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Federal Reserve Bank of Chicago

Medicaid Insurance in Old Age

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Abstract

Medicaid was primarily designed to protect and insure the poor against medical shocks. Yet, poorer people tend to live shorter lifespans and incur lower medical expenses before death than richer people. Taking these and other important dimensions of heterogeneity into account, and carefully modeling key institutional aspects, we estimate a structural model of savings and endogenous medical expenses to assess the costs and benefits of Medicaid for single retirees.

We show that even higher-income retirees benefit from Medicaid, if they live long enough for their resources to be depleted by medical expenses. We also find that all retirees value Medicaid insurance coverage highly, compared to the value of the Medicaid transfers that they actually receive on average.

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1 Introduction

The pervasive discussions on the “fiscal cliff” have made it clear that most entitlement programs in the United States will be scrutinized for cost-saving reforms. One of the most debated programs is Medicaid, a means-tested, public health insurance program for the poor that covers any medical expenses not picked up by other insurance programs. In this paper we analyze the properties of Medicaid during old age.

It has been argued that Medicaid has outgrown its initial mandate, (e.g. Brown and Finkelstein [5]) and is now also insuring also middle- and higher-income retirees, besides the lower income ones. One force generating Medicaid transfers to higher income people is that richer people are more likely to live long and face expensive medical conditions, such as nursing home stays, when very old. In contrast, poorer people tend to live shorter lives and to die before incurring large medical expenses. Another force reducing Medicaid redistribution is that while Medicaid was initially designed to protect and insure the lifetime poor, it was later expanded to insure richer people impoverished by high medical expenses, including nursing homes, which are large and not generally covered by other public or private insurance.

Despite the increasing importance (and cost) of Medicaid in the presence of an aging population and ever increasing medical costs, very little is known about the insurance properties of Medicaid, its degree of redistribution through transfers, the degree to which various segments in the population benefit by it, and how much retirees value Medicaid insurance. These are important aspects to know before setting out to implement reforms to the system currently in place. This paper seeks to fill this gap.

In this paper, first, we document who in the Assets and Health Dynamics of the Oldest Old (AHEAD) receives Medicaid. We find that even high income people become Medicaid recipients if they live long enough and are hit by expensive medical conditions. The Medicaid reciprocity rate for those at the bottom income quintile stays flat around 60%-70% throughout their retirement. In contrast, the reciprocity rate by higher-income retirees is initially much lower, but it increases by age, reaching 5-20% after age 90.

Then, taking life expectancy and other important dimensions of heterogeneity into account, we estimate a structural model of savings and endogenous medical expenses to assess the costs and benefits of Medicaid for single retirees. Our model matches key aspects of the data well and produces parameter estimates within the bounds previously used in many works. It also generates an elasticity of total medical expenditures to co-payment changes that is close to the one estimated by Manning et al. [35] using the RAND Health Insurance Experiment.

Finally, we set out to use our estimated model. We 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 dif-

ferent 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 find that, per-period of life, the retirees at the bottom income quintile receive transfers that are almost three times larger than that of the higher-income people. Once we compute discounted present values over all of one's remaining expected lifetime, however, this ratio decreases to two. Hence, differential life expectancy and medical needs that increase with age do have a significant impact on the amount of redistribution performed by Medicaid.

Our model also allows us to compute the valuation that a retiree attributes to Medicaid insurance, thus enabling us to perform a cost and benefit analysis of the program. We find that, with an estimated aversion against medical expense risk of just over 3, and a long tail risk of outliving ones' life expectancy, retirees in all income quintiles and asset levels value Medicaid insurance much more than its expected cost and that cutting the program would impose very large welfare costs compared to the resulting savings.

Our findings come from 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. Consistent with program rules, we model two pathways to Medicaid.

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.

2 Literature review

This paper is related to several previous papers on savings, health risks, and social insurance. Hurd [26] and Hurd, McFadden, Merrill [27] highlight the importance of accounting for the link between wealth and mortality risk when estimating life-cycle models. Kotlikoff [33] stresses the importance of modeling health expenditures to understand precautionary savings.

Hubbard et al. [24] and Palumbo [45] 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. DeNardi et al. [12] and Marshall, McGarry, and Skinner [37] find that late life medical expenses are large and generate powerful savings incentives. Furthermore, Poterba, Venti, and Wise [48] show that those in poor health have considerably lower assets than similar individuals in good health. Lockwood [34] and Nakajima and Telyukova [39] add to the literature by estimating life cycle models that allow for longevity and medical expense risk jointly with bequest motives.

Hubbard et al. [25] and Scholz et al. [52] 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 [32] 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.

Several new papers (Hansen et al. [23], Paschenko and Porapakkarm [46], İmrohoroğlu and Kitao [28]) study the importance of medical expense risk in the aggregate. Our contribution relative to these papers is that medical spending is endogenous in our model, and we estimate the parameters of the model.

Koijen, Van Nieuwerburgh, and Yogo [30] 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.

Three recent papers contain life-cycle models where the choice of medical expenditures are endogenous. In addition to having different emphases, these papers model Medicaid in ways different from ours. Feng [16] models Medicaid as an insurance policy with no premiums and extremely low—possibly zero—co-payment rates. Fonseca et al. [20] and Scholz and Seshadri [51] assume that the consumption floor is invariant to medical needs. Ozkan [43] assumes that indigent individuals receive curative, but not preventative, care.

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. 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.

3 Some important aspects of the Medicaid program

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 governments¹.

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, 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. In fact, Medicaid ends up financing 70% of nursing home residents (Kaiser Foundation [42]), and these costs are of the order of \$60,000 to \$75,000 a year (in 2005).

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.

¹We document many important aspects of Medicaid insurance in old age in [13].

4 Some Data

4.1 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, 2006, 2008, and 2010. This leaves us with 3,243 individuals, of whom 588 are men and 2,655 are women. Of these 3,243 individuals, 370 are still alive in 2010. We do not use 1994 assets or medical expenses. Assets in 1994 were underreported (Rohwedder et al. [50]) 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 92-102.² We use data for 8 different years; 1996, 1998, 2000, 2002, 2004, 2006, 2008, and 2010. 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

²Even 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, although we use many of the observations when estimating the model.

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.

4.2 Medicaid Reciprocity

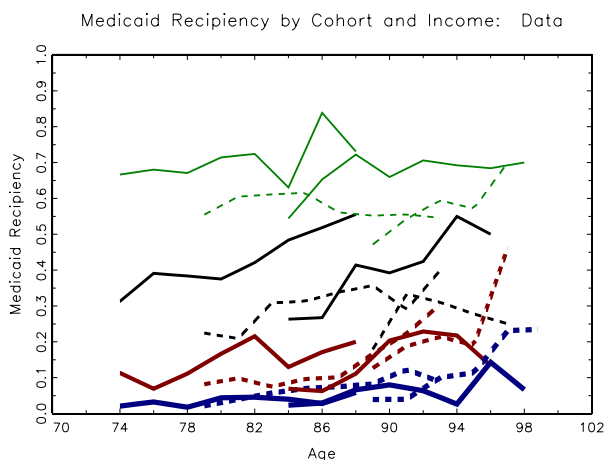


Figure 1: Medicaid reciprocity rates by age, cohort, and permanent income. Thicker lines refer to higher PI groups.

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 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 richest 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 2010. 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.

4.3 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.

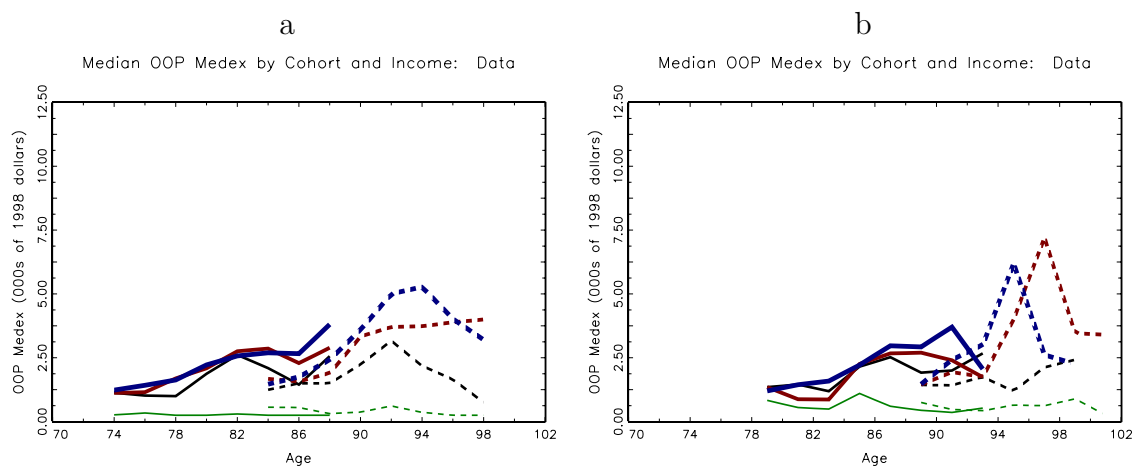


Figure 2: Median out-of-pocket medical expenditures by age, cohort, and permanent income.

French and Jones [21] show that the medical expense data in the AHEAD line up with the aggregate statistics. For our sample, mean medical expenses are \$4,605 with a standard deviation of \$14,450 in 2005 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

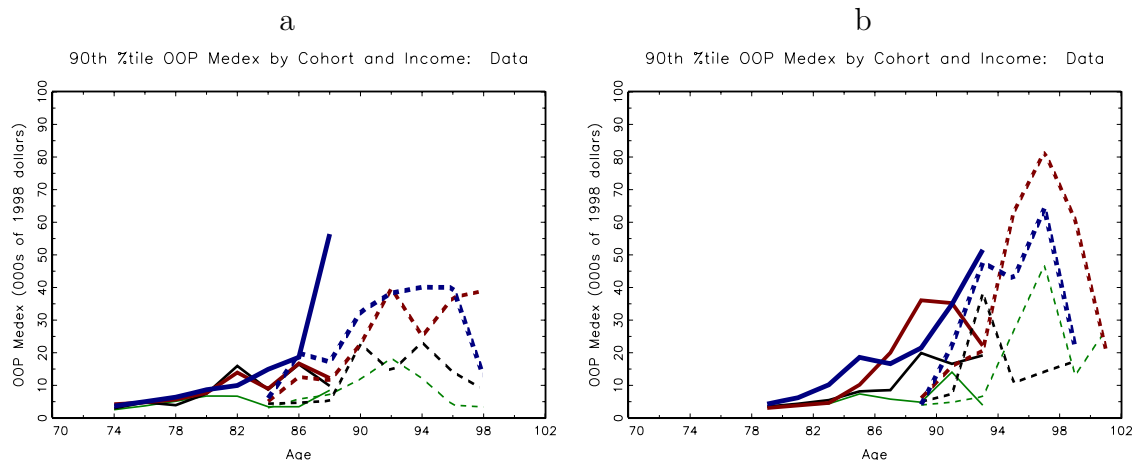


Figure 3: 90th percentile out-of-pocket medical expenditures by age, cohort, and permanent income.

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 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.

4.4 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 \$200,000 and then stayed rather stable until the final time period: \$170,000 at age 76, \$190,000 at age 78, \$220,000 at age 80, \$210,000 at age 82, \$220,000 at age 84, \$200,000 at age 86, and \$130,000 at age 88.

For all PI quintiles in these cohorts, the assets of surviving individuals do not decline rapidly with age. Those with high income do not run down their assets until their late 80s, although those with low income tend to have their assets decrease throughout the sample period. The slow rate at which the elderly deplete their wealth

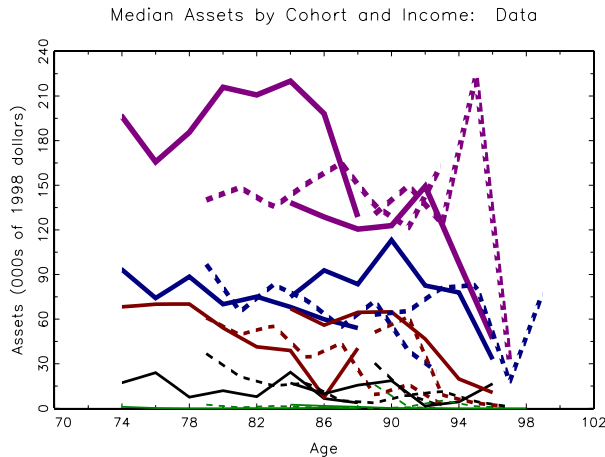


Figure 4: Median assets by age, cohort, and permanent income. Thicker lines refer to higher PI groups.

has been a long-standing puzzle (see for example, Mirer [38]). However, as De Nardi, French, and Jones [12] show, the risk of medical spending rising with age and income goes a long way toward explaining this puzzle.

5 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.

5.1 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 ζ_t and ξ_t . Individuals optimally choose how much to spend in response to these shocks.

A complementary approach is that of Grossman [22], in which medical expenses represent investments in health capital, which in turn decreases mortality (e.g., Yogo [53]) or improves health. While a few studies find that medical expenditures have significant effects on health and/or survival (Card et al. [8]; Doyle [11], Finkelstein et al. [18], Chay et al. [10]), most others find small effects (Brook et al. [3]; Fisher et al. [19]; Finkelstein and McKnight [17]; Khwaja [29]); see De Nardi et al. [12] 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.

5.2 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 \underline{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, ζ_t, ξ_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).

5.3 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 ξ_t and ϵ_t are serially and mutually independent. We thus allow the need for medical services to have temporary (ξ_t) and persistent (ζ_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:

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

5.4 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 and 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 τ 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 θ 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 β to denote the discount factor, we can then write the individual's value function as:

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

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:

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

where λ_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).

6 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 4. We then compare data and model-generated cell medians in 5 different years (1998, 2000, 2002, 2004, and 2006).³
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 ζ and ξ 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 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.

7 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. [12], and is described in more detail there. The procedure for estimating demographic transition probabilities and co-pay rates are new.

³Simulated agents are endowed with asset levels drawn from the 1996 data distribution. Cells with less than 10 observations are excluded from the moment conditions.

7.1 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 \$5,000 per year in the bottom PI quintile to about \$23,000 in the top quintile; median wealth holdings for the two groups are zero and just under \$200,000, respectively.

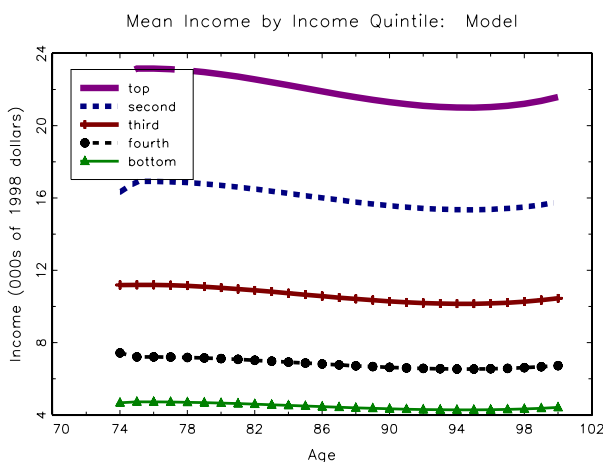


Figure 5: Average income, by permanent income quintile.

7.2 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	<u>Males</u>		<u>Females</u>			All [†]
		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: [‡]							
Men							9.41
Women							13.54
By health status: [◊]							
Bad Health							10.56
Good Health							13.93

Notes: Life expectancies calculated through simulations using estimated health transition and survivor functions. [†] Using gender and health distributions for entire population; [‡] Using health and permanent income distributions for each gender; [◊] 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 calculations 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]).

7.3 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: $q_t = q(h_t)$.

Income Percentile	<u>Males</u>		<u>Females</u>		All [†]
	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: [‡]					
Men					17.9
Women					30.1
By health status: [◊]					
Bad Health					25.4
Good Health					29.0

Notes: Entry probabilities calculated through simulations using estimated health transition and survivor functions; [†] Using gender and health distributions for entire population; [‡] Using health and permanent income distributions for each gender; [◊] 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.

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%.

8 Second step results and model fit

8.1 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.

β : discount factor	.99 (NA)
ν : RRA, consumption	2.87 (0.034)
ω : RRA, medical expenditures	3.33 (0.041)
$\underline{u}_c = \underline{u}_m$: utility floor, [†]	1,740 (61.8)
θ : bequest intensity	191 (39.6)
k : bequest curvature (in 000s)	149 (17.7)

[†] 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 .

Our estimate of β , the discount factor, is 0.99. 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 β .

The estimate of ν , the coefficient of relative risk aversion for “regular” consumption, is 2.9, while the estimate of ω , the coefficient of relative risk aversion for medical goods, is 3.3; the demand for medical goods is less elastic than the demand for consumption.

To start, we constrain the two utility floors to be the same, as Medicaid generosity does not appear to be drastically different across the two categories of recipients. The utility floor corresponds to the utility level of consuming \$1,740 a year when healthy. It should be noted that the medically needy are guaranteed a minimum income level of \$7,000 by SSI, so that their total consumption when healthy is actually \$7,000 a year. However, when there are large medical needs, transfers are determined by the Medicaid-induced utility floor.

The point estimates of $\theta = 191$ and $k = 149,000$ imply that, before the period before certain death, the bequest motive becomes operative once consumption exceeds \$24,000 per year. (See De Nardi, French, and Jones [12] for a derivation.) For individuals in this group, the marginal propensity to bequeath above that consumption level is high, with 86 cents of every extra dollar above the threshold being left as bequests.

These preference parameters are identified jointly. There are multiple ways to generate high saving by the elderly: large values of the discount rate β , low values of the utility floors u_c and u_m , large values of the curvature parameters ν and ω , or strong and pervasive bequest motives (high values of θ and small values of k). Dynan, Skinner and Zeldes [15] point out that the same assets can simultaneously address both precautionary and bequest needs. There are also multiple ways to ensure that the income-poorest elderly do not save, including high utility floors and bequest motives that become operative only at high levels of consumption. We acquire additional identification in several ways. The most obvious of these is that we fix β to 0.99, a standard value. Another step is that we require our model to match Medicaid reciprocity rates, which helps pin down the utility floors. Matching disaggregated out-of-pocket medical expenditures also helps identify the utility floors, as Medicaid affects the way in which out-of-pocket medical expenditures (which exclude Medicaid payments) vary by income.

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 ζ_t and ξ_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. Matching the median and 90th percentile of out-of-pocket medical expenditures, along with their first and second autocorrelations, is of course the principal way in which we identify these parameters. The fact that the medical needs shocks do not depend directly on income—the only link is through the health transition probabilities—also helps us identify other parameters, as the expenditure profiles we match are

disaggregated by income. Most notably, the income gradient of medical expenditures helps us pin down the curvature parameters ν and ω .

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.

8.2 Medicaid reciprocity

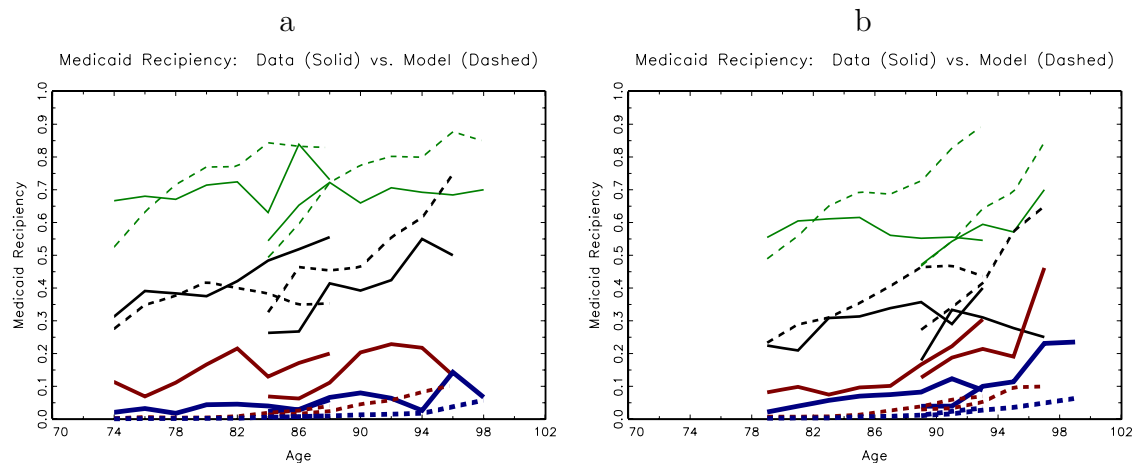


Figure 6: Medicaid reciprocity by cohort and PI quintile: data (solid lines) and model (dashed lines).

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 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.

8.3 Net worth profiles

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.

8.4 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

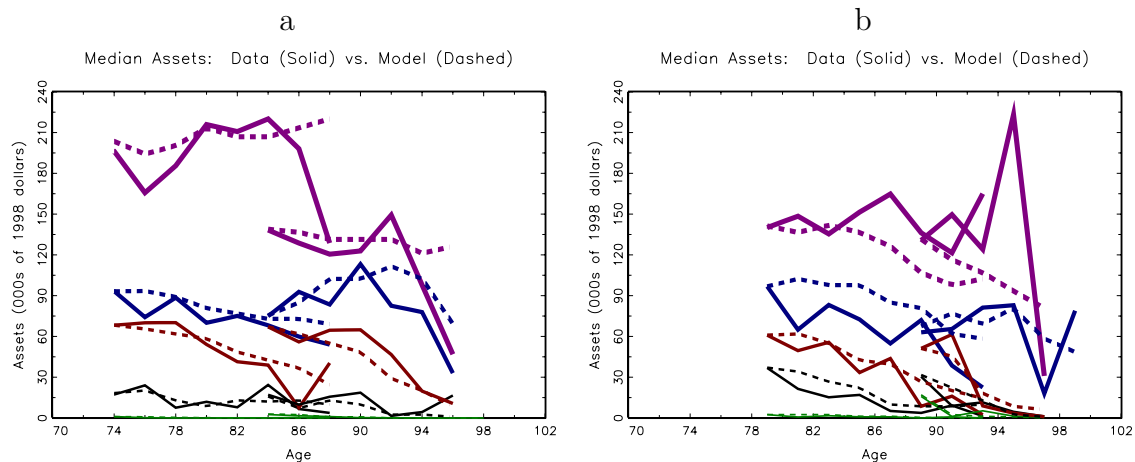


Figure 7: Median net worth by cohort and PI quintile: data (solid lines) and model (dashed lines).

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 \$1,500 a year at age 75. By age 100, they stay flat for those in the bottom quintile of the income distribution but often exceed \$5,000 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 \$4,000 or less at age 74, staying flat over time for the lower PI people, but understates the medical expenditures of high-PI people in their late nineties.

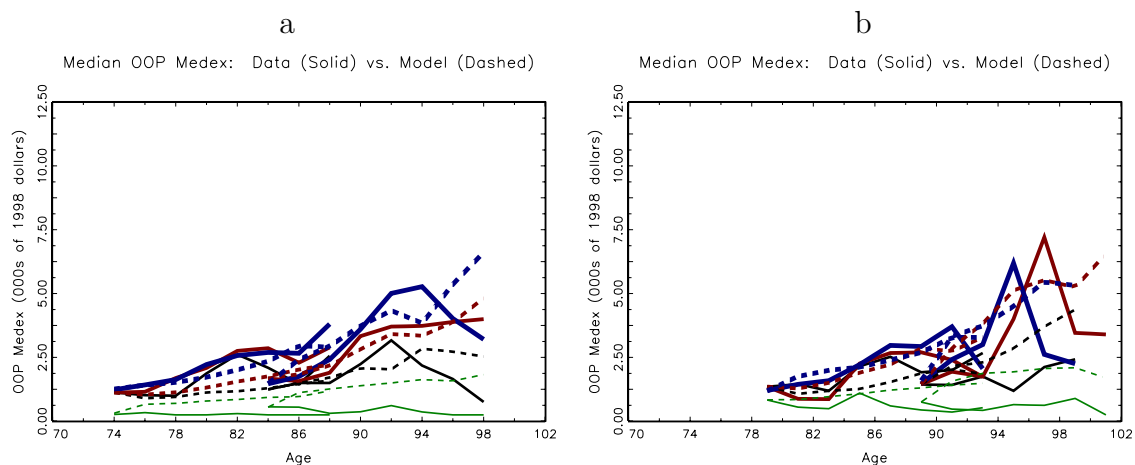


Figure 8: Median out-of-pocket medical expenses by cohort and PI quintile: data (solid lines) and model (dashed lines).

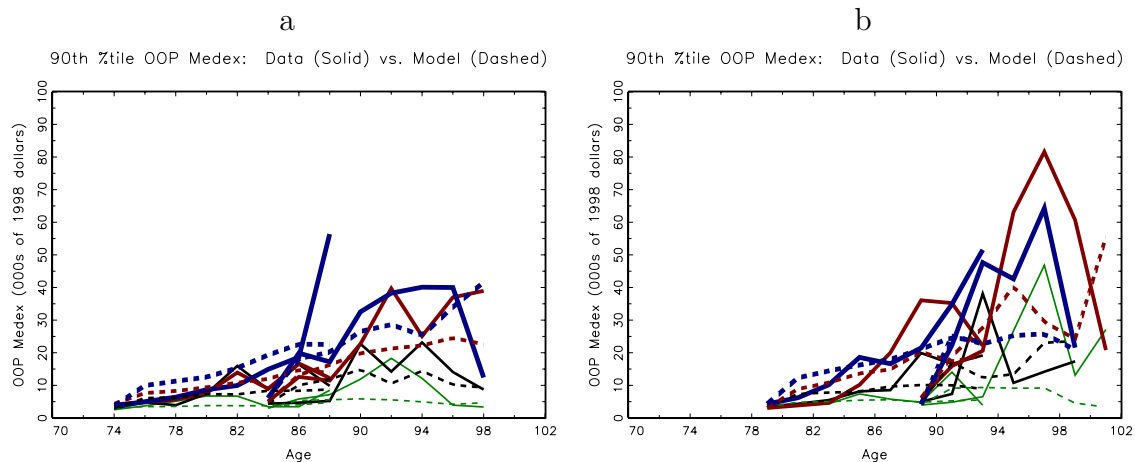


Figure 9: Ninetieth percentile of out-of-pocket medical expenses by cohort and PI quintile: data (solid lines) and model (dashed lines).

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.

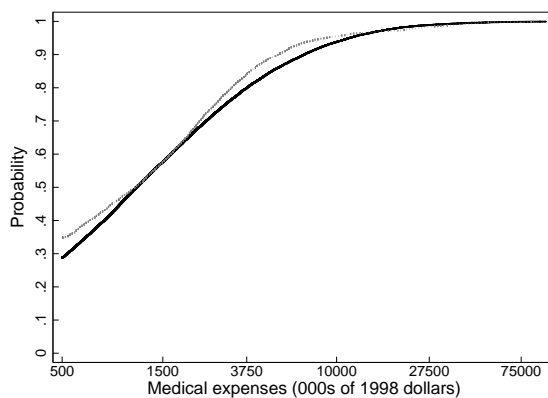


Figure 10: Cumulative distribution function of out-of-pocket medical expenses: data (solid line) and model (lighter line).

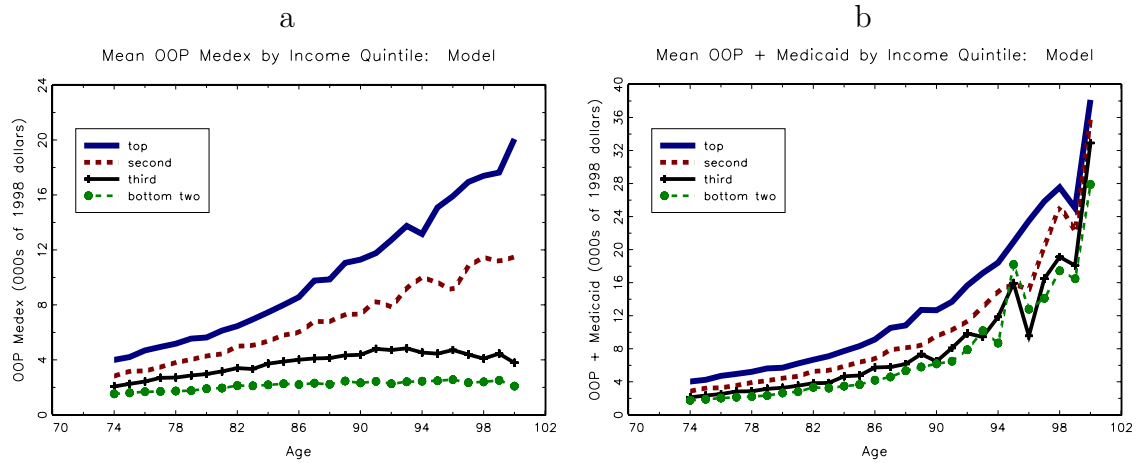


Figure 11: Average medical expenses by age and permanent income. Panel a: paid out-of-pocket. Panel b: paid out-of-pocket or by Medicaid.

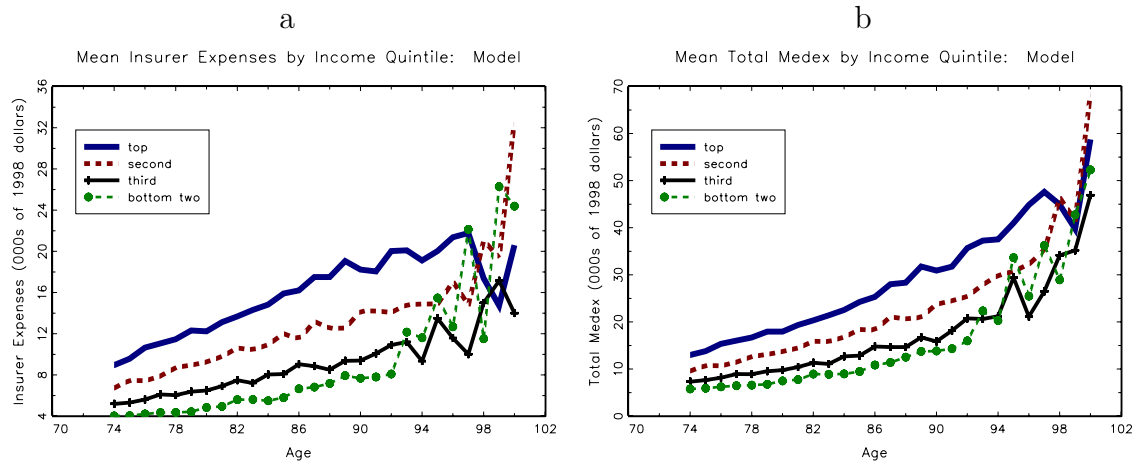


Figure 12: Average medical expenses by age and permanent income. Panel a: paid by insurers. Panel b: total.

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 \$3,000 at age 74 to \$35,000 at age 100. 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.

8.5 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 relative to their resources. 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.

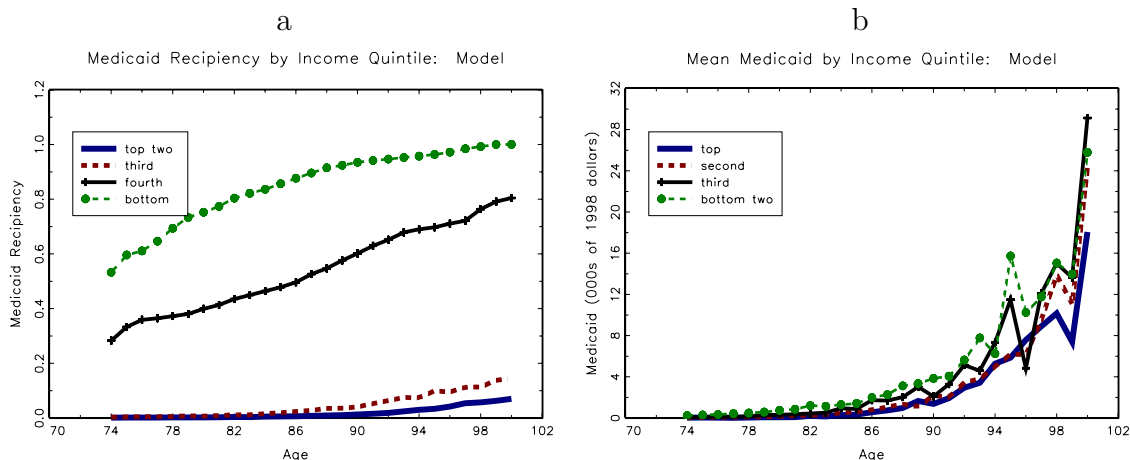


Figure 13: Medicaid. Panel a: fraction receiving Medicaid. Panel b: average Medicaid transfers.

9 The Distribution of Medicaid Insurance Benefits

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. Some things are worth noticing. First, and consistently with the people in the highest income quintiles also being on Medicaid, the present discounted value of Medicaid Payments received by people in the highest income quintile is \$3,300, which is about 10% of their yearly income level. Second, while these transfers decrease by income quintile, they are basically flat and around \$7,000 for the richest two income quintiles. Thus, the richest receive about 50% of the value of Medicaid transfers received by the poorest, despite the fact that the income of those in the bottom fifth of the income distribution is only one fifth of the income of those in the top quintile of the income distribution. Although the poor are more likely to be receiving Medicaid, they tend to die before they develop the most costly health conditions. On the other hand, the richest, while having the most medical expenses, have the most resources to pay for medical care themselves. The interaction of these two mechanisms mitigates the amount of distribution to the income-poorest, who have more expensive medical conditions, but still modest financial resources, as the ones receiving the most benefits.

These flows, reinforce the view that middle- and higher-income people also benefit from Medicaid transfers in old age.

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	7,100	1,010
Fourth	6,900	900
Third	5,700	680
Second	4,200	480
Top	3,300	380
Men	2,300	360
Women	5,800	680
In Good Health	5,000	550
In Bad Health	5,600	770

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. Looking at these numbers, we see that the ratio of yearly benefit from the highest to lowest income people is just over one thirs, compared to one half when taking into account the whole life cycle and life expectancy heterogeneity.

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 understating Medicaid payments throughout income quintiles. 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. However, these estimates are still extremely preliminary and do not correspond exactly to the type of life-long computations that we perform in the model, and we will further work on improving our models' estimates.

Income Quintile	Present Discounted Value	Annuity Value
Bottom	50,200	7,110
Fourth	65,100	8,460
Third	86,700	10,330
Second	124,600	14,280
Top	169,500	19,240
Men	92,100	14,060
Women	112,000	12,970
In Good Health	126,800	14,040
In Bad Health	82,500	11,360

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

Table 5 shows that the rich consume more medical services than the poor: people at the bottom PI quintile consume less than 40% of the medical goods and services consumed by those in the top income quintile. While this difference in part reflects wealth effects, it also illustrates the way in which medical needs rise with age. Interestingly, while men consume more medical goods and services per period of life, the discounted present value is much larger for women, as they tend to live almost 4 years longer. Table 6 shows that out-of-pocket medical expenses rise quickly with income. While the income-poorest consume 40% of the medical goods and services that the richest do, they only pay 25% of the costs paid by the income-richest.

Finally, Table 7 shows that non-medical consumption rises more quickly in income than medical spending, with the ratio of this variable for the poorest to the richest being less than 30%. Given that the curvature parameter for medical expenditures ω is larger than the curvature parameter for non-medical consumption ν , this is not surprising.

Bottom	11,000	1,560
Fourth	16,600	2,150
Third	24,900	2,970
Second	38,600	4,420
Top	54,800	6,230
Men	28,700	4,380
Women	33,300	3,860
In Good Health	38,900	4,300
In Bad Health	23,000	3,170

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

9.1 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 50%.

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 at least ten times larger than the decrease 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.

Income Quintile	Present Discounted Value	Annuity Value
Bottom	59,000	8,350
Fourth	82,600	10,730
Third	114,700	13,680
Second	182,500	20,910
Top	264,200	30,000
Men	152,400	23,260
Women	157,100	18,210
In Good Health	191,600	21,210
In Bad Health	103,900	14,310

Table 7: Consumption at age 74.

Income Quintile	Benchmark Floor	Reduced Floor
Bottom	7,100	3,300
Fourth	6,900	3,000
Third	5,700	2,200
Second	4,200	1,500
Top	3,300	1,200
Men	2,300	800
Women	5,800	2,400
In Good Health	5,000	1,900
In Bad Health	5,600	2,400

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

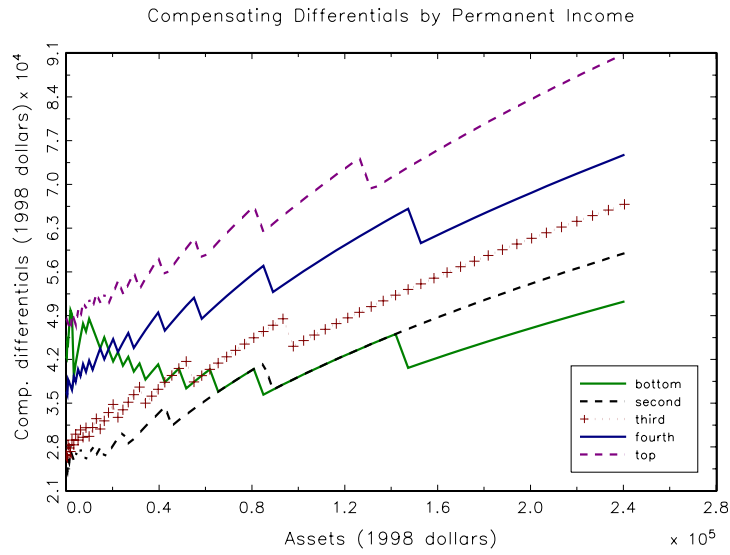


Figure 14: Compensating differentials by assets and permanent income quintile.

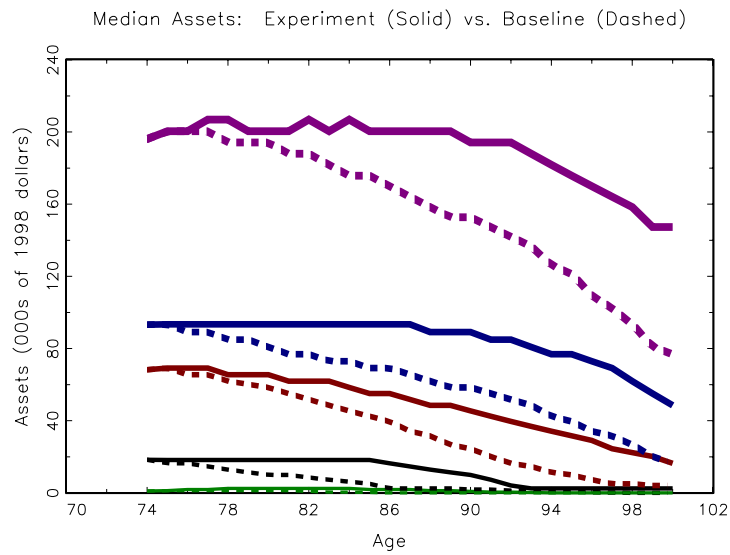


Figure 15: Net worth by age and permanent income. Dashed line: benchmark, solid line: experiment with less generous utility floor.

10 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, even retirees in the highest income quintile expect to receive non-trivial Medicaid transfers. 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. Hence they receive lifetime payments that are almost half of 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 excess of the payments they expect to receive, it is the rich, who have the most to lose, who value Medicaid most highly.

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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 χ , 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 Δ . The elements of Δ are ν , ω , β , \underline{c} , θ , k , and the parameters of $\ln \mu(\cdot)$. Our estimate, $\hat{\Delta}$, of the “true” parameter vector Δ_0 is the value of Δ 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.⁴ 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 χ 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

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

The preceding equation can be rewritten as a moment condition (Manski [36], Powell [49] and Buchinsky [7]). In particular, applying the indicator function produces

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

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

⁴Because 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 ζ (ρ_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 σ_{pqt} as

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

Both $\overline{\ln m_{pqt}}$ and σ_{pqt} can be estimated non-parametrically as elements of χ . 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 σ_{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 τ is the ratio of the number of observations to the number of simulated observations.

In practice, we estimate χ_0 as well, using the approach described in the main text. Computational concerns, however, compel us to treat χ_0 as known in the analysis that follows. Under regularity conditions stated in Pakes and Pollard [44] and Duffie and Singleton [14], 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 [40] 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 [47]. 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 [44], Newey and McFadden [41] (section 7), and Powell [49].

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 [31]. 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.

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