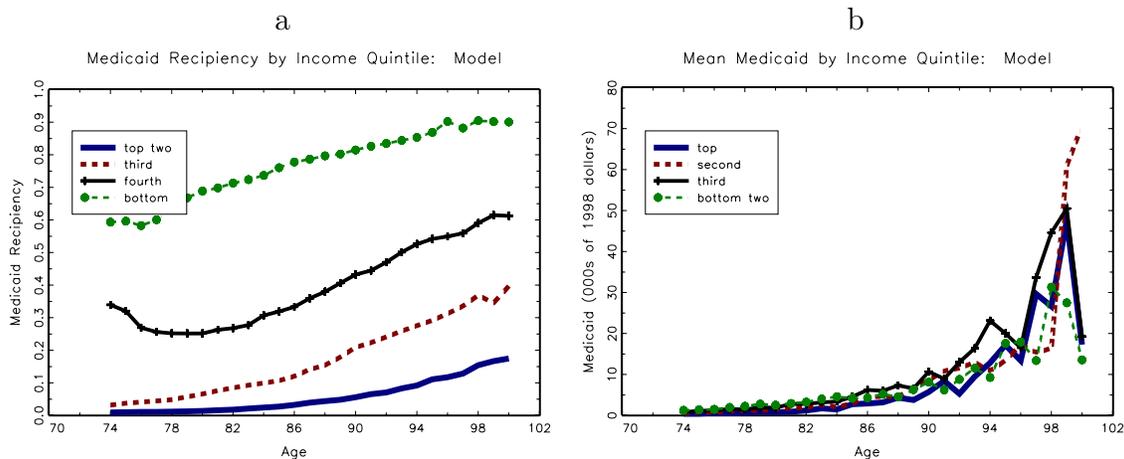
Panel a of Figure 12 displays average medical expenses covered by private and public insurers. These payments are very large and also increase by age and permanent income, reaching over \$20,000 for the oldest members of the top permanent income quintile. The oldest in the poorest permanent income quintile, however, also benefit from these payments, which reach around \$12,000 at age 98. Panel b of Figure 12 displays total medical expenses, which in this case also coincide with total consumption of medical goods and services. Comparing the two panels makes it clear that most elderly individuals consume far more medical care than they pay out-of-pocket. The increase in total medical expenses after retirement is very large, going from around \$10,000 at age 74 to \$60,000 at age 100.

## 7.5 Utility floor, preference shocks, and implied insurance system

Through the interaction of the utility floor and medical needs shocks, the model has interesting implications on the insurance provided by means-tested programs.

Figure 13 describes the transfers generated by the model. Panel a of this figure shows the fraction of individuals receiving transfers, while panel b shows average transfers, taken across both recipients and non-recipients. Panel a shows that people in the bottom two permanent income quintiles receive Medicaid at fairly high rates throughout their retirement. Most of these people qualify through the categorically needy pathway. People in the top income quintiles, in contrast, use Medicaid much more heavily at older ages, when large medical expenditures make them eligible through the medically needy pathway.

Panel b of Figure 13 shows average Medicaid transfers. While low-income people are much more likely to qualify for Medicaid, the categorically needy provision allows them to qualify with small medical needs. The medically needy provision allows high-income people to qualify only when their medical expenses are high as well. Although the poor on average receive more Medicaid benefits than the rich at younger ages, at very old ages the two groups receive similar benefits.



**Figure 13:** Medicaid. Panel a: fraction receiving Medicaid. Panel b: average Medicaid transfers.

## 8 The Distribution of Medicaid Insurance Benefits

In this section we perform some preliminary experiments to assess the amount of redistribution that Medicaid produces.

### 8.1 The distribution of Medicaid payments

We estimate the Medicaid payments received by elderly individuals by simulating our estimated model. Each simulated individual receives a value of the state vector  $(t, a_t, g, h_t, I)$  drawn from the data distribution of 72- to 76-year-olds in 1996. He or she then receives a series of health, medical expense, and mortality shocks consistent with the stochastic processes described in the model section, and is tracked to age 100. We calculate the present discounted value of Medicaid payments for each simulated individual.

The left-hand column of Table 4 reports the average present discounted value of payments conditional on income quintile, gender and health status at age 74. Surprisingly, those in the third income quintile receive the largest lifetime transfers (\$31,200). Although the poor are more likely to be receiving Medicaid, the poor tend to die before they develop the most costly health conditions. On the other hand, the most rich, while having the most medical expenses, have the most resources to pay for medical care themselves. The interaction of these two mechanisms leaves those in the middle of the income distribution, who have more expensive medical conditions, but still modest financial resources, as the ones receiving the most benefits.

Women benefit more than men from Medicaid, both because they live longer and because they tend to be poorer. Finally, those in good health at age 74 receive almost as many benefits as those in bad health at 74, because they tend to live long enough to require costly procedures and long nursing home stays.

Income Quintile	Present Discounted Value	Annuity Value
Bottom	22,800	2,890
Fourth	26,200	3,030
Third	31,200	3,300
Second	26,500	2,640
Top	19,600	1,950
Men	12,800	1,790
Women	27,500	2,790
In Good Health	24,700	2,410
In Bad Health	25,400	3,090

**Table 4:** Medicaid payments at age 74.

The right-hand column of Table 4 reports the annuity value of the same Medicaid payments. We calculate the annuity value as the average present discounted sum divided by the average lifespan (adjusted for discounting). The annuity value calculations show that an important part of the reason for why rich people benefit from Medicaid is the mechanical relationship between income and lifespan. Rich people have more years to collect benefits. Another part of the explanation, however, is that the older ages at which rich people are more likely to be alive are the ages when the most expensive medical conditions hit; all else equal, average transfers are an increasing function of one's lifespan.

The AHEAD data does not have direct measures of Medicaid payments. We must infer these payments indirectly using the model. In order to verify that these model predictions are accurate, we are in the process of acquiring MCBS data. Preliminary analysis from the MCBS suggests that we might be overstating Medicaid payments to the richest, but that these payments are considerable for this group. For example, average payments to those in the bottom two quintiles of the income distribution are \$3,628 per year, whereas those in the top three quintiles receive on average \$1,096 per year. But these estimates are still extremely preliminary and do not correspond exactly to the type of life-long computations that we perform in the model.

Income Quintile	Present Discounted Value	Annuity Value
Bottom	85,400	10,850
Fourth	108,000	12,480
Third	148,700	15,740
Second	184,300	18,410
Top	228,000	22,620
Men	130,500	18,220
Women	168,600	17,090
In Good Health	181,600	17,720
In Bad Health	134,700	16,370

**Table 5:** Consumption of medical goods and services at age 74.

Table 5 confirms that the rich do in fact consume more medical services than the poor: people in the top PI quintile spend over twice as much per year (\$22,620) on medical goods as people at the bottom (\$10,850). While this difference in part reflects wealth effects, it also illustrates the way in which medical needs rise with age. Table 6 shows that out-of-pocket medical expenses rise even more quickly with income. Although Medicaid delivers fairly similar benefits across the income distribution in absolute terms, it pays a much larger fraction of poor people’s expenses.

Finally, Table 7 shows that non-medical consumption rises more quickly in income than medical spending. Given that the curvature parameter for medical expenditures  $\omega$  is larger than the curvature parameter for non-medical consumption  $\nu$ , this is not surprising.

Bottom	10,800	1,370
Fourth	15,100	1,740
Third	24,800	2,630
Second	41,400	4,130
Top	62,700	6,220
Men	32,200	4,500
Women	35,700	3,620
In Good Health	42,200	4,120
In Bad Health	24,200	2,940

**Table 6:** Out-of-Pocket costs for medical goods and services at age 74.

## 8.2 Compensating differentials

If Medicaid provides retirees with insurance they would not otherwise have, the value retirees place on Medicaid may greatly exceed the actuarial value of expected benefits. To explore this hypothesis, we cut the consumption value of the utility floors in half, and simulate our model again. We measure changes in payments, and we calculate compensating differentials. In particular, we find the increase in assets that would make an individual with the reduced utility floor as well off—as measured by her value function—as an otherwise identical individual with the full utility floor.

Table 8 compares lifetime Medicaid benefits under the benchmark and reduced utility floors. Reducing the floors significantly reduces Medicaid benefits, with the average lifetime benefit falling by more than \$14,000.

Figure 14 shows compensating differentials at age 74 for women who are in bad health and are facing the median realizations of both medical needs shocks. Results are shown for women at the 0th, 25th, 50th, 75th, and 100th permanent income percentiles. Figure 14 immediately shows that the value these women place on having better Medicaid coverage is several times larger than the increase in expected benefits. Moreover, with the exception of people at the very bottom of the income distribution, the value of Medicaid is increasing in both income and assets. Rich people, with more to lose, most value the insurance provided by Medicaid. This can also be seen in the simulated profiles shown in Figure 15. Reducing the utility floor leads wealthier households to accumulate considerably more assets.

The Medicaid valuation of the very poor behaves differently because they qualify for Medicaid under the categorically needy, rather than medically needy, pathway. Because the categorically needy utility floor is much lower than the medically needy

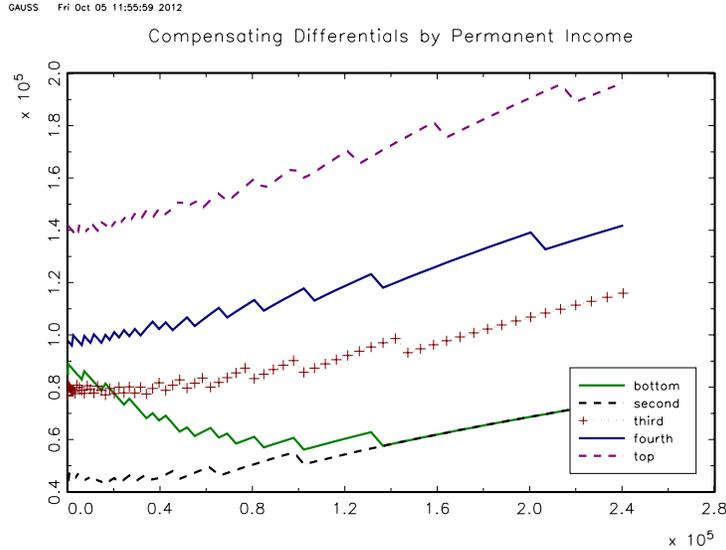
Income Quintile	Present Discounted Value	Annuity Value
Bottom	51,200	6,500
Fourth	66,600	7,690
Third	101,900	10,790
Second	154,500	15,430
Top	222,300	22,060
Men	129,000	18,010
Women	133,600	13,540
In Good Health	160,400	15,660
In Bad Health	91,400	11,110

**Table 7:** Consumption at age 74.

Income Quintile	Benchmark Floor	Reduced Floor	Difference
Bottom	22,800	11,000	11,800
Fourth	26,200	12,600	13,600
Third	31,200	12,700	18,500
Second	26,500	10,600	15,900
Top	19,600	7,600	12,000
Men	12,800	5,000	7,800
Women	27,500	11,800	15,700
In Good Health	24,700	10,300	14,400
In Bad Health	25,400	11,100	14,300

**Table 8:** Present discounted value of Medicaid payments at age 74 for different levels of the utility floor

floor, cutting the categorically needy floor in half exposes individuals to more consumption risk, increasing the value of better coverage. The categorically needy also face separate income and asset tests; the medically needy face a simple cash-on-hand threshold. As a result, as the income poor hold increasing amounts of assets, they are increasingly likely to qualify for Medicaid under the medically needy provision. This switch in coverage causes compensating differentials for the most income poor (the “bottom” group) to initially fall in assets.

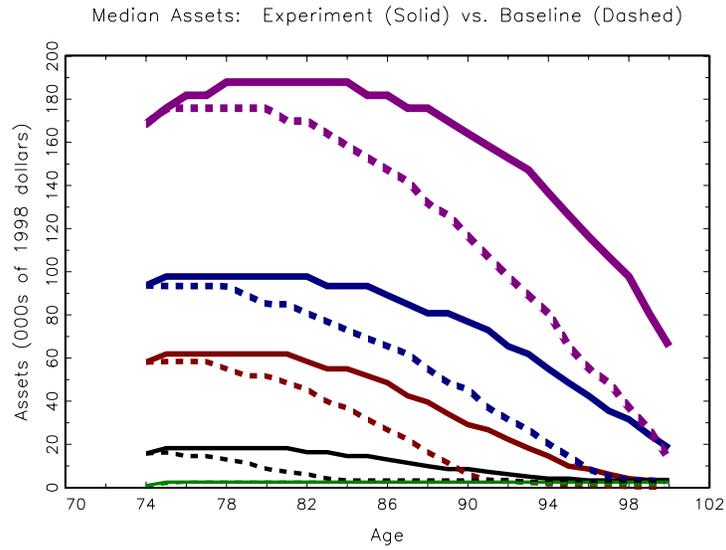


**Figure 14:** Compensating differentials by assets and permanent income quintile.

## 9 Conclusion

In this paper we assess both the distribution of Medicaid payments and the valuation placed on these payments by elderly singles. Our initial results for age 74 show that even though the poorest individuals use Medicaid most frequently, on average more payments go to middle income individuals. Although richer people qualify for Medicaid only if their medical conditions deplete their financial resources, they live longer and are more likely to face expensive medical conditions. This dynamic leaves middle income people, who lack the financial resources to thoroughly self-insure, as the ones receiving the most benefits. People at the top of the income distribution have the highest lifetime medical expenses, but qualify for Medicaid much less frequently. They nonetheless receive lifetime payments almost as large as those for people at the bottom of the income distribution, who die much more quickly.

Once one accounts for risk, Medicaid is even less redistributive. Compensating differential calculations suggest that although all individuals value Medicaid well in



**Figure 15:** Net worth by age and permanent income. Dashed line: benchmark, solid line: experiment with less generous utility floor.

excess of the payments they expect to receive, it is the rich, who have the most to lose, who value Medicaid most highly.

## References

- [1] Lisa Alecxih. Nursing home use by “oldest old” sharply declines. Mimeo, 2006.
- [2] Joseph G. Altonji and Lewis M. Segal. Small sample bias in gmm estimation of covariance structures. *Journal of Business and Economic Statistics*, 14(3):353–366, 1996.
- [3] Robert Brook, John E. Ware, William H. Rogers, Emmett B. Keeler, Allyson R. Davies, Cathy A. Donald, George A. Goldberg, Kathleen N. Lohr, Patricia C. Masthay, and Joseph P. Newhouse. Does free care improve adults’ health? results from a randomized trial. *New England Journal of Medicine*, 309(23):1426–1434, 1983.
- [4] Jeff Brown and Amy Finkelstein. The interaction of public and private insurance: Medicaid and the long term care insurance market. NBER Working Paper 10989, 2004.
- [5] Jeff Brown and Amy Finkelstein. The interaction of public and private insurance: Medicaid and the long term care insurance market. *American Economic Review*, 98(5):837–880, 2008.
- [6] Jeffrey R. Brown, Norma B. Coe, and Amy Finkelstein. Medicaid crowd-out of private long-term care insurance demand: Evidence from the health and retirement survey. In James M. Poterba, editor, *Tax Policy and the Economy*. MIT Press, 2007.
- [7] Moshe Buchinsky. Recent advances in quantile regression models: A practical guideline for empirical research. *Journal of Human Resources*, 33:88–126, 1998.
- [8] David Card, Carlos Dobkin, and Nicole Maestas. Does medicare save lives? *The Quarterly Journal of Economics*, 124(2):597–636, 2009.
- [9] Gary Chamberlain. Comment: Sequential moment restrictions in panel data. *Journal of Business & Economic Statistics*, 10(1):20–26, 1992.
- [10] Joseph Doyle. Returns to local-area healthcare spending: Using health shocks to patients far from home. *American Economic Journal: Applied Economics*, 3(3):221–243, 2011.
- [11] Mariacristina De Nardi, Eric French, and John B. Jones. Why do the elderly save? the role of medical expenses. *Journal of Political Economy*, 118(1):39–75, 2010.
- [12] Darrell Duffie and Kenneth J. Singleton. Simulated moments estimation of markov models of asset prices. *Econometrica*, 61(4):929–952, 1993.

- [13] Zhigang Feng. Macroeconomic consequences of alternative reforms to the health insurance system in the u.s. Mimeo, 2009.
- [14] Amy Finkelstein and Robin McKnight. What did medicare do? the initial impact of medicare on mortality and out of pocket medical spending. *Journal of Public Economics*, 92(7):1644–1669, 2008.
- [15] Amy Finkelstein, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Heidi Allen Joseph P. Newhouse, Katherine Baicker, and Oregon Health Study Group. The oregon health insurance experiment: Evidence from the first year. *Quarterly Journal of Economics*, 127(3):1057–1106, 2012.
- [16] Elliott S. Fisher, David E. Wennberg, Therese A. Stukel, Daniel J. Gottlieb, F.L. Lucas, and Etoile L. Pinder. The implications of regional variations in medicare spending. part 2: Health outcomes and satisfaction with care. *Annals of Internal Medicine*, 138(4):288–322, 2003.
- [17] Raquel Fonseca, Pierre-Carl Michaud, Titus Galama, and Arie Kapteyn. On the rise of health spending and longevity. Rand Working Paper WR-722, 2009.
- [18] Eric French and John Bailey Jones. On the distribution and dynamics of health care costs. *Journal of Applied Econometrics*, 19(4):705–721, 2004.
- [19] Michael Grossman. On the concept of health capital and the demand for health. *Journal of Political Economy*, 80(2):223–255, 1972.
- [20] R. Glenn Hubbard, Jonathan Skinner, and Stephen P. Zeldes. Expanding the life-cycle model: Precautionary saving and public policy. *American Economic Review*, 84:174–179, 1994.
- [21] R. Glenn Hubbard, Jonathan Skinner, and Stephen P. Zeldes. Precautionary saving and social insurance. *Journal of Political Economy*, 103(2):360–399, 1995.
- [22] Michael D. Hurd. Mortality risk and bequests. *Econometrica*, 57(4):779–813, 1989.
- [23] Michael D. Hurd, Daniel McFadden, and Angela Merrill. Predictors of mortality among the elderly. Working Paper 7440, National Bureau of Economic Research, 1999.
- [24] Ahmed Khwaja. Estimating willingness to pay for medicare using a dynamic life-cycle model of demand for health insurance. *Journal of Econometrics*, 156(1):130–147, 2010.
- [25] Ralph S. J. Koijen, Stijn Van Nieuwerburgh, and Motohiro Yogoijen. Health and mortality delta: Assessing the welfare cost of household insurance choice. Mimeo, 2012.

- [26] Ruud H. Koning. Kernel: A gauss library for kernel estimation. <http://www.xs4all.nl/>
- [27] Karen Kopecky and Tatyana Koreshkova. The impact of medical and nursing home expenses and social insurance policies on savings and inequality. Mimeo, 2009.
- [28] Laurence J. Kotlikoff. Health expenditures and precautionary savings. In Laurence J. Kotlikoff, editor, *What Determines Saving?* Cambridge, MIT Press, 1988, 1988.
- [29] Charles F. Manski. *Analog Estimation Methods in Econometrics*. Chapman and Hall, 1988.
- [30] Samuel Marshall, Kathleen M. McGarry, and Jonathan S. Skinner. The risk of out-of-pocket health care expenditure at the end of life. Working Paper 16170, National Bureau of Economic Research, 2010.
- [31] Thad Mirer. The wealth-age relation among the aged. *American Economic Review*, 69:435–443, 1979.
- [32] Whitney K. Newey. Generalized method of moments specification testing. *Journal of Econometrics*, 29(3):229–256, 1985.
- [33] Whitney K. Newey and Daniel L. McFadden. Large sample estimation and hypothesis testing. In Robert Engle and Daniel L. McFadden, editors, *Handbook of Econometrics, Volume 4*. Elsevier, Amsterdam, 1994.
- [34] The Kaiser Commission on Medicaid and the Uninsured. *Medicaid: A Primer*. Menlo Park, CA, The Henry J. Kaiser Family Foundation, 2010.
- [35] Serdar Ozkan. Income inequality and health care expenditures over the life cycle. Mimeo, Federal Reserve Board, 2011.
- [36] Ariel Pakes and David Pollard. Simulation and the asymptotics of optimization estimators. *Econometrica*, 57(5):1027–1057, 1989.
- [37] Michael G. Palumbo. Uncertain medical expenses and precautionary saving near the end of the life cycle. *Review of Economic Studies*, 66:395–421, 1999.
- [38] Jorn-Steffen Pischke. Measurement error and earnings dynamics: Some estimates from the PSID validation study. *Journal of Business & Economics Statistics*, 13(3):305–314, 1995.
- [39] James M. Poterba, Steven F. Venti, and David A. Wise. The asset cost of poor health. Working Paper 16389, National Bureau of Economic Research, 2010.

- [40] James Powell. Estimation of semiparametric models. In Robert Engle and Daniel L McFadden, editors, *Handbook of Econometrics, Volume 4*. Elsevier, Amsterdam, 1994.
- [41] Susann Rohwedder, Steven J. Haider, and Michael Hurd. Increases in wealth among the elderly in the early 1990s: How much is due to survey design? *Review of Income and Wealth*, 52(4):509–524, 2006.
- [42] John Karl Scholz, Ananth Seshadri, and Surachai Khitatrakun. Are americans saving optimally for retirement? *Journal of Political Economy*, 114:607–643, 2006.
- [43] Motohiro Yogo. Portfolio choice in retirement: Health risk and the demand for annuities, housing, and risky assets. Mimeo, University of Pennsylvania, 2009.

## Appendix A: Moment conditions and asymptotic distribution of parameter estimates

Recall that we estimate the parameters of our model in the two steps. In the first step, we estimate the vector  $\chi$ , the set of parameters than can be estimated with explicitly using our model. In the second step, we use the method of simulated moments (MSM) to estimate the remaining parameters, which are contained in the  $M \times 1$  vector  $\Delta$ . The elements of  $\Delta$  are  $\nu$ ,  $\omega$ ,  $\beta$ ,  $\underline{c}$ ,  $\theta$ ,  $k$ , and the parameters of  $\ln \mu(\cdot)$ . Our estimate,  $\hat{\Delta}$ , of the “true” parameter vector  $\Delta_0$  is the value of  $\Delta$  that minimizes the (weighted) distance between the life-cycle profiles found in the data and the simulated profiles generated by the model.

For each calendar year  $t \in \{t_0, \dots, t_T\} = \{1996, 1998, 2000, 2002, 2004, 2006\}$ , we match median assets for  $Q_A = 5$  permanent income quintiles in  $P = 5$  birth year cohorts.<sup>6</sup> The 1996 (period- $t_0$ ) distribution of simulated assets, however, is bootstrapped from the 1996 data distribution, and thus we match assets to the data for 1998, ..., 2006. In addition, we require each cohort-income-age cell have at least 10 observations to be included in the GMM criterion.

Suppose that individual  $i$  belongs to birth cohort  $p$  and his permanent income level falls in the  $q$ th permanent income quintile. Let  $a_{pqt}(\Delta, \chi)$  denote the model-predicted median asset level for individuals in individual  $i$ 's group at time  $t$ , where  $\chi$  includes all parameters estimated in the first stage (including the permanent income boundaries). Assuming that observed assets have a continuous conditional density,  $a_{pqt}$  will satisfy

$$\Pr \left( a_{it} \leq a_{pqt}(\Delta_0, \chi_0) \mid p, q, t, \text{individual } i \text{ observed at } t \right) = 1/2.$$

The preceding equation can be rewritten as a moment condition (Manski [29], Powell [40] and Buchinsky [7]). In particular, applying the indicator function produces

$$E \left( 1\{a_{it} \leq a_{pqt}(\Delta_0, \chi_0)\} - 1/2 \mid p, q, t, \text{individual } i \text{ observed at } t \right) = 0. \quad (18)$$

Letting  $\mathcal{I}_q$  denote the values contained in the  $q$ th permanent income quintile, we can convert this conditional moment equation into an unconditional one (e.g., Chamberlain [9]):

$$\begin{aligned} E \left( [1\{a_{it} \leq a_{pqt}(\Delta_0, \chi_0)\} - 1/2] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \right. \\ \left. \times 1\{\text{individual } i \text{ observed at } t\} \mid t \right) = 0 \end{aligned} \quad (19)$$

for  $p \in \{1, 2, \dots, P\}$ ,  $q \in \{1, 2, \dots, Q_A\}$ ,  $t \in \{t_1, t_2, \dots, t_T\}$ .

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<sup>6</sup>Because we do not allow for macro shocks, in any given cohort  $t$  is used only to identify the individual's age.

We also include several moment conditions relating to medical expenses. To use these moment conditions, we first simulate medical expenses at an annual frequency, and then take two-year averages to produce a measure of medical expenses comparable to the ones contained in the AHEAD.

As with assets, we divide individuals into 5 cohorts and match data from 5 waves covering the period 1998-2006. The moment conditions for medical expenses are split by permanent income as well. However, we combine the bottom two income quintiles, as there is very little variation in out-of-pocket medical expenses in the bottom quintile until very late in life;  $Q_M = 4$ .

We require the model to match the median out-of-pocket medical expenditures in each cohort-income-age cell. Let  $m_{pqt}^{50}(\Delta, \chi)$  denote the model-predicted 50th percentile for individuals in cohort  $p$  and permanent income group  $q$  at time (age)  $t$ . Proceeding as before, we have the following moment condition:

$$E\left([1\{m_{it} \leq m_{pqt}^{50}(\Delta_0, \chi_0)\} - 0.5] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \times 1\{\text{individual } i \text{ observed at } t\} \mid t\right) = 0 \quad (20)$$

for  $p \in \{1, 2, \dots, P\}$ ,  $q \in \{1, 2, \dots, Q_M\}$ ,  $t \in \{t_1, t_2, \dots, t_T\}$ .

To fit the upper tail of the medical expense distribution, we require the model to match the 90th percentile of out-of-pocket medical expenditures in each cohort-income-age cell. Letting  $m_{pqt}^{90}(\Delta, \chi)$  denote the model-predicted 90th percentile, we have the following moment condition:

$$E\left([1\{m_{it} \leq m_{pqt}^{90}(\Delta_0, \chi_0)\} - 0.9] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \times 1\{\text{individual } i \text{ observed at } t\} \mid t\right) = 0 \quad (21)$$

for  $p \in \{1, 2, \dots, P\}$ ,  $q \in \{1, 2, \dots, Q_M\}$ ,  $t \in \{t_1, t_2, \dots, t_T\}$ .

To pin down the autocorrelation coefficient for  $\zeta$  ( $\rho_m$ ), and its contribution to the total variance  $\zeta + \xi$ , we require the model to match the first and second autocorrelations of logged medical expenses. Define the residual  $R_{it}$  as

$$R_{it} = \ln(m_{it}) - \overline{\ln m_{pqt}},$$

$$\overline{\ln m_{pqt}} = E(\ln(m_{it}) \mid p_i = p, q_i = q, t)$$

and define the standard deviation  $\sigma_{pqt}$  as

$$\sigma_{pqt} = \sqrt{E(R_{it}^2 \mid p_i = p, q_i = q, t)}.$$

Both  $\overline{\ln m_{pqt}}$  and  $\sigma_{pqt}$  can be estimated non-parametrically as elements of  $\chi$ . Using these quantities, the autocorrelation coefficient  $AC_{pqtj}$  is:

$$AC_{pqtj} = E\left(\frac{R_{it}R_{i,t-j}}{\sigma_{pqt}\sigma_{pq,t-j}} \mid p_i = p, q_i = q\right).$$

Let  $AC_{pqtj}(\Delta, \chi)$  be the  $j$ th autocorrelation coefficient implied by the model, calculated using model values of  $\overline{\ln m_{pqt}}$  and  $\sigma_{pqt}$ . The resulting moment condition for the first autocorrelation is

$$E \left( \left[ \frac{R_{it}R_{i,t-1}}{\sigma_{pqt} \sigma_{pq,t-1}} - AC_{pqt1}(\Delta_0, \chi_0) \right] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \right. \\ \left. \times 1\{\text{individual } i \text{ observed at } t \text{ \& } t-1\} \mid t \right) = 0. \quad (22)$$

The corresponding moment condition for the second autocorrelation is

$$E \left( \left[ \frac{R_{it}R_{i,t-2}}{\sigma_{pqt} \sigma_{pq,t-2}} - AC_{pqt2}(\Delta_0, \chi_0) \right] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \right. \\ \left. \times 1\{\text{individual } i \text{ observed at } t \text{ \& } t-2\} \mid t \right) = 0. \quad (23)$$

Finally, we match Medicaid utilization (take-up) rates. Once again, we divide individuals into 5 cohorts, match data from 5 waves, and stratify the data by permanent income. We combine the top two quintiles because in many cases no one in the top permanent income quintile is on Medicaid:  $Q_U = 4$ .

Let  $\bar{u}_{pqt}(\Delta, \chi)$  denote the model-predicted utilization rate for individuals in cohort  $p$  and permanent income group  $q$  at age  $t$ . Let  $u_{it}$  be the  $\{0, 1\}$  indicator that equals 1 when individual  $i$  receives Medicaid. The associated moment condition is

$$E \left( \left[ u_{it} - \bar{u}_{pqt}(\Delta_0, \chi_0) \right] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \right. \\ \left. \times 1\{\text{individual } i \text{ observed at } t\} \mid t \right) = 0 \quad (24)$$

for  $p \in \{1, 2, \dots, P\}$ ,  $q \in \{1, 2, \dots, Q_U\}$ ,  $t \in \{t_1, t_2, \dots, t_T\}$ .

To summarize, the moment conditions used to estimate model with endogenous medical expenses consist of: the moments for asset medians described by equation (19); the moments for median medical expenses described by equation (20); the moments for the 90th percentile of medical expenses described by equation (21); the moments for the autocorrelations of logged medical expenses described by equations (22) and (23); and the moments for the Medicaid utilization rates described by equation (24). In the end, we have a total of  $J = 478$  moment conditions.

Suppose we have a dataset of  $I$  independent individuals that are each observed at up to  $T$  separate calendar years. Let  $\varphi(\Delta; \chi_0)$  denote the  $J$ -element vector of moment conditions described immediately above, and let  $\hat{\varphi}_I(\cdot)$  denote its sample analog. Letting  $\widehat{\mathbf{W}}_I$  denote a  $J \times J$  weighting matrix, the MSM estimator  $\hat{\Delta}$  is given by

$$\underset{\Delta}{\operatorname{argmin}} \frac{I}{1 + \tau} \hat{\varphi}_I(\Delta; \chi_0)' \widehat{\mathbf{W}}_I \hat{\varphi}_I(\Delta; \chi_0),$$

where  $\tau$  is the ratio of the number of observations to the number of simulated observations.

In practice, we estimate  $\chi_0$  as well, using the approach described in the main text. Computational concerns, however, compel us to treat  $\chi_0$  as known in the analysis that follows. Under regularity conditions stated in Pakes and Pollard [36] and Duffie and Singleton [12], the MSM estimator  $\hat{\Delta}$  is both consistent and asymptotically normally distributed:

$$\sqrt{I} \left( \hat{\Delta} - \Delta_0 \right) \rightsquigarrow N(0, \mathbf{V}),$$

with the variance-covariance matrix  $\mathbf{V}$  given by

$$\mathbf{V} = (1 + \tau)(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\mathbf{S}\mathbf{W}\mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1},$$

where:  $\mathbf{S}$  is the variance-covariance matrix of the data;

$$\mathbf{D} = \left. \frac{\partial \varphi(\Delta; \chi_0)}{\partial \Delta'} \right|_{\Delta=\Delta_0} \quad (25)$$

is the  $J \times M$  gradient matrix of the population moment vector; and  $\mathbf{W} = \text{plim}_{I \rightarrow \infty} \{\widehat{\mathbf{W}}_I\}$ . Moreover, Newey [32] shows that if the model is properly specified,

$$\frac{I}{1 + \tau} \hat{\varphi}_I(\hat{\Delta}; \chi_0)' \mathbf{R}^{-1} \hat{\varphi}_I(\hat{\Delta}; \chi_0) \rightsquigarrow \chi_{J-M}^2,$$

where  $\mathbf{R}^{-1}$  is the generalized inverse of

$$\begin{aligned} \mathbf{R} &= \mathbf{P}\mathbf{S}\mathbf{P}, \\ \mathbf{P} &= \mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}. \end{aligned}$$

The asymptotically efficient weighting matrix arises when  $\widehat{\mathbf{W}}_I$  converges to  $\mathbf{S}^{-1}$ , the inverse of the variance-covariance matrix of the data. When  $\mathbf{W} = \mathbf{S}^{-1}$ ,  $\mathbf{V}$  simplifies to  $(1 + \tau)(\mathbf{D}'\mathbf{S}^{-1}\mathbf{D})^{-1}$ , and  $\mathbf{R}$  is replaced with  $\mathbf{S}$ .

But even though the optimal weighting matrix is asymptotically efficient, it can be biased in small samples. (See, for example, Altonji and Segal [2].) To check for robustness, we also use a “diagonal” weighting matrix, as suggested by Pischke [38]. This diagonal weighting scheme uses the inverse of the matrix that is the same as  $\mathbf{S}$  along the diagonal and has zeros off the diagonal of the matrix. This matrix delivers parameter estimates very similar to our benchmark estimates.

We estimate  $\mathbf{D}$ ,  $\mathbf{S}$ , and  $\mathbf{W}$  with their sample analogs. For example, our estimate of  $\mathbf{S}$  is the  $J \times J$  estimated variance-covariance matrix of the sample data. When estimating this matrix, we use sample statistics, so that  $a_{pqt}(\Delta, \chi)$  is replaced with the sample median for group  $pqt$ .

One complication in estimating the gradient matrix  $\mathbf{D}$  is that the functions inside the moment condition  $\varphi(\Delta; \chi)$  are non-differentiable at certain data points; see

equation (19). This means that we cannot consistently estimate  $\mathbf{D}$  as the numerical derivative of  $\hat{\varphi}_I(\cdot)$ . Our asymptotic results therefore do not follow from the standard GMM approach, but rather the approach for non-smooth functions described in Pakes and Pollard [36], Newey and McFadden [33] (section 7), and Powell [40].

To find  $\mathbf{D}$ , it is helpful to rewrite equation (19) as

$$\Pr \left( p_i = p \ \& \ I_i \in \mathcal{I}_q \ \& \ \text{individual } i \text{ observed at } t \right) \times \left[ \int_{-\infty}^{a_{pqt}(\Delta_0, \chi_0)} f \left( a_{it} \mid p, I_i \in \mathcal{I}_q, t \right) da_{it} - \frac{1}{2} \right] = 0. \quad (26)$$

It follows that the rows of  $\mathbf{D}$  are given by

$$\Pr \left( p_i = p \ \& \ I_i \in \mathcal{I}_q \ \& \ \text{individual } i \text{ observed at } t \right) \times f \left( a_{pqt} \mid p, I_i \in \mathcal{I}_q, t \right) \times \frac{\partial a_{pqt}(\Delta_0; \chi_0)}{\partial \Delta'}. \quad (27)$$

In practice, we find  $f(a_{pfqt}|p, q, t)$ , the conditional p.d.f. of assets evaluated at the median  $a_{pqt}$ , with a kernel density estimator written by Koning [26]. The gradients for equations (20) and (21) are found in a similar fashion.

## Appendix B: Demographic Transition Probabilities in the HRS/AHEAD

Let  $h_t \in \{0, 1, 2, 3\}$  denote death ( $h_t = 0$ ) and the 3 mutually exclusive health states of the living (nursing home = 1, bad = 2, good = 3, respectively). Let  $x$  be a vector that includes a constant, age, permanent income, gender, and powers and interactions of these variables, and indicators for previous health and previous health interacted with age. Our goal is to construct the likelihood function for the transition probabilities.

Using a multivariate logit specification, we have, for  $i \in \{1, 2, 3\}$ ,  $j \in \{0, 1, 2, 3\}$ ,

$$\begin{aligned} \pi_{ij,t} &= \Pr(h_{t+1} = j \mid h_t = i) \\ &= \gamma_{ij} / \sum_{k \in \{0,1,2,3\}} \gamma_{ik}, \\ \gamma_{i0} &\equiv 1, \quad \forall i, \\ \gamma_{1k} &= \exp(x\beta_k), \quad k \in \{1, 2, 3\}, \\ \gamma_{2k} &= \exp(x\beta_k), \quad k \in \{1, 2, 3\}, \\ \gamma_{3k} &= \exp(x\beta_k), \quad k \in \{1, 2, 3\}, \end{aligned}$$

where  $\{\beta_k\}_{k=0}^3$  are sets of coefficient vectors and of course  $\Pr(h_{t+1} = 0 \mid h_t = 0) = 1$ .

The formulae above give 1-period-ahead transition probabilities,  $\Pr(h_{t+1} = j | h_t = i)$ . What we observe in the AHEAD dataset, however, are 2-period ahead probabilities,  $\Pr(h_{t+2} = j | h_t = i)$ . The two sets of probabilities are linked, however, by

$$\begin{aligned} \Pr(h_{t+2} = j | h_t = i) &= \sum_k \Pr(h_{t+2} = j | h_{t+1} = k) \Pr(h_{t+1} = k | h_t = i) \\ &= \sum_k \pi_{kj,t+1} \pi_{ik,t}. \end{aligned}$$

This allows us to estimate  $\{\beta_k\}$  directly from the data using maximum likelihood.