

Medicaid Insurance in Old Age

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Abstract

The old age provisions of the Medicaid program were designed to insure poor retirees against medical expenses. However, it is the rich who are most likely to live long and face expensive medical conditions when very old. We estimate a structural model of savings and endogenous medical spending with heterogeneous agents, and use it to compute the distribution of lifetime Medicaid transfers and Medicaid valuations across currently single retirees.

We find that retirees with high lifetime incomes can end up on Medicaid, and often value Medicaid's insurance features the most, as they face a larger risk of catastrophic medical needs at old ages, and face the greatest consumption risk. Compensating variation calculations indicate that current retirees value Medicaid insurance at more than its actuarial cost, but that most would value an expansion of the current Medicaid program at less than its cost. These findings suggest that for current single retirees, the Medicaid program may be of the approximately right size.

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1 Introduction

Many elderly households benefit from Medicaid, a means-tested, public health insurance program. Despite the increasing importance of Medicaid in the presence of an aging population and rising medical costs, very little is known about how Medicaid payments are distributed among the elderly and how the elderly value these payments. Which elderly households receive Medicaid transfers? How redistributive are these transfers and the taxes needed to finance them? What is the insurance value of these transfers? Is Medicaid of about the right size? How much would people lose if it were cut? These are important questions to answer before reforming the programs currently in place. This paper seeks to fill this gap.

We focus on single retirees, who comprise about 50% of age 70+ people and 70% of age 70+ households. We document who in the Assets and Health Dynamics of the Oldest Old (AHEAD) data 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 in the bottom income quintile stays around 60%-70% throughout retirement. In contrast, the reciprocity rate of higher-income retirees is initially very low, but increases by age, reaching 20% by age 95. Moreover, data from the Medicare Current Beneficiary Survey (MCBS) shows that high income individuals, conditional on receiving Medicaid transfers, receive larger transfer than low income individuals.

The data show who ends up on Medicaid, how much they receive from Medicaid, how much wealth they hold and how much they spend on medical goods and services. However, to assess how much retirees value the insurance provided by Medicaid, and to perform counterfactuals, we need a model. We thus develop 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 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, one for the lifelong poor, and one for people impoverished by large medical expenses.

To appropriately evaluate Medicaid redistribution, we allow for heterogeneity in wealth, permanent income, 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. We estimate the model by matching life-cycle profiles of assets, out-of-pocket medical spending, and Medicaid reciprocity rates for elderly singles across different cohorts and permanent income groups. Matching Medicaid reciprocity introduces an unexpected angle in the identification of bequest motives. To match Medicaid reciprocity rates, Medicaid must be fairly generous, which in turn reduces medical expense risk. To reconcile high observed asset holdings with reduced medical expense risk, a bequest motive is necessary.

Our model matches its targets well and produces parameter estimates within the bounds established by previous work. It also generates an elasticity of total medical expenditures to co-payment changes that is close to the one estimated by Manning et al. [47] using the RAND Health Insurance Experiment. Moreover, although our model was not required to match the distribution of out-of-pocket and total medical expenditures, and Medicaid payments, it turns out to match the corresponding data from the MCBS survey.

Our model shows 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, while 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 transfers, but when they do, these transfers are very big and correspond to severe and expensive medical conditions. Therefore, and consistent with the MCBS data, Medicaid is an effective insurance device for the poorest, but also offers valuable insurance to the rich, by insuring them against catastrophic medical conditions, which are the most costly in terms of utility and the most difficult to insure in the private market.

We also find that, with moderate risk aversion and realistic lifetime and medical needs risk, the value most retirees place on Medicaid insurance exceeds the actuarial value of their expected payments. For example, if we decrease the discounted present value of Medicaid payments by a dollar, to maintain the same level of utility a retired person at the bottom of the income distribution would have to be compensated by more than a dollar, and a person at the top of the distribution would have to be compensated by more than three dollars. On the other hand, we find that a Medicaid expansion would be valued by most retirees at less than its cost. These comparisons of the transfers' actuarial values to the recipient's valuations suggests that the current Medicaid program for most currently single retirees is about the right size.

Our calculations also show that it is the richer retirees who value Medicaid most highly, and thus might be most in favor of a Medicaid expansion. However, this comparison does not take into account the subsidization implied by Medicaid taxes.

Using data from the Panel Survey of Income Dynamics (PSID), we estimate the distribution of Medicaid-related taxes. Our PSID computations indicate if we decrease the discounted present value of Medicaid payments by a dollar, a retired person at the bottom of the income distribution would save 0.2 dollars in taxes, and a person at the top of the distribution would save nearly five dollars. Therefore under the current tax system the rich would not support an expansion of Medicaid insurance, because the increase in their Medicaid tax burden would exceed the increase in their Medicaid valuation.

The paper thus contributes to the literature in multiple ways. First, it evaluates how Medicaid redistributes across people in a model with rich heterogeneity. Second, it uses the model to compute retirees' valuation of Medicaid insurance in a framework that matches the data well and explicitly models the response of savings and medical expenditures to the Medicaid rules. Finally, it provides additional identification of the bequest motive by carefully modeling risks and insurance and by matching Medicaid reciprocity and payment rates.

2 Literature review

This paper is related to several previous papers on savings, health risks, and social insurance. Hurd [37] and Hurd, McFadden, Merrill [38] highlight the importance of accounting for the link between wealth and mortality when estimating life-cycle models. Kotlikoff [44] stresses the importance of modeling health expenditures when studying precautionary savings. Laitner et al. [45] provide analytic expressions providing intuition for how uncertain longevity and medical expense risk affect savings decisions.

Hubbard et al. [35] and Palumbo [59] solve dynamic programming models of saving under medical expense risk, and find that medical expenses have relatively small effects. These papers likely underestimated medical spending risk, however, because the data sets available at that time were missing late-in-life medical spending and had poor measures of nursing home costs. As a result, the data understated the extent to which medical expenses rise with age and income. De Nardi et al. [19] and Marshall, McGarry, and Skinner [49] find that late-in-life medical expenses are large and generate powerful savings incentives. Furthermore, Poterba, Venti, and Wise [62] show that those in poor health have considerably lower assets than similar individuals in good health. Lockwood [46], Nakajima and Telyukova [52], and Yogo [68] add to the literature by estimating life cycle models that include additional insurance choices,

housing, and portfolio choices respectively.

De Nardi et al. [18] and [19] focus on the role of medical expense risk in shaping savings. This paper extends their endogenous medical spending framework and focuses on the role of Medicaid. Specifically, this paper identifies the groups that benefit from the Medicaid program, and how much they value their Medicaid transfers. In order to answer these questions, we develop a more realistic model of Medicaid eligibility. Consistent with the institutions, we explicitly model two separate ways to become Medicaid eligible: having low income and assets (the “categorically needy” pathway), and becoming impoverished by high medical needs (the “medically needy” pathway), in addition to modeling eligibility for Supplemental Security Income (SSI). This richness allows us to evaluate policy reforms that change the eligibility of medically and categorically needy recipients differentially. To better capture key aspects of the Medicaid program, we match Medicaid eligibility rates, which adds an important new source of identification. Because approximately $\frac{2}{3}$ of Medicaid payments to the elderly are to those in a nursing home, we model the nursing home state explicitly. Furthermore, we compare Medicaid payments predicted by the model to those observed in the Medicare Current Beneficiary Survey (MCBS). We show that our model matches Medicaid payment flows well, although they are not matched by construction. This provides additional validation that the model is useful for Medicaid policy evaluation.

Hubbard et al. [36] and Scholz et al. [66] 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. Consistent with this evidence, Gardner and Gilleskie [31] exploit cross-state variation in Medicaid rules and find Medicaid has significant effects on savings. Brown and Finkelstein [9] develop a dynamic model of optimal savings and long-term care purchase decisions. They conclude that Medicaid crowds out private long-term care insurance for about two-thirds of the wealth distribution. Consistent with this evidence, Brown et al. [11] exploit cross-state variation in Medicaid rules and also find significant crowding out.

Several new papers (Hansen et al. [33], Paschenko and Porapakkarm [60], İmrohoroglu and Kitao [39]) study the importance of medical expense risk in the aggregate. Kopecky and Koreshkova [43] find that old-age medical expenses, and the coverage of these expenses provided by Medicaid, have large effects on aggregate capital accumulation. Braun et al. [6] use a model with medical expense risk to assess the incentive and welfare effects of Social Security and other social programs. We focus on redistribution, and behavior and valuation at the individual level. Hence, consistent with the data, we use a partial equilibrium model that allows for much more

heterogeneity. In addition, in our model people can adjust medical spending (as well as consumption and savings), and we estimate our model, rather than calibrating it.

We model endogenous medical expenditures so that we can consider individuals' valuation of quality of care. Some recent papers also contain life-cycle models where the choice of medical expenditures is endogenous. In addition to having different emphases, these papers model Medicaid in a more stylized way. Fonseca et al. [28] and Scholz and Seshadri [65] assume that the consumption floor is invariant to medical needs, whereas our specification allows for a more realistic link between medical needs and Medicaid transfers. Ozkan [57] studies health investments over the life cycle, but does not focus on the role of Medicaid.

This paper also contributes to the literature on the redistribution generated by 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 comprehensively examine how Medicaid transfers to the elderly are distributed across income groups, and to document how even people with higher lifetime income can end up on Medicaid. Furthermore, we assess the valuation individuals place on their expected Medicaid transfers.¹ We also estimate the distribution of the taxes used to finance these transfers. 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. Adapting the approach of McClellan and Skinner [50], we assume that the Medicaid tax burden is proportional to the general tax burden.

3 Key features of the Medicaid program

In the United States, there are two major public insurance programs helping the elderly with their medical expenses. The first one is Medicare, a federal program that provides health insurance to almost every person over the age of 65. The second one is Medicaid, a means-tested program that is run jointly by the federal and state governments.²

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

¹Using a simpler, calibrated model, Brown and Finkelstein [9] analyze how Medicaid affects the valuation of long-term care insurance.

²De Nardi et al. [20] and Gardner and Gilleskie [31] document many important aspects of Medicaid insurance in old age.

the individual spends down his assets to a “disregard” amount. Whereas non-means-tested insurance reduces savings only by reducing risks, Medicaid’s asset test provides an additional savings disincentive.

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. More generally, Medicaid ends up financing 70% of nursing home residents (Kaiser Foundation [56]), and these costs are of the order of \$60,000 to \$75,000 a year (in 2005). Furthermore, 62% of Medicaid’s \$81 billion per year transfers for the elderly in 2009 were for nursing home payments (Kaiser Foundation [29]).

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 financial resources are 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 their medical conditions.

4 Some data

We use two main data sets, the AHEAD and the MCBS. We begin this section with an overview of each dataset.

4.1 The AHEAD dataset

The Assets and Health Dynamics of the Oldest Old (AHEAD) dataset 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 3,727 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. We drop 229 individuals who were partnered with another individual at some point during the sample period

or who did not remain single until death, and 252 individuals with labor income over \$3,000 at some point during the sample period. We are left with 3,246 individuals, of whom 588 are men and 2,658 are women. Of these 3,246 individuals, 370 are still alive in 2010. We do not use 1994 assets or medical expenses. Assets in 1994 were underreported (Rohwedder et al. [64]) 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 on average 60 days per year) 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, each of which contains people born within a 5 year window. 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. Throughout, we will refer to each of these 5-year birth cohorts as a cohort.

Since we want to understand the role of income, we further stratify the data by post-retirement permanent income (PI). We measure PI as the individual’s average non-asset income over all periods during which he or she is observed. Non-asset income includes 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 non-asset income variables that we use, our measure of PI is also a good measure of lifetime permanent income.

4.2 The MCBS dataset

An important limitation of the AHEAD data is that it lacks information on other payers of medical care, such as Medicaid and Medicare. Although there are some self-reported survey data on total billable medical expenditures in the AHEAD, these data are mostly imputed, and are considered to be of low quality. To circumvent this issue, we use data from the 1996-2010 waves of the Medicare Current Beneficiary Survey (MCBS).

The MCBS is a nationally representative survey of disabled and elderly Medi-

care beneficiaries. Respondents are asked about health status, health insurance, and health care expenditures paid out-of-pocket, by Medicaid, by Medicare and by other sources. The MCBS data are matched to Medicare records, and medical expenditure data are created through a reconciliation process that combines survey information with Medicare administrative files. As a result, it gives extremely accurate data on Medicare payments and fairly accurate data on out-of-pocket and Medicaid payments. Both the AHEAD and the MCBS survey include information on those who enter a nursing home or die. This is an important advantage compared to the Medical Expenditure Panel Survey (MEPS), which does not capture late-life or nursing home expenses.

MCBS respondents are interviewed up to 12 times over a 4-year period, forming short panels. We aggregate the data to an annual level. We use the same sample selection rules in the MCBS that we use for the AHEAD data. Specifically, we drop those who were observed to be married over the sample period, work, or be younger than 72 in 1996, 74 in 1998, etc. These sample selection procedures leave us 17,103 different individuals who contribute 40,157 person-year observations. Details of sample construction, as well as validation of the MCBS relative to the aggregate national statistics, are in Appendix A.

As with the AHEAD data, 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 define an individual as being in a nursing home if that individual was in a nursing home at least 60 days over the year. In the MCBS, individuals are asked about total income, not annuitized income. Fortunately, we found that this variable lines up well with total income in the AHEAD. Furthermore, in the AHEAD, the correlation between total income and annuitized income is 0.8. Consistent with our computations in the AHEAD, we use average total income, over the time that we observe an individual, as our measure of permanent income (PI) in the MCBS.

4.3 Medicaid reciprocity and payments

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 PI quintile.

The approach we use to stratify the data behind Figure 1 is one we will use repeatedly throughout the paper. Recall that we stratify the data by PI quintile and cohort. For each cohort-quintile cell, we calculate the Medicaid reciprocity rate in

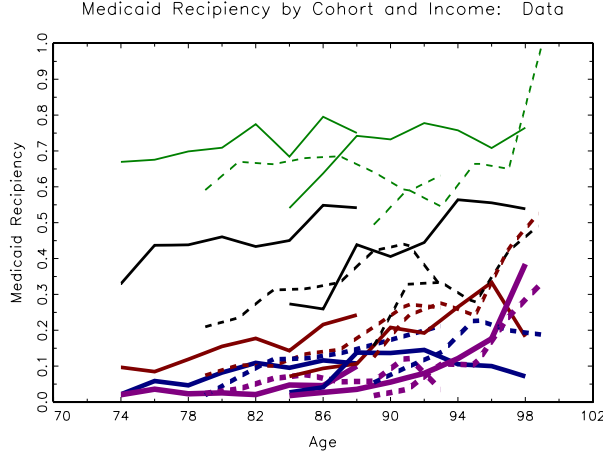


Figure 1: Each line represents Medicaid reciprocity rates for a cohort-income cell, traced over the time period 1996-2010. Thicker lines refer to higher permanent income groups.

each calendar year. We then construct life-cycle profiles by ordering the reciprocity rates 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. (We omit the profiles for the oldest cohort because the sample sizes are tiny.) For each cohort in the figure there are five horizontal lines, one for each PI quintile. To indicate PI rank, we vary the thickness of the lines on our graphs: thicker lines represent observations for higher-ranked PI groupings.

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 other year until 2010. The other cohorts start from older initial ages and are also followed for fourteen years. The graph reports the Medicaid reciprocity rate for each cohort and PI grouping at eight dates over time. At each sample date, we calculate the Medicaid reciprocity rate for individuals alive at that date — we use an unbalanced panel. Cohort-income-year cells with fewer than 10 observations are dropped.

Unsurprisingly, Medicaid reciprocity is inversely related to PI: the thin top line shows the fraction of Medicaid recipients in the bottom 20% of the PI distribution, while the thick bottom line shows median assets in the top 20%. 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 is because the poorest people qualify for Medicaid under the categorically needy provision, where eligibility depends on income and assets, but not the amount of medical expenses.

The Medicaid reciprocity rate tends to rise with age most quickly for people in the middle and highest PI groups. For example, in the oldest cohort and top two PI quintiles the fraction of people receiving Medicaid 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.

Permanent Income Quintile	Average Payment	Reciprocity Rate	Average Payment/ Beneficiary
Bottom	9,080	.70	12,990
Fourth	5,720	.42	13,690
Third	2,850	.16	18,350
Second	1,950	.08	24,360
Top	1,280	.05	23,790

Table 1: Average Medicaid payments, reciprocity, and payments per beneficiary, MCBS.

Table 1 shows average Medicaid payments, the reciprocity rate, and payments per beneficiary in the MCBS data, conditional on PI quintile. Average payments decline with PI. However, this is because reciprocity rates also decline by PI. In fact, the payments received by each Medicaid recipient increases with PI, from \$12,990 at the bottom quintile to \$23,790 at the top.

4.4 Medical expense profiles

In all survey waves, AHEAD respondents are asked about the 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,³ doctor visits, dental visits, and outpatient care. It does

³Nursing home costs include a food and shelter component, besides medical costs, thus raising the question of whether the food and shelter components should be eliminated from the nursing home costs to avoid double counting these items. There are two reasons why this is not as important

not include expenses covered by insurance, either public or private. The AHEAD's expenditure measure is retrospective, as it measures spending over the previous two years. It includes medical expenses during the last year of life, collected through interviews with the deceased's survivors.

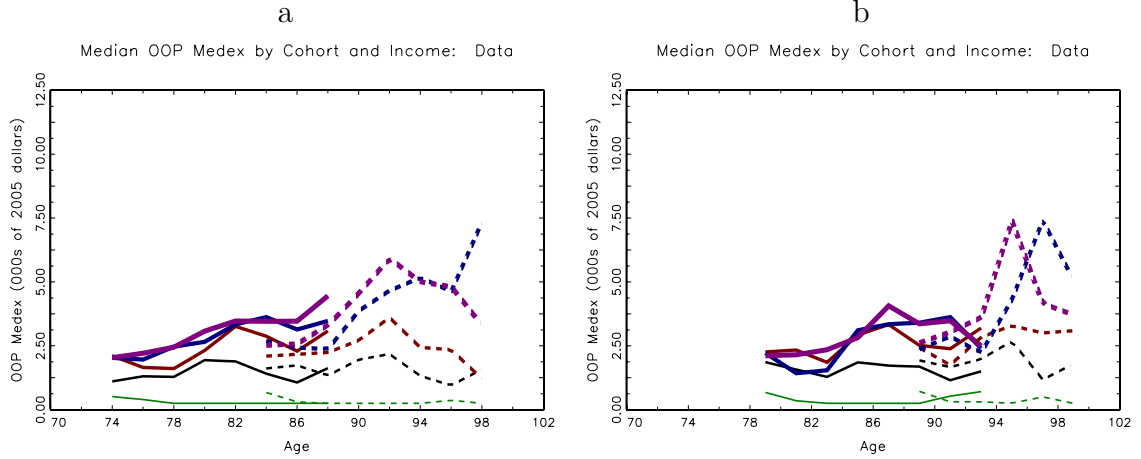


Figure 2: Each line represents median out of pocket medical expenditures for a cohort-income cell, traced over the time period 1996-2010. Thicker lines refer to higher permanent income groups. Panel a: cohorts aged 74 and 84 in 1996. Panel b: cohorts aged 79 and 89 in 1996.

French and Jones [30] show that the medical expense data in the AHEAD line up with the aggregate statistics. For our sample, mean out-of-pocket 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 graphs highlight the large increase in out-of-pocket medical expenses that occurs as people reach very advanced ages, and

as one might expect. First, the food and shelter component of nursing home costs make up for a small share of total nursing home costs. In fact, when we eliminate the food and shelter component of nursing home costs, our medical expense profiles do not change much. Second, many retirees in nursing homes keep their houses (whether owned or rented), expecting to go back to them. Hence, they are paying for two dwellings and it would be wrong to remove the shelter component of nursing homes from for these people. Finally, it should be noted that the shelter component is larger than the food component for most single retirees. For these reasons we believe that our approach most closely approximates reality.

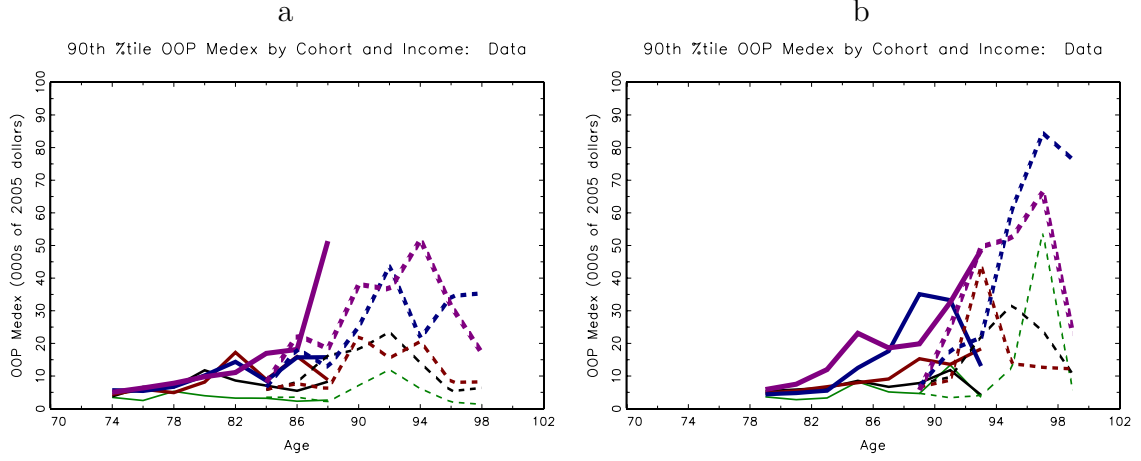


Figure 3: Each line represents the 90th percentile of out-of-pocket medical expenditures for a cohort-income cell, traced over the time period 1996-2010. Thicker lines refer to higher permanent income groups. Panel a: cohorts aged 74 and 84 in 1996. Panel b: cohorts aged 79 and 89 in 1996.

show that this increase is especially pronounced for people in the highest PI quintiles. Protected by Medicaid, individuals in the bottom income quintiles pay less out-of-pocket.

4.5 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 PI, so that the thin bottom line shows median assets in the lowest PI quintile, while the thick 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 88.⁴

⁴The jumps in the profiles are due to the fact that there is dispersion in assets within a cell, and



Figure 4: Each line represents median assets for a cohort-income cell, traced over the time period 1996-2010. Thicker lines refer to higher permanent income groups.

For all PI quintiles in these cohorts, the assets of surviving individuals do not decline rapidly with age. Those with high PI do not run down their assets until their late 80s, although those with low PI tend to have their assets decrease throughout the sample period. The slow rate at which the elderly deplete their wealth has been a long-standing puzzle (see for example, Mirer [51]). However, as De Nardi, French, and Jones [19] 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.

very rapid attrition due to death, especially at very advanced ages. For example, for the highest PI grouping in the oldest cohort, the cell count goes from 29 observations, to 20, and finally to 12 toward the end of the sample. Our GMM criterion weights each moment condition in proportion to the number of observations, so these cells have little effect on the GMM criterion function and thus the estimates.

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. One way to interpret the medical spending in the utility function formulation is that medical spending improves within-period health status. This is a simple way to capture endogenous medical spending, and is similar to other specifications used in the literature (Einav et al. [23], McClellan and Skinner [50], Bajari et al. [3]).

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 [32], in which medical expenses represent investments in health capital, which in turn decreases mortality (e.g., Yogo [68]) or improves health. While a few studies find that medical expenditures have significant effects on health and/or survival (Card et al. [13]; Doyle [16], Finkelstein et al. [26], Chay et al. [15]), most studies find small effects (Brook et al. [7]; Fisher et al. [27]; and Finkelstein and McKnight [25]). These findings confirm that the effects of medical expenditures on the health outcomes are extremely difficult to identify. Identification problems include reverse causality (sick people have higher health expenditures) and lack of insurance variation (most elderly individuals receive baseline coverage through Medicare). To get around these problems, Khwaja [40] estimates a structural model in which medical expenditures both improve health and provide utility. He finds (page 143) that medical utilization would only decline by less than 20% over the life cycle if medical care was purely mitigative and had no curative or preventive components. Blau and Gilleskie [5] also estimate a structural model and reach similar conclusions.

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 are 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 potentially differs between categorically needy ($i = c$) and medically needy ($i = m$) recipients. In practice, the floors for categorically and medically needy recipients are very similar, and we will set them equal in the estimation. We will allow the floors to differ, however, in some policy experiments.

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 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).

In the standard consumption-savings model with exogenous medical spending (e.g., Hubbard et al. [36]), means-tested social insurance is typically modeled as a government-provided consumption floor. In that framework a consumption floor is equivalent to a utility floor, as a lower bound on consumption provides a lower bound on the utility that an individual can achieve. Our utility floor formulation is thus a straightforward generalization of means-tested insurance from the workhorse model, generalized to the case in which people choose their medical expenditures.

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 determined. The individual then chooses consumption, medical expenditure, and savings. 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 do not allow any component of $\mu(\cdot)$ to depend on PI, which 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 .

Since non-asset post-retirement income y_t , is mainly composed of social security and defined benefit pension income, it is not subject to shocks. For example, we found that negative health shocks have little effect on income changes in our AHEAD data. Thus, we model it 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, a person must be eligible for SSI, by satisfying the SSI income and asset tests:

$$y_t + ra_t - y_d \leq \underline{Y} \text{ and } a_t \leq A_d, \quad (11)$$

where: a_t denotes assets; r is the real interest rate; $\underline{Y}$ is the SSI income limit; y_d is the SSI income disregard; and A_d is the SSI asset limit *and* asset disregard. Note that SSI eligibility is based on income *gross* of taxes. Low-income individuals with assets in excess of A_d can spend down their wealth and qualify for SSI in the future.

If a person is categorically needy and applies for SSI and Medicaid, he receives the SSI transfer, $\underline{Y} - \max\{y_t + ra_t - y_d, 0\}$, regardless of his health; in addition to determining income eligibility, $\underline{Y}$ is the largest possible SSI benefit. A sick person, defined here as one who can not achieve the utility floor with expenditures of $\underline{Y}$, receives additional resources in accordance with equation (2). The combined SSI/Medicaid transfer for a categorically needy person is thus given by

$$b_c(a_t, y_t, \mu(\cdot)) = \underline{Y} - \max\{y_t + ra_t - y_d, 0\} + \max\{-\underline{Y}, 0\}, \quad (12)$$

recalling the restrictions on y_t and a_t in equation (11).

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

$$b_m(a_t, y_t, \mu(\cdot)) = \max\{\underline{x}_m(\cdot) - (\max\{y_t + ra_t - y_d, 0\} + \max\{a_t - A_d, 0\}), 0\}, \quad (13)$$

where we assume that the income disregard y_d and the asset disregard A_d are 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_{Mt} to denote this choice, with $I_{Mt} = 1$ if the person applies for Medicaid and $I_{Mt} = 0$ 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

$$V_t(a_t, g, h_t, I, \zeta_t, \xi_t) = \max_{c_t, m_t, a_{t+1}, I_{Mt}} \left\{ u(c_t, m_t, \mu(\cdot)) + \beta s_{g,h,I,t} E_t \left(V_{t+1}(a_{t+1}, g, h_{t+1}, I, \zeta_{t+1}, \xi_{t+1}) \right) + \beta (1 - s_{g,h,I,t}) \theta \frac{(e(a_{t+1}) + k)^{(1-\nu)}}{1 - \nu} \right\}, \quad (14)$$

subject to the laws of motion for the shocks and the following constraints. If $I_{Mt} = 0$, i.e., the person does not apply for SSI and Medicaid,

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

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

$$a_{t+1} = b_i(\cdot) + a_t + y_n(ra_t + y_t) - c_t - q(h_t)m_t \geq 0, \quad (16)$$

$$a_{t+1} \leq \min\{A_d, a_t\}, \quad (17)$$

where $b_i(\cdot) = b_c(\cdot)$ if equation (11) holds, and $b_i(\cdot) = b_m(\cdot)$ otherwise. Equations (15) and (16) both prevent the individual from borrowing against future income. Equation (17) forces the individual to spend at least $\underline{x}_i(\cdot)$, and to keep assets below the limit A_d up through the beginning of the next period.

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 λ_t is the multiplier on the intratemporal budget constraint. The first-order conditions for this problem reduce to

$$m_t = \left(\frac{\mu(\cdot)}{q(h_t)} \right)^{1/\omega} c_t^{\nu/\omega}. \quad (18)$$

This expression can be used to eliminate m_t from the dynamic programming problem in equation (14), and to simplify the computation of $b_i(\cdot)$.

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 ($\nu, \omega, \beta, u_c, u_m$, 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, 5 year birth cohort and year cell (with the top two PI quintiles merged together).
2. Because the effects of Medicaid depend directly on an individual’s asset holdings, we match median asset holdings by PI-cohort-year cell.
3. We match the median and 90th percentile of the out-of-pocket medical expense distribution in each PI-cohort-year cell (the bottom two quintiles are merged). Because the AHEAD’s out-of-pocket 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 PI-cohort-year cell.

The first three sets of moment conditions are those described in section 4.⁵

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. This way we generate attrition in our simulations that mimics precisely the attrition relationships in the

⁵As was done when constructing the figures in section 4, we drop cells with less than 10 observations from the moment conditions. Simulated agents are endowed with asset levels drawn from the 1996 data distribution, and thus we only match asset data 1998-2010.

data (including the relationship between initial wealth and mortality). 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 D 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. Using more waves of data, we update the procedure for estimating the income process described in De Nardi et al. [19]. The procedures for estimating demographic transition probabilities and co-pay rates are new.

7.1 Income profiles

We model non-asset income as a function of age, sex, and the individual’s PI ranking. Figure 5 presents average income profiles, conditional on PI 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.

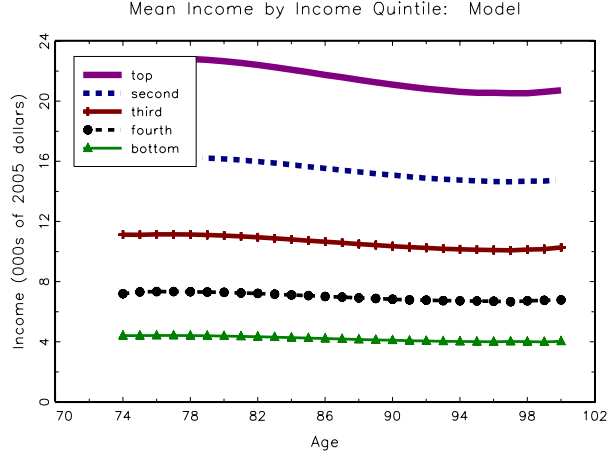


Figure 5: Average income, by permanent income quintile.

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 PI. 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 E 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 2 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 PI percentile in a nursing home expects to live only 1.65 more years, while a female at the 90th percentile in good health expects to live 16.15 more years.⁶

Another important driver of saving is the risk of needing nursing home care. Table 3 shows the probability at age 70 of ever entering a nursing home. The calculations show that 46.1% of women will ultimately enter a nursing home, as opposed to 30.6% for men. These numbers are similar to those from the Robinson model described in

⁶Our predicted life expectancy at age 70 is about three years less than what the aggregate statistics imply. This discrepancy stems from using data on singles only: when we re-estimate the model for both couples and singles, predicted life expectancy is within a year of the aggregate statistics for both men and women. In addition, our estimated income gradient is similar to that in Waldron [67], who finds that those in the top of the income distribution live 3 years longer than those at the bottom, conditional on being 65.

Permanent Income Percentile		<u>Males</u>			<u>Females</u>		
	Nursing Home	Bad Health	Good Health	Nursing Home	Bad Health	Good Health	All [†]
10	1.65	6.02	7.51	2.48	10.01	12.01	10.44
30	1.67	6.63	8.47	2.60	10.98	13.15	11.49
50	1.69	7.32	9.47	2.73	11.99	14.26	12.53
70	1.72	8.04	10.42	2.86	13.02	15.26	13.52
90	1.75	8.81	11.31	3.00	13.94	16.15	14.39
By gender: [‡]							
Men							9.71
Women							13.55
By health status: [◇]							
Bad Health							10.69
Good Health							13.99

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 2: Life expectancy in years, conditional on reaching age 70.

Brown and Finkelstein [8], which show 27% of 65-year-old men and 44% of 65-year-old women require nursing home care.

Permanent	<u>Males</u>		<u>Females</u>		
Income	Bad	Good	Bad	Good	
Percentile	Health	Health	Health	Health	All [†]
10	26.4	30.1	41.2	45.2	40.7
30	26.9	31.2	42.5	46.8	42.2
50	27.2	32.0	43.6	47.9	43.3
70	27.2	32.5	44.1	48.8	43.9
90	27.2	32.4	44.4	49.0	43.9
By gender: [‡]					
Men					30.6
Women					46.1
By health status: [◊]					
Bad Health					39.9
Good Health					45.0

Notes: Percentages 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 3: Percentage of people ever entering a nursing home, conditional on being alive at age 70.

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: $q_t = q(h_t)$.

Using data from the MCBS, we estimate the co-pay rate by taking the ratio of mean out-of-pocket spending plus Medicaid payments to mean total medical expenses. The co-pay rate for people not in a nursing home averages 27% and does not vary much with demographics. The co-pay rate for those in nursing homes is 68%. For every dollar spent on nursing homes, 34 cents come from Medicaid and 34 cents are from out-of-pocket, with 32 cents coming from Medicare or other sources. We cross-checked these co-pay rates with data from the 1997-2008 waves of the Medical Expenditure Panel Survey (MEPS), again making the same sample selection decisions as in the AHEAD. For those not in a nursing home, the MCBS and MEPS estimated co-pay rates were very similar. However, MEPS does not contain information on individuals in nursing homes, so we rely on the estimated co-pay rates from MCBS.

8 Second step results, model fit, and identification

8.1 Parameter values

Table 4 presents our estimated parameters. Our estimate of β , the discount factor, is 0.994. This number has to be multiplied by the survival probability to obtain the effective discount factor. As Table 2 shows, the survival probability for our sample of older individuals is low, implying an effective discount factor much lower than β .

Our estimate of ν , the coefficient of relative risk aversion for “regular” consumption, is 2.8, while our estimate of ω , the coefficient of relative risk aversion for medical goods, is 3.0. Bajari et al. [3] estimate the same utility function in a static model of health insurance choice and medical care utilization. They estimate $\nu = 1.9$ and $\omega = 3.2$. Thus, they also find $\nu < \omega$. However, their estimated value for ν is lower than ours. Because we allow for self-insurance through savings, for given parameters, demand for health insurance will be lower. Thus we need a higher coefficient of consumption risk aversion to explain health insurance and medical spending choices. Einav et al. [23] and McClellan and Skinner [50] also study two period problems in which utility also depends on medical care.

Our estimates imply that the demand for medical goods is less elastic than the

β : discount factor	.994 (0.013)
ν : RRA, consumption	2.825 (0.025)
ω : RRA, medical expenditures	2.986 (0.029)
$\underline{Y}$: SSI income level,	\$6,670 (207)
$\underline{u}_c = \underline{u}_m$: utility floor, [†]	\$4,600 (144)
θ : bequest intensity	39.71 (2.51)
k : bequest curvature (in 000s)	13.0 (0.650)

[†] The estimated utility floor is indexed by the consumption level that provides the floor when $\mu = 0$.

Table 4: Estimated preference parameters. Standard errors are in parentheses below estimated parameters.

demand for consumption. In a recent study, Fonseca et al. [28] calculate that the co-insurance elasticity for total medical expenditures ranges from -0.27 to -0.35, which they find to be consistent with existing micro evidence. Repeating their experiment (a 150% increase in co-pay rates) with our model reveals that elasticities range by age and income: richer and younger people have higher elasticities. To calculate a summary number, we use our model of mortality and an annual population growth rate of 1.5% to find a cross-sectional distribution of ages. Combining this number with our simulations, we find an aggregate cross-sectional elasticity of -0.25.

The SSI income benefit (which is also the income threshold to be categorically needy) is estimated at \$6,670, a number close to the \$6,950 statutory threshold used in many states.

In our baseline estimates, 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 from consuming \$4,604 a year when healthy. It should be noted that the medically needy are guaranteed a minimum income of \$6,670 (\$7,270 including the income disregard) so that their total consumption when healthy is at least \$7,270 a year. However, when there are large medical needs, transfers are determined by the Medicaid-induced utility floor.

The point estimates of θ and k imply that, in the period before certain death, the bequest motive becomes operative once consumption exceeds \$3,500 per year. (See De Nardi, French, and Jones [19] for a derivation.) For individuals in this group, the marginal propensity to bequeath, above the threshold level, is 78 cents out of every additional dollar. Several other authors have recently estimated bequest motives inside structural models of old age saving.⁷ Imposing a linear bequest motive, Kopczuk and Lupton [42] find that agents with bequest motives (around three quarters of the population) would, when facing certain death, bequeath all wealth in excess of \$29,700. De Nardi et al. [19] find that, depending on the specification, the bequest motive becomes active between \$31,500 and \$43,4000, and generates a marginal propensity to bequeath of 88-89%. Lockwood [46] finds a threshold of \$18,400 and a propensity to bequeath of 92%. While these studies suggest bequests are more of a luxury good than do our estimates, none of them seek to explain Medicaid usage. In contrast, Ameriks et al. [2] estimate their model using survey data questions, including hypothetical questions about bequests and long-term care insurance, in a model aimed at assessing Medicaid and medical expense risk. They find a terminal bequest threshold of \$7,100 and a propensity to bequeath of 98%. Compared to them, we find a lower

⁷Assembling these figures requires a few derivations and inflation adjustments. Calculations are available on request.

threshold, but a much higher marginal propensity to consume.

We now turn to discussing how well the model fits the some key aspects of the data, the identification of the model's parameters, and to highlighting some interesting model implications.

8.2 Model fit

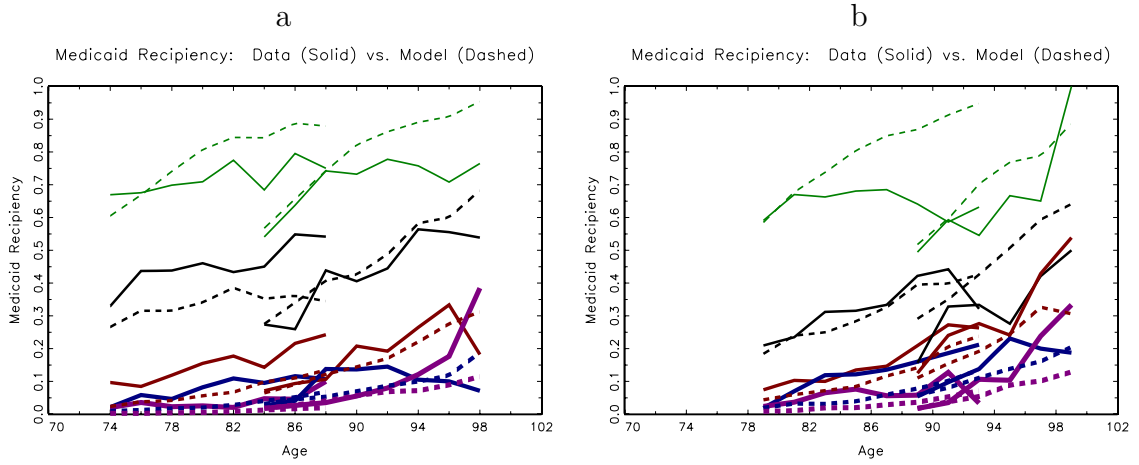


Figure 6: Each line represents Medicaid reciprocity for a cohort-income cell, traced over the time period 1996-2010: data (solid lines) and model (dashed lines). Thicker lines refer to higher permanent income groups. Panel a: cohorts aged 74 and 84 in 1996. Panel b: cohorts aged 79 and 89 in 1996.

Figure 6 compares the Medicaid reciprocity profiles generated by the model (dashed line) to those in the data (solid line) for the members of four 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 the general patterns of Medicaid usage. The model tends to over-predict usage by the poor, especially at older ages, and to underpredict usage by the rich, especially at younger ages.

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

Figure 8 displays the median and ninetieth percentile of out-of-pocket medical expenses (that is, net of Medicaid payments and private and public insurance co-

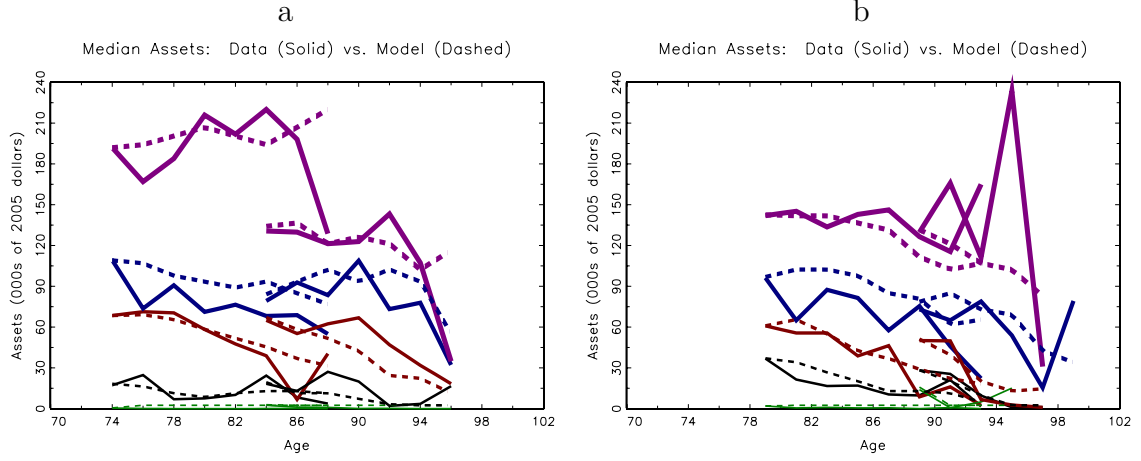


Figure 7: Each line represents median net worth for a cohort-income cell, traced over the time period 1996-2010: data (solid lines) and model (dashed lines). Thicker lines refer to higher permanent income groups. Panel a: cohorts aged 74 and 84 in 1996. Panel b: cohorts aged 79 and 89 in 1996.

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 \$1,500 a year at age 75. By age 100, they stay flat for those in the bottom quintile of the PI distribution but often exceed \$5,000 for those at the top of the PI distribution. Panels a and b show that the model does a reasonable job of matching the medians found in the data. The other two panels report the 90th percentile of out-of-pocket medical expenses in the model and in the data and thus provides a better idea of the tail risk by age and PI. Here the model reproduces medical expenses of \$4,000 or less at age 74, staying flat over time for the lower PI people, but tends to understate the medical expenditures of high-PI people in their late nineties.

Turning to cross-sectional distributions of medical spending, Figure 9 presents three panels. Panel a, in the top left corner, presents the cumulative distribution function (CDF) of out-of-pocket medical expenditures found in the AHEAD and MCBS data, as well as that produced by the model. The solid line is the model-predicted CDF, the dashed line is the AHEAD CDF, and the dotted line is the MCBS CDF. Because the model's parameters are estimated in part by fitting AHEAD out-of-pocket spending profiles—although not the CDF itself—it is not surprising that AHEAD and model-predicted CDFs are very similar. The model CDF also resembles the MCBS CDF, although out-of-pocket medical spending in the MCBS is higher up to the 98th percentile of the spending distribution.

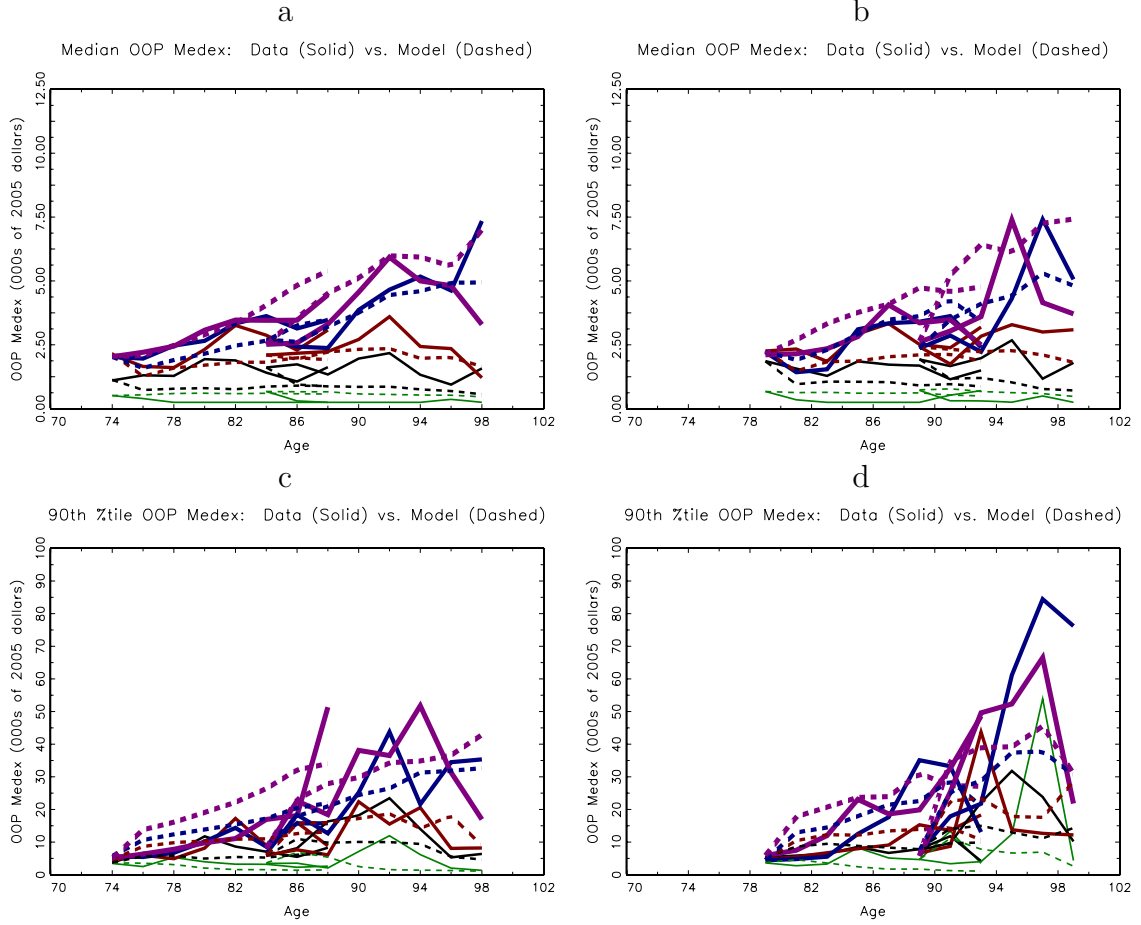


Figure 8: Each line represents median (top panels) and 90th percentile (bottom panels) of medical expenditures for a cohort-income cell, traced over 1996-2010: data (solid lines) and model (dashed lines). Thicker lines: higher permanent income groups. Panels a and b: different cohorts.

Panel b shows the CDF of Medicaid payments, both as predicted by the model and in the MCBS data. Medicaid expenditures in the MCBS data are higher than those predicted by the model up to the 98th percentile, but are lower thereafter. Panel c, at the bottom, shows the CDF of total medical expenditures from all payers. Total expenditures in the MCBS are higher than the model predictions up to the 92nd percentile at \$48,000, and are lower thereafter. In summary, these differences are not large and the model fits well the distribution of-out-of-pocket, Medicaid, and total medical spending. Because Medicaid and total medical expenditures are *not* part of the GMM criterion we use to estimate the model, the ability of the model to fit these data provides additional validation. This feature is important for policy analysis, as

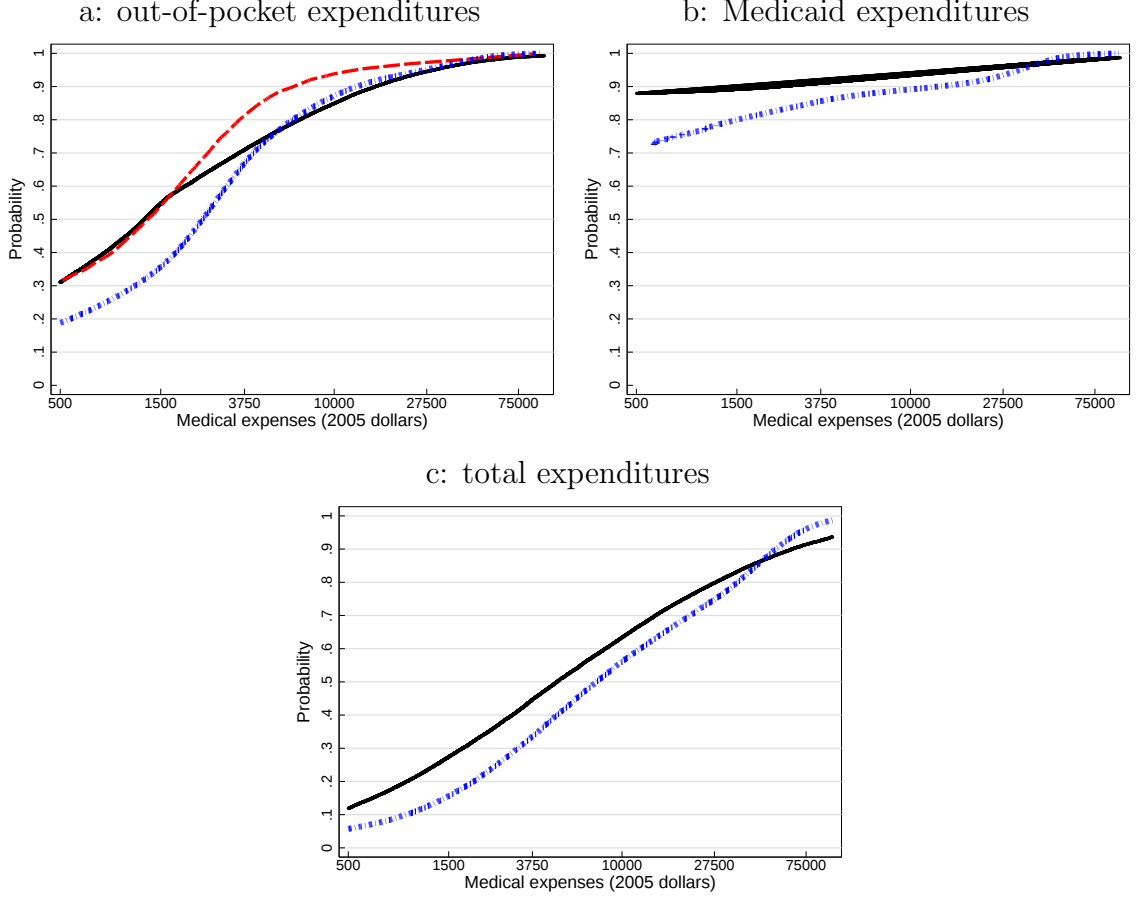


Figure 9: Cumulative distribution functions of medical spending: model (solid line), AHEAD data (dashed line) and MCBS data (dotted line). Panel a: out-of-pocket expenditures. Panel b: Medicaid expenditures. Panel c: total expenditures.

it means the model is able to match the risk of catastrophic medical spending.

Table 5 shows average Medicaid and out-of-pocket expenditures for each PI quintile, both as predicted by the model and as in the data. The first two columns of Table 5 compare Medicaid expenditures in the MCBS data to those predicted by the model. It shows that retirees at the bottom of the PI distribution have average Medicaid expenditures of \$9,080 and \$10,070 in the data and model, respectively. For those at the top of the PI distribution, Medicaid expenditures are \$1,280 and \$2,250 in data and model, respectively. It bears noting that the Medicaid payments reported in the MCBS are on average smaller than those reported in the administrative records: De Nardi et al. [17] find the administrative payments to be nearly

Permanent Income Quintile	Medicaid payments		Out-of-pocket expenses		
	MCBS	Model	MCBS	AHEAD	Model
	Data		Data	Data	
Bottom	9,080	10,070	4,050	2,550	2,210
Fourth	5,720	7,960	5,340	4,270	3,800
Third	2,850	6,000	6,470	5,050	6,330
Second	1,950	3,910	7,300	6,360	8,500
Top	1,280	2,250	8,020	7,000	10,600
Men	2,850	3,780	5,440	4,760	8,280
Women	4,410	5,980	6,470	5,230	6,420

Table 5: Average Medicaid payments and out-of-pocket medical expenditures (2005 dollars), model, MCBS data, and AHEAD data, 1996-2010, for all individuals 72 and older in 1996.

40% higher. Keeping this in mind, Table 5 shows that the model matches Medicaid payments fairly well.

As shown in Table 1, although average Medicaid payments in the MCBS are smaller at the top of the PI distribution, conditional on receiving Medicaid those at the top of the PI distribution receive much larger payments. This is also true in the model. To the best of our knowledge, we are the first to document the progressivity of Medicaid payments among the elderly.⁸

The last three columns of Table 5 compare out-of-pocket expenditures from the MCBS, the AHEAD and the model. The MCBS data shows a less steep PI gradient than the AHEAD data or the model. Those at the bottom of the PI distribution spend \$4,050 in the MCBS data and \$2,380 in the AHEAD data, while expenditures at the top are \$8,020 in the MCBS versus \$6,390 in the AHEAD. Overall, however, the gradients are similar. This similarity in average out-of-pocket expenditures gives us confidence that our facts are robust across datasets. The final column shows the average out-of-pocket expenditures predicted by the model. Overall the model fits the data well for both out-of-pocket and Medicaid expenditures. Details on the

⁸Work by Bhattacharya and Lakdawalla [4] and McClellan and Skinner [50] studied Medicare progressivity.

construction of these cross-sectional comparisons, and additional comparisons, can be found in Appendix A.

8.3 Identification

The preference parameters are identified jointly. There are multiple ways to generate high saving by the elderly: large values of the discount factor 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 [22] point out that the same assets can simultaneously address both precautionary and bequest motives. 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. First, and importantly, we require our model to match Medicaid reciprocity rates, which helps pin down the utility floors and the SSI threshold $\underline{Y}$. To be able to match the fraction of people on Medicaid by PI, cohort, and age, the Medicaid insurance floors have to be substantial, in excess of \$4,500 of consumption by the healthy. A lower floor would generate too few people on Medicaid, especially at higher PI quintiles. By way of comparison, the model with endogenous medical expenses in De Nardi, French and Jones [19], the one most comparable with the model in this paper, was not estimated to match Medicaid reciprocity rates. That model was able to fit the asset data using a similar value of β , no bequest motives, and lower utility floors. This specification matches the asset data very well even with our current, richer specification of the Medicaid program; the combination in fact matches the asset data better than our baseline estimates. However, the Medicaid program implied by those estimates is too stingy to generate the Medicaid fractions observed in the data. Requiring the model to match Medicaid reciprocity thus introduces a tension in the estimation process: Medicaid needs to be fairly generous to generate both a high fraction of people on Medicaid and the pattern of Medicaid reciprocity across age and PI. However, a more generous Medicaid program reduces the need to accumulate assets. To match the same asset profiles under a more generous insurance system we need a higher discount factor and/or a stronger bequest motive.

Requiring the model to match observed out-of-pocket medical expenses, in addition to the other moments discussed above, helps identify the discount factor and the bequest motive. While the two have similar implications for asset holdings, they have different implications for the pattern of non-medical consumption and medical

expenditures over time. A person saving because of high patience will tend to consume more at relatively later ages, and hence will on average, in an environment in which medical needs increase with age, incur more out-of-pocket medical costs in old age. If, instead, people save more due to bequest motives, consumption of medical goods and services does not need to rise as much in old age. Our combination of the Medicaid floor, discount factor, and bequest motives, yields the best fit of these three sets of moment conditions.

The income gradient of medical expenditures helps us pin down the coefficients of relative risk aversion for non-medical and medical goods, ν and ω . The larger these parameters, the less willing individuals are to substitute non-medical and medical goods, over time and with each other. In a world without medical needs shocks, as the coefficient of relative risk aversion for medical goods rises to infinity, the price and income elasticity of its demand falls to zero and consumption of medical goods and services is constant and independent of one's resources (see equation (18)). In a world with medical needs shocks, this result generalizes, and the price and income elasticity of its demand is still zero, the consumption of medical goods and services is just a function of these medical needs shocks and does not depend on one's resources. In contrast, when the coefficient of relative risk aversion for medical goods is finite, equation (18) shows that, holding preferences and prices constant, medical goods expenditure is rising in total expenditure (and resources).

Dividing equation (18) by consumption allows us to obtain the equation governing the optimal ratio of medical goods and services to consumption goods

$$\frac{m_t}{c_t} = \left(\frac{\mu(\cdot)}{q(h_t)} \right)^{1/\omega} c_t^{\frac{\nu-\omega}{\omega}}. \quad (19)$$

This ratio depends on the relative size of the two risk aversion coefficients, ω and μ . As resources (and thus consumption) grow, $\frac{m_t}{c_t}$ falls if people are more risk averse over medical than non-medical goods $\omega > \mu$. Put differently, people with higher wealth and permanent income spend a smaller share of their resources on medical goods than on consumption goods when $\omega > \mu$. Our estimates suggest this is the empirically relevant case. Given our permanent income profiles that the model takes as given, requiring that our model matches the observed out-of-pocket medical expenses as a function of permanent income helps identify the size of these two parameters. In the data, out-of-pocket medical spending rises with permanent income, suggesting ω is finite. However, prior to age 90, the increase in medical expenditure is smaller than the increase in income, suggesting that medical expenditures share of total expenditure is falling in total expenditure, and thus $\omega > \mu$. Hence, inspection of equation (19)

and Figures 2, 3, and 5 help explain how ω and μ are separately identified.

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 the principal way in which we identify these parameters.

8.4 Medical and non-medical spending in old age: trajectories and present discounted values

Figure 10 presents profiles that arise when the youngest cohort is simulated from ages 74 to (potentially) 100. Each simulated individual receives a value of the state vector (t, a_t, g, h_t, I) drawn from the empirical 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.

Panel a of Figure 10 shows average out-of-pocket medical expenses. Out-of-pocket expenditures rise rapidly with age for people in the top PI groups, but remain low throughout retirement for those at the bottom. Panel b shows the sum of medical expenses paid out-of-pocket and the expenses paid by Medicaid. Because the costs picked up by Medicaid are co-pays (part of $q_t m_t$), the sums in panel b are in many ways a better measure of an individual's co-payment expenses than the "pure" out-of-pocket expenditures in panel a. These sums also increase rapidly with age, going from around \$4,000 at age 74 to \$80,000 at age 100. Medicaid allows poorer people to consume far more medical goods and services than they pay for. As a result, the expense sums shown in panel b rise much more slowly with income than do the out-of-pocket expenses shown in panel a.

Panel c displays non-medical consumption, including that funded by government transfers. The consumption profiles differ from the medical expense profiles shown in panel b in two important ways. First, while average medical expenditures rise over retirement by a factor of twenty, average non-medical consumption expenditures decline, albeit slightly, over the same horizon. Second, non-medical consumption rises much more rapidly with PI than does medical expenses. This is consistent with our parameter estimates, which imply that the demand for medical goods is less elastic than the demand for consumption.

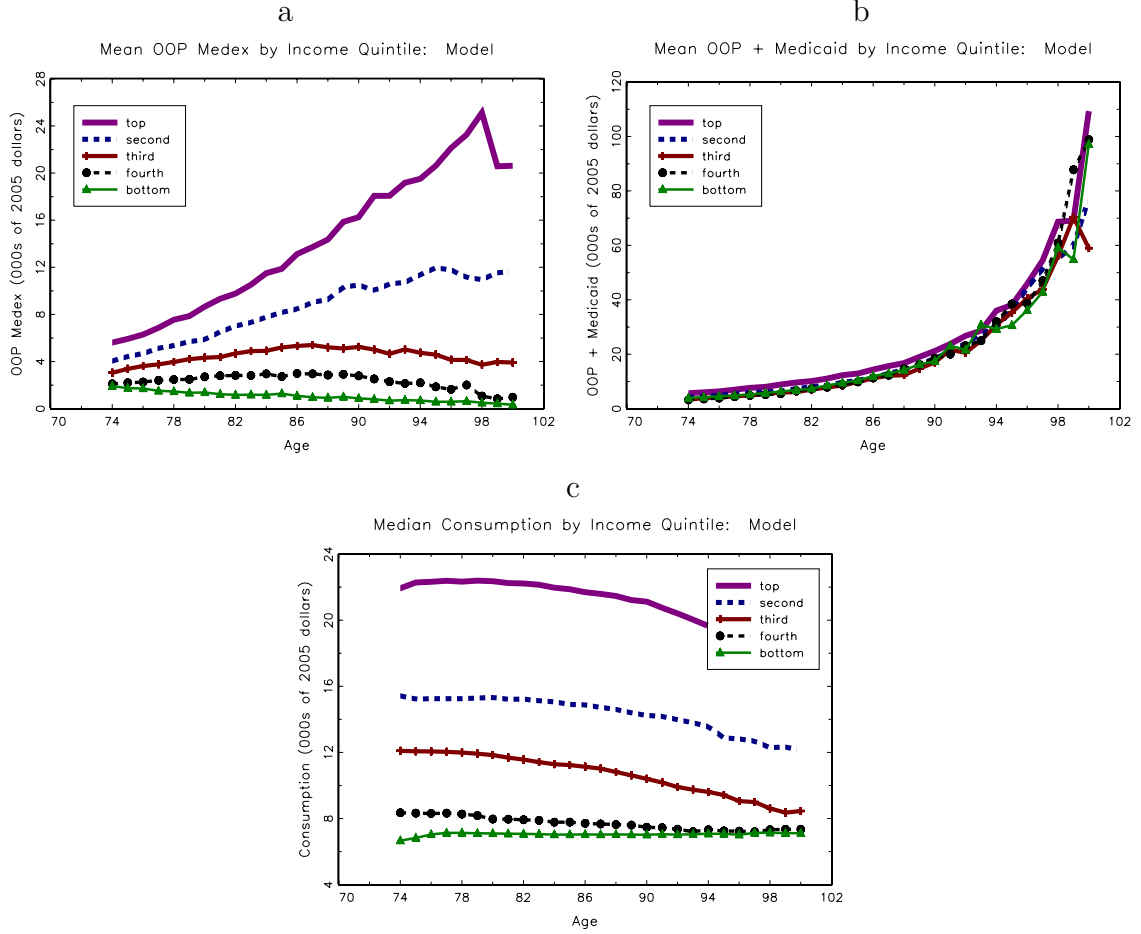


Figure 10: Simulated average expenditures by age and permanent income for the cohort aged 74 in 1996. Panel a: medical expenses paid out-of-pocket. Panel b: medical expenses paid out-of-pocket or by Medicaid. Panel c: consumption.

Figure 11 describes the Medicaid transfers generated by the model, and illuminates the interaction of the utility floor and medical needs shocks. 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 PI quintiles receive Medicaid at fairly high rates throughout their retirement. Most of these people qualify through the categorically needy pathway. People in the top PI 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 11 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 receive greater Medicaid benefits than the rich at all ages, Medicaid transfers to the rich rise more rapidly with age, so that the ratio of transfers received by the rich relative to those received by the poor rises with age.

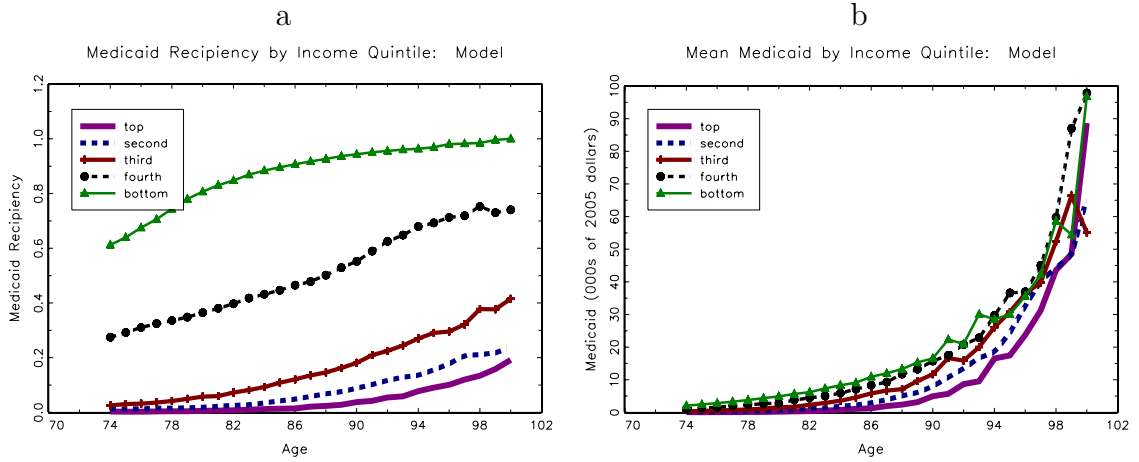


Figure 11: Simulated fraction of people receiving Medicaid (panel a) and average Medicaid transfers (panel b) for the cohort aged 74 in 1996.

After simulating life histories, we convert the expenditure streams into present discounted values, using the model's assumed pre-tax interest rate of 4%. Table 6 shows the present discounted value of both non-medical and medical consumption as of age 74. Table 6 reveals that the consumption of medical goods and services is large relative to the consumption of non-medical goods at all PI levels. However, non-medical consumption rises more quickly in PI than total medical spending, as $\mu < \omega$. Non-medical spending for the poorest is 25% of non-medical spending for the richest. In contrast, the total medical spending of the bottom PI quintile is nearly 50% of the total medical spending of the top quintile. In fact, for low PI individuals, the present discounted value of total medical spending exceeds the present discounted value of non-medical consumption; for high PI individuals, the opposite is true.

The final column of Table 6 shows that out-of-pocket medical expenses rise in PI even more quickly. This is because Medicaid covers a higher share of medical expenses for the poor. Over their lifetime, the out-of-pocket costs of medical goods and services for the income-richest are over 7 times as large as those of the income-poorest. The table also shows that the present discounted value of all spending, medical and non-

Permanent Income Quintile	Non-medical consumption	Medical goods and services	
		Total	Out-of-pocket
Bottom	59,200	108,300	11,200
Fourth	79,700	121,100	20,400
Third	106,800	139,500	35,100
Second	163,900	178,800	55,200
Top	234,900	229,700	80,600
Men	136,000	133,900	42,700
Women	143,800	172,200	46,300
Good Health	173,200	182,200	54,300
Bad Health	97,500	144,000	33,000

Table 6: Present discounted value of non-medical consumption and the consumption of medical goods and services at age 74.

medical, is larger for women than men, as they tend to live almost 4 years longer. Furthermore, those in good health also tend to spend more, as they tend to have longer lives and higher PI.

9 Medicaid payments, taxes, and valuations

9.1 Medicaid payments and taxes

The first column of Table 7 shows the present discounted value of Medicaid payments, beginning at age 74. Although the payments decrease by PI quintile, they are non-trivial for all PI groups. For instance, those in the the highest PI quintile expect to receive \$8,800, which is about 40% of their yearly income. Although the poor are more likely to be receive Medicaid, even the rich are sometimes impoverished by expensive medical conditions, making them eligible for Medicaid benefits too.

These flows reinforce the view that middle- and higher-income people also benefit from Medicaid transfers in old age. Women receive more Medicaid transfers than men, both because they live longer and because they tend to be poorer. Finally,

Permanent Income Quintile	Medicaid Payments	Medicaid Taxes	Taxes/ Payments
Bottom	33,600	6,700	0.20
Fourth	29,400	8,600	0.29
Third	20,400	20,600	1.01
Second	15,100	30,300	2.00
Top	8,800	40,200	4.59
Men	8,600	28,800	3.34
Women	22,400	20,000	0.89
Good Health	17,800	26,400	1.48
Bad Health	23,700	12,500	0.53

Table 7: Present discounted value of Medicaid payments received (simulated from the model), Medicaid taxes paid (computed from the PSID), and the ratio of Medicaid taxes to Medicaid payments, all from the standpoint of age 74.

those in good health at age 74 receive almost as much as those in bad health at 74, because they tend to live long enough to require costly procedures and long nursing home stays.

The middle column of Table 7 calculates the present discounted value at age 74 of the taxes paid to finance Medicaid transfers over all of one’s life, including the working period. Since we do not explicitly model the working period, to calculate Medicaid tax payments, we modify the approach found in Skinner and McClellan (2006), who calculate tax payments for Medicare. We first use data from the Panel Study of Income Dynamics (PSID) to calculate lifetime taxes paid by different groups. Because Medicaid has no dedicated funding source, we assume that it is financed by a tax schedule that is proportional to total tax payments, and that the average Medicaid tax rate in this progressive tax schedule balances the Medicaid budget for this cohort. See Appendix B for more details.

We use the PSID because it includes income from spouses who have died before the AHEAD sample begins. A large share of our sample consists of elderly widows. To capture the progressivity of the taxes they paid when young, we need a data source that includes income from their deceased husbands. Because high income women

tend to marry high income men, ignoring the income and taxes paid by husbands would understate the taxes paid by higher-income widows relative to lower-income people, who might have not been married, or married with lower-earning spouses. Although the AHEAD has tax records from working years, information on taxes paid by deceased spouses is incomplete.

Those in the top PI quintile pay on average \$42,400 in taxes towards Medicaid, nearly 6 times as much as those in the bottom of the PI distribution. This reflects both higher income and higher marginal tax rates. As a result, those at the top of the PI distribution pay in much more than they receive in Medicaid payments. The rightmost column of Table 7 shows the ratio of taxes paid to transfers received. Those at the top of the distribution pay on average \$5 in taxes for every \$1 in payments received, whereas those at the bottom of the distribution pay \$0.21 for every \$1 in transfers received.

9.2 Household valuations of Medicaid

In this section, we simulate changes in Medicaid generosity and compare the resulting increases (or decreases) in government costs to the resulting gains (or losses) in consumer welfare. To measure the costs of a Medicaid reform we compute by how much the present discounted value of Medicaid payments changes when the program changes. This represents the increase (or decrease) in the lifetime actuarial cost of providing Medicaid insurance. To measure the welfare gains, we compute the compensating variation; that is, the immediate payment made after the Medicaid reform that would leave the retiree as well off as before the reform. In particular, the compensating variation at age 74, $\lambda_{74} = \lambda(a_{74}, g, h_{74}, I, \zeta_{74}, \xi_{74})$, is computed as:

$$V_t(a_t, g, h_t, I, \zeta_t, \xi_t; \text{current Medicaid}) = V_t(a_t + \lambda_{74}, g, h_t, I, \zeta_t, \xi_t; \text{Medicaid reform}),$$

where $V_t(a_t, g, h_t, I, \zeta_t, \xi_t; \cdot)$ is the value function for a given set of state variables, either in the world with current Medicaid (left hand side of the equation above) or in a world with a reformed Medicaid program. Our measure is similar to the ones computed for Medicare by Finkelstein and McKnight [25] and McClellan and Skinner [50], but it uses a forward-looking value function, rather than a static utility function. When considering a group, we simply take averages across all its members.

If Medicaid provides retirees with valuable insurance, the compensating variation may exceed the change in the actuarial value of Medicaid payments. On the other hand, people may value the transfer flows at less than their actuarial value. For example, if they are very impatient, they might prefer having the cash today, to

dispose of as they wish, over receiving Medicaid transfers in the future. Furthermore, assets are taxed at 100% for those receiving Medicaid transfers, which in turn distorts savings decisions.

	Categorical floor down 10%			Both floors down 10%		
	(1)	(2)	(3)	(4)	(5)	(6)
Permanent Income Quintile	Reduction in PDV of Payments	Compensating Variation	Ratio of (2)/(1)	Reduction in PDV of Payments	Compensating Variation	Ratio of (5)/(4)
Bottom	4,100	5,600	1.37	4,500	6,300	1.40
Fourth	2,100	2,200	1.05	4,000	5,000	1.25
Third	0.0	0.0	NA	2,900	4,400	1.52
Second	0.0	0.0	NA	2,200	4,100	1.86
Top	0.0	0.0	NA	1,400	4,400	3.14
Men	300	200	0.67	1,300	1,100	0.85
Women	1,200	1,600	1.33	3,100	5,600	1.81
Good Health	700	900	1.29	2,600	4,800	1.85
Bad Health	1,700	2,200	1.29	3,300	5,000	1.52

Notes. Left panel: the categorically needy floor is cut by 10%. Right panel: both Medicaid floors are cut by 10%. Columns (1) and (4): decrease in the present discounted value of Medicaid payments as of age 74. Columns (2) and (5): dollar amount needed to compensate people for the Medicaid benefit cut. Columns (3) and (6): ratio of column (2) to column (1) and column (5) to column (4), respectively, which give the average compensating variation per dollar of reduced Medicaid benefits.

Table 8: The costs and benefits of cutting Medicaid by 10%.

To distinguish the insurance provided by the categorically and the medically needy programs, we first analyze a 10% decrease in the categorically needy utility floor. This corresponds to the consumption of the categorically needy when healthy dropping from \$4,610 to \$4,140. Columns (1) and (2) of Table 8 show that this change only affects people in the bottom two PI quintiles, as people with higher incomes never qualify as categorically needy. The discounted present value of Medicaid payments drops by \$4,100 and \$2,100, respectively, for people in the two bottom PI quintiles. Column (2) reports the compensating variation.

Column (3) presents the ratio of column (2) to column (1), and reveals that the categorically needy people value their lost Medicaid insurance at more than the cost of providing it. However, the ratio is not very large, suggesting that the insurance value of these transfers, at the margin, is not very large. Nonetheless, because this group pays only a small fraction of the transfers' cost (see Table 7), the value they place on their Medicaid benefits almost surely exceeds their associated tax burden.

We next cut the consumption value of both utility floors (that is, both the categorically and medically needy floors) by 10%, and simulate our model again. The right-hand-side panel of Table 8 shows the resulting reductions in Medicaid payments and their compensating variations. A striking feature of this table is that while people in the lowest three PI quintiles value Medicaid fairly close to its cost, people in the top two PI quintiles value Medicaid at two to three times its cost. In fact, the compensating variation for retirees in the top PI quintile, \$4,400, is as big as that of the middle quintile, and is two-thirds as big as the compensating variation at the bottom. The insurance value of Medicaid is very high for these people because of two reasons. First, because these people are high-income they have a high lifetime level of consumption, and thus have more consumption to lose should it fall. Second, they face the double compounded risk of living well past their life expectancy, and facing extremely high medical needs. It is in those states of the world that insurance is most valuable. Offsetting these insurance gains, however, is a redistributive tax system. While individuals in the top income quintile place a value of \$3.14 on each dollar of transfers, they pay \$4.82 of taxes. (See Table 7).

In Table 9, we analyze the benefits of making the Medicaid program more generous, by increasing the Medicaid consumption floor by 10% (from \$4,610 to \$5,070). Table 9 shows that people at the bottom PI quintiles value these Medicaid increases at less than their cost, people in the next two quintiles value them at slightly above cost, and people in the top quintile value them by twice as much. Even though high-income retirees would receive the most bang per buck from a Medicaid expansion, under the current redistributive tax system they would not support it, as their tax burden would rise far more than their valuation. In the aggregate, taking averages over all retirees reveals that the cost increase associated with a more generous Medicaid program exceeds the average valuation.

Put together, the results in Tables 8 and 9 indicate that under current programs rules people value Medicaid transfers at more than their actuarial cost, but that increasing Medicaid's generosity would raise its insurance value by less than its cost. Our model therefore suggests that the current Medicaid system is of about the right size for most currently retired singles.

Permanent Income Quintile	Both floors up 10%		
	(1) Payment Increase	(2) Compensating Variation	(3) Ratio (2)/(1)
Bottom	4,700	2,600	0.55
Fourth	4,200	3,100	0.74
Third	3,100	3,600	1.16
Second	2,300	2,900	1.26
Top	1,300	2,600	2.00
Men	1,400	600	0.43
Women	3,300	3,500	1.06
Good Health	2,500	3,000	1.20
Bad Health	3,500	3,000	0.86

Notes. Column (1): increase in the present discounted value of Medicaid payments at age 74. Column (2): dollar amount people would be willing to pay to receive the higher Medicaid benefits. Column (3) is the ratio of column (2) to column (1), which show the average compensating variation per dollar of reduced Medicaid benefits.

Table 9: The costs and benefits of increasing Medicaid payments by 10%.

9.3 Long-term-care insurance

While our model includes endogenous medical spending and several dimensions of individual-level heterogeneity, it abstracts from the decision to purchase long term care insurance (LTCI). Only about 9% of elderly singles have LTCI (Lockwood [46]) and only 4% of LTC expenditures are paid for by LTCI (Congressional Budget Office [55]). Given that our results suggest that the elderly, and especially the high income elderly, value Medicaid insurance heavily, it is surprising that the market for LTCI is so small.

Brown and Finkelstein argue that that one major reason that the LTCI market is so small is that Medicaid crowds out LTCI and thus that major reductions in Medicaid would increase LTCI use. This is due to the fact that Medicaid is a payer of last resort and is subject to asset and income tests. Therefore LTCI payments for nursing home care would often reduce Medicaid payments for the same services.

If there are fixed costs to acquiring/providing or discarding LTCI, larger changes in Medicaid generosity are more likely to induce changes in LTCI holdings. Our experiments thus involve relatively small changes to the Medicaid program, which imply smaller incentives to change LTCI positions. But even in the absence of transaction costs, there are other important reasons why LTCI use is limited and why it would likely stay limited even if Medicaid generosity was reduced. These factors include:

1. Lack of efficiency in the private market for long-term care insurance. Prices are high: Brown and Finkelstein [9] report that imperfect competition and transaction costs result in prices that are marked up substantially above expected claims, with loads on typical policies about from 18 to 51 cents on the dollar, depending on whether one takes into account lapsed policies. These loads are much higher than loads that have been estimated in other private insurance markets and point to the existence of one or more supply side imperfections.
2. Limited insurance against nursing home risk. Brown and Finkelstein [10] report that comprehensive LTCI contracts are offered but are not purchased. The typical LTCI contracts held by households cap both the maximum number of days covered over the life of the policy and the maximum daily payment for a nursing home stay, a daily payment that is often fixed in nominal terms (Fang [24]). Even the policies that provide some kind of indexation of the daily maximum payment are typically linked to aggregate price indexes rather than actual nursing home costs, thus generating substantial purchasing power risk between the time a person purchases the policy and the time she enters a nursing home. As a result, most available policies do not provide insurance against tail risk, which is exactly the risk that the richest in our model fear the most, due to longer longevity and higher risk of large medical needs when very old.
3. Severe adverse selection. Hendren [34] shows that when private information problems are sufficiently large, within certain subgroups insurance markets will fail to emerge. His main empirical findings are that a large fraction of those applying for insurance are rejected by underwriters, and that those who are rejected hold significant private information. He also finds that 23% of 65 year olds have health conditions that preclude them from purchasing LTCI.
4. Bequest motives (Lockwood [46]). In a framework with exogenous medical spending, Lockwood argues that reasonably estimated bequest motives, together with medical expense risk, help fit the patterns of both asset decumu-

lation and LTCI purchases seen in the data. We also estimate a significant bequest motive, which reduces the value of LTCI.

9.4 Adverse selection and moral hazard

Because our model allows individuals to choose their savings and medical expenditures, it generates moral hazard along those dimensions. Moral hazard arises within our model both contemporaneously, in that retirees may purchase too much subsidized health care, and dynamically, in that people might be over-spending over a number of periods to qualify for Medicaid in the future.

A change in Medicaid generosity has two effects. First, it mechanically changes eligibility and transfers at any given level of individual resources. Second, it changes the incentives to consume and save. To help disentangle these effects, Figure 12 compares the asset, spending and Medicaid reciprocity profiles from the estimated baseline model (dashed line) and the model with a 10% reduction in the Medicaid utility floor, the same cut considered in columns (4)-(6) of Table 8. Figure 12 shows that the effects of a 10% Medicaid cut on the asset and spending profiles are smaller than its effects on the Medicaid reciprocity profiles, especially for the second and third income quintiles. This indicates that the mechanical effects of changing Medicaid are larger than the effects of moral hazard. Moreover, while cutting Medicaid leads to a small decrease in total medical expenditures, out-of-pocket expenditures *increase*, again suggesting that the mechanical effects dominate the moral hazard effects.

Using data from a large self-insured employer, Bajari et al. [3] find significant moral hazard. The exercise they use to measure moral hazard, however, involves the effective elimination of insurance: the co-pay rate q is set to 1. In our Medicaid reforms, the copay rates remain at their baseline values, as we are not considering changes to Medicare.

Our model generates considerable heterogeneity in health, mortality, and expected medical expenditures. To quantify the extent to which the Medicaid population are adversely selected on the basis of their medical spending, Table 10 compares Medicaid recipients to other retirees along several dimensions. We construct Table 10 by simulating the baseline model over the sample period 1996-2010 and taking cross-sectional averages. The first row of the table shows, unsurprisingly, that Medicaid recipients are considerably poorer. The second row shows that Medicaid recipients indeed have much higher total medical spending.

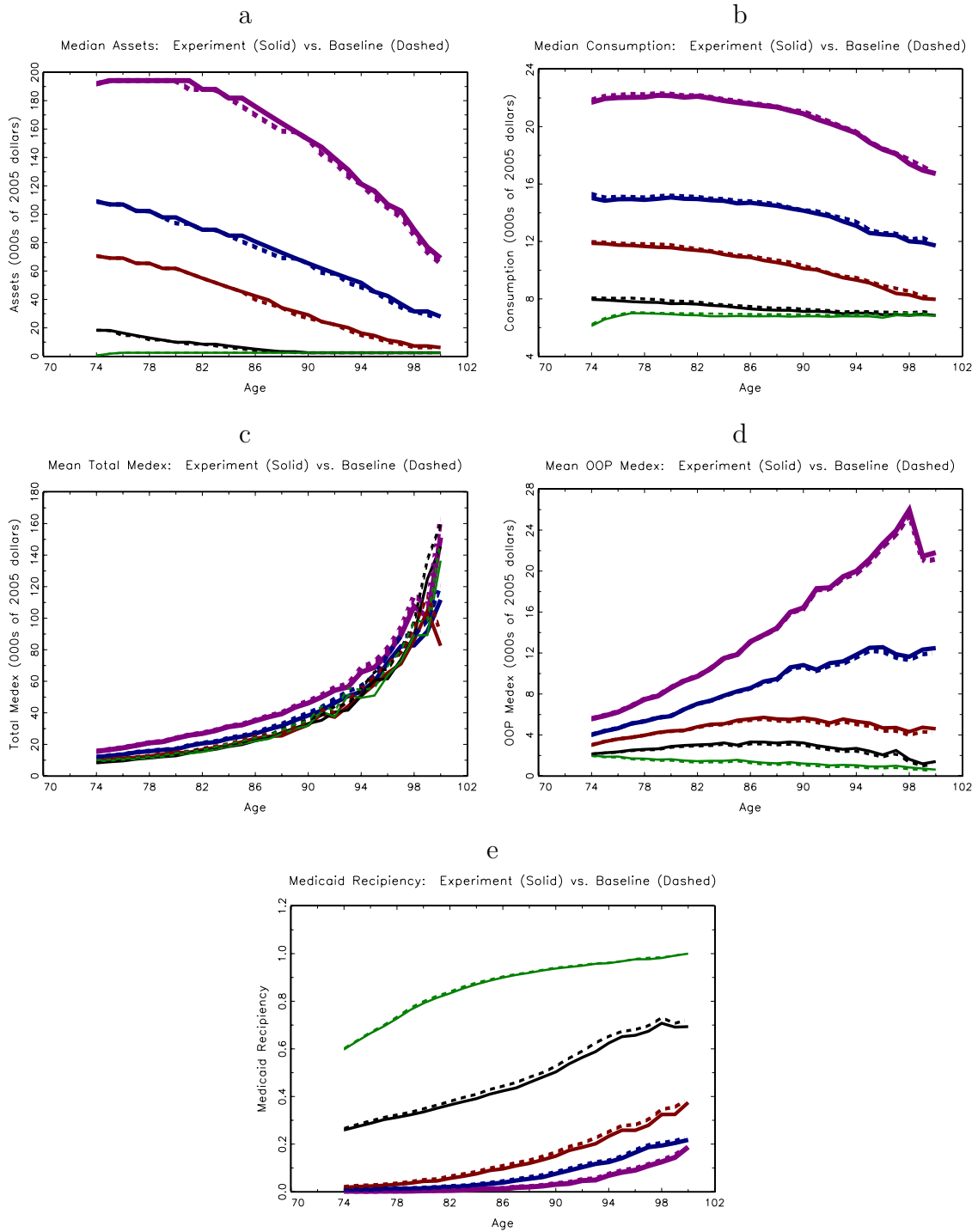


Figure 12: Assets (panel a), consumption (panel b), total and out-of-pocket medical spending (panels c and d), and Medicaid reciprocity rates (panel e) by age and permanent income. Dashed line: benchmark, solid line: 10% Medicaid cut.

Because medical spending in our model represents the convolution of medical needs (μ) and financial incentives, we also present means of the medical preference shifter mu . Bajari et al. [3] measure adverse selection in a similar, if more detailed, way. Although the absolute levels of the shifters are not easily interpreted, it is clear that Medicaid recipients have a much higher demand for medical services. The increased demand comes not only from observable factors such as health and age, but also from unobservable factors, which the model captures with the idiosyncratic shock ψ . In short, Medicaid recipients are sicker than average, consistent with Medicaid’s role as the payer of last resort, and consistent with our argument that Medicaid provides valuable insurance against catastrophic medical events.

	All Retirees	Medicaid Recipients	Non- Recipients
Net Income	16,270	6,240	19,020
Medical spending			
Total	28,930	61,820	19,920
Out-of-pocket	6,680	2,940	7,700
Medicaid	5,680	26,440	0
Medical needs shifter (μ)	1,270	5,150	210
Medical spending shock ($\ln(\psi)$)	-0.003	0.250	-0.072
Fraction of population (%)	100.0	19.7	80.3

Table 10: Comparison of Medicaid and non-Medicaid recipients: Simulations

10 Conclusion

In this paper we assess the effects of Medicaid insurance on single retirees. Although Medicaid payments do decrease with permanent income, even higher income people can receive sizeable Medicaid payments, as they tend to live longer and face higher medical needs in very old age. Furthermore, our compensating variation calculations show that many higher income retirees value Medicaid insurance as much or more than lower-income ones.

Our compensating variation calculations also indicate that retirees value Medicaid insurance at more than its actuarial cost, but that most would value expansions of the current Medicaid program at less than cost. This suggests that the Medicaid program may currently be of the approximate right size for single retirees.

In focusing on single retirees, we study the population that is most likely to receive Medicaid transfers. The data shows that couples tend to be much richer and less likely to end up in nursing homes, and thus receive much smaller Medicaid payments. For example, singles in our MCBS sample on average receive \$3,760 in Medicaid transfers a year, while couples in the same age range on average receive \$2,140, or \$1,070 per person. It nonetheless would be interesting in future work to extend our analysis to include the valuation of Medicaid insurance by couples.

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Appendix A: for online publication: the MCBS data

In order to assess the accuracy of the model’s predictions, we compare model-predicted distributions of out-of-pocket and Medicaid medical spending to the distributions observed in the AHEAD and MCBS data in the main text of the paper. Here, we describe in greater detail the construction and accuracy of the MCBS data.

The MCBS is a nationally representative survey of disabled and age-65+ Medicare beneficiaries. The survey contains an over-sample of beneficiaries older than 80 and disabled individuals younger than 65. Respondents are asked about health status, health insurance, and health care expenditures (from all sources). The MCBS data are matched to Medicare records, and medical expenditure data are created through a reconciliation process that combines information from survey respondents with Medicare administrative files. As a result, the survey is thought to give extremely accurate data on Medicare payments and fairly accurate data on out-of-pocket and Medicaid payments. As in the AHEAD survey, the MCBS survey includes information on those who enter a nursing home or die. Respondents are interviewed up to 12 times over a 4 year period. We aggregate the data to an annual level.

In order to assess the quality of the medical expenditure data in the MCBS, we benchmark it against administrative data from the Medicaid Statistical Information System (MSIS) and survey data from the AHEAD. For Medicare payments, the match is close. For example, when using population weights, the number of Medicare beneficiaries lines up almost exactly with the aggregate statistics. More important, Medicare expenditures per beneficiary are very close. Over the 1996-2006 period, MCBS Medicare expenditures per capita for the age 65+ population are \$6,070, only 11% smaller than the value of \$6,820 in the official statistics.⁹

The MCBS also accurately measures the share of the population receiving Medicaid payments.¹⁰ However, MCBS Medicaid payments for the age 65+ population are on average 32% smaller than what administrative data from the MSIS suggest.

⁹Medicare statistics are located at http://www.census.gov/compendia/statab/cats/health_nutrition/medicare_medicaid.html.

¹⁰According to MCBS data, there were on average 5.1 million age 65+ Medicaid beneficiaries over the 1996-2006 period, versus 4.7 million “aged” (which mostly refers to aged 65+) Medicaid beneficiaries in the MSIS data. This difference potentially reflects a small number of Medicaid age 65+ individuals who are classified as “disabled” instead of “aged” in the MSIS data. Medicaid MSIS statistics are located at <https://www.cms.gov/Research-Statistics-Data-and-Systems/Computer-Data-and-Systems/MedicaidDataSourcesGenInfo/MSIS-Tables.html>. See De Nardi et al. [17] for further comparisons of the MCBS data to administrative data on Medicare and Medicaid beneficiaries and payments.

Expenditure Percentile	Percentage of Medicaid enrollees	Percentage of Medicaid expenditures (MSIS)	Average expenditure per enrollee (MSIS)	Average expenditure per enrollee (MCBS)
everyone	100%	100%	13,410	8,630
95-100%	5%	40.5%	100,060	69,410
90-95%	5%	20.1%	50,180	37,510
70-90%	20%	32.5%	21,940	13,150
50-70%	20%	5.9%	3,690	2,460
0-50%	50%	1.0%	240	330

Note: 2010 MSIS data, adjusted to 2005 dollars

Table A1: Medicaid enrollment and expenditures by enrollee spending percentile, MSIS versus MCBS.

Table A1 compares the distribution of the MSIS administrative payment data (taken from Young et al. [69]) to data from the MCBS. We show the MCBS distribution for all dual Medicare/Medicaid beneficiaries, the set closest to the sample in the MSIS data. 59% of all dual eligibles are age 65+, the other 41% being disabled individuals under age 65 who are potentially more costly than the age 65+ dual eligibles. Table A1 shows both means and means conditional on the distribution of payments. The MSIS data show that the least costly 50% of all Medicaid enrollees account for only 0.9% of total Medicaid payments, whereas the most costly 5% of all beneficiaries are responsible for 41% of payments. Although the MCBS data match the MSIS data well across the bottom 70% of the distribution, the top 5% of all payments in the MSIS average \$100,060, whereas in the MCBS they are \$69,810. Limiting the MCBS sample to our estimation sample (retired singles who meet our age selection criteria: greater than 70 in 1994, 72 in 1996, 74 in 1998, etc.) leads to higher payments: average Medicaid payments of Medicaid beneficiaries in this MCBS subsample are \$13,620.

The next set of benchmarking exercises that we perform is for out-of-pocket medical spending, Medicaid reciprocity and income between the AHEAD and MCBS. We restrict the sample to singles (over the sample period) who meet the AHEAD age criteria (at least 70 in 1994, 72 in 1996, ...) and who are not working over the sample period, just as we do in the AHEAD data. We construct a measure of permanent income, which is the percentile rank of total income over the period we observe these

Income Quintile	Total income	AHEAD data			Total income	MCBS data	
		Annuity income	Out-of-pocket expenses	Medicaid reciprocity		Out-of-pocket expenses	Medicaid reciprocity
1	7,740	4,820	2,550	60.9%	6,750	4,050	69.9%
2	10,290	8,270	4,270	28.1%	10,020	5,340	41.8%
3	15,500	10,900	5,050	11.0%	13,740	6,470	15.5%
4	19,290	14,390	6,360	5.6%	19,710	7,300	8.0%
5	33,580	26,300	7,000	3.0%	44,150	8,020	5.4%

Table A2: Income, out-of-pocket spending, and Medicaid reciprocity rates, AHEAD versus MCBS, 1996-2010, for those age 72 and older in 1996.

individuals (the MCBS asks only about total income). The first four columns of Table A2 show sample statistics from the full AHEAD sample while the final three columns of the table shows sample statistics from the MCBS sample. The first statistics we compare are income. Total income in the AHEAD data (including asset and other non-annuitized income) lines up well with total income in the MCBS data, although income in the top quintile of the MCBS is higher than in the AHEAD. Next we compare out-of-pocket medical spending in the MCBS and AHEAD. Out-of-pocket medical expenditure (including insurance payments) averages \$2,360 in the bottom PI quintile and \$6,340 in the top quintile in the AHEAD. In comparison, the same numbers in the MCBS data are \$3,540 and \$7,020. Overall, out-of-pocket medical spending in the MCBS and AHEAD are similar, which may be surprising given that the two surveys each have their own advantages in terms of survey methodology.¹¹ The share of the population receiving Medicaid transfers is also very similar in the AHEAD and MCBS. 61% and 70% of those in the bottom PI quintile are on Medicaid in the the AHEAD and MCBS, respectively. In the top quintile, 3% of people are on Medicaid in the AHEAD whereas 5% are in the MCBS. The higher Medicaid reciprocity rate in the MCBS might reflect that the MCBS data has administrative information on whether individuals are on Medicaid, which eliminates underreporting

¹¹There are more detailed questions underlying the out-of-pocket medical expense questions in the AHEAD, including the use of “unfolding brackets”. Respondents can give ranges for medical expense amounts, instead of a point estimate or “don’t know” as in the MCBS. The MCBS has the advantage that forgotten medical out-of-pocket medical expenses will be imputed if Medicare had to pay a share of the health event.

problems.

We also assessed the usefulness of the Medicaid-related data in MEPS. A key problem with the MEPS data, however, is that it does not include information on nursing home stays or expenses in the last few months of life. Using data from MSIS, Young et al. [69] report that among those aged 65 and older, 79% of all Medicaid expenses are for long term care (although only 14% of these beneficiaries are receiving long term care). The MEPS data are useful for understanding the remaining 21% of Medicaid payments. Consistent with this fact, mean Medicaid payments in the MEPS for elderly beneficiaries are only \$3,499, whereas they are \$8,630 in the MCBS, and \$13,414 according to the administrative data from the MSIS.

Appendix B: For online publication: the PSID data and our tax calculations

The lifetime contribution towards Medicaid is calculated using data on household federal tax payments from the PSID. Our calculations require two steps. The first one creates a PSID sample that is comparable to the AHEAD sample. The second step computes the present discounted value of lifetime taxes for each individual and aggregates it by PI quintile, gender, and health status.

To generate a sample from the PSID that matches that from the AHEAD as closely as possible, we use only individuals that by 1996 are single, make no significant labor income, and are aged 70 to 79. In the AHEAD sample the cohort is aged 72 to 76 but for sample size reasons in the PSID we increase the window from 5 years to 10 years. This leaves a sample of 112 individuals, who are then sorted by permanent income into income quintiles as is done with the AHEAD data.

To compute taxes, we start by computing permanent income, which is the average annuity income for each person, where annuity income is calculated as the sum of Social Security, VA Pensions, non-VA Pensions, and Annuities. To match the AHEAD data this is calculated for the years the individual remained alive in 1996, 1998, 2000, 2002, 2004, 2008, and 2010.

Table A4 compares mean annuity income for each income quintile in the PSID sample and the AHEAD sample and shows that they match closely. After being sorted by income quintiles, the PDV of total household federal taxes (value in 1995, measured in 2005 dollars) is calculated for each income quintile-gender group g , as follows:

$$PDV(taxes, g) = \frac{\sum_{t=1967}^{2015} w(g, t) \frac{1}{I(g)} \left(\sum_{i \in g} tax(i, t) \prod_{j=t+1}^{2015} (1 + r(j)) \right)}{\left(\prod_{z=1995}^{2015} (1 + r(z)) \right) \cdot \left(\prod_{q=2005}^{2015} (1 + i(q)) \right)}$$

	AHEAD data		PSID data	
	Number	%	Number	%
Men	138	19.4	19	17.0
Women	573	80.6	93	83.0
Good Health	433	60.9	72	64.3
Bad Health	258	36.3	40	35.7
Nursing Home	20	2.8	0	0.0
Total Observations	711	100	112	100

Table A3: Sample size comparison, AHEAD versus PSID, 1996-2010.

where $w(g, t)$ is the probability that a member of group g is alive at time t , conditional on being alive in 1967. The mortality rates behind $w(g, t)$ are taken from McClellan and Skinner (2006) until age 70 and are then updated using data from the US Life Tables for 2009. $I(g)$ is the number of people in group g , $tax(i, t)$ is the household federal taxes of individual i in year t , $r(j)$ is the nominal interest rate in year j , and $i(j)$ is the inflation rate. Since after 1990 the PSID no longer reports the value of taxes paid, we assume that tax payments after that year equal those paid in 1990, inflation-adjusted. We also assume a 3% real interest rate. We sum across all individuals to calculate the aggregate PDV of federal taxes. Given the total taxes paid for each

PI Quintile	AHEAD data	PSID data
Bottom	4,830	4,530
Fourth	8,900	8,960
Third	12,550	11,920
Second	16,930	16,970
Top	32,250	31,160
Overall Average	15,710	15,880

Table A4: Annuity income comparison, AHEAD versus PSID, 1996-2010.

group, we need to determine what fraction of these taxes was related to Medicaid.

To determine the average Medicaid tax rate necessary to balance the Medicaid budget for this cohort, we sum the present discounted value of Medicaid transfers reported in table 7 across individuals. The ratio of the present discounted value of Medicaid transfers to the present value of total taxes paid is $\aleph$, the share of total taxes used to fund Medicaid for the elderly.

Finally, the PDV of contributions to Medicaid for each PI quintile (or gender and health group) is calculated for each group as $\aleph$ multiplied by the PDV of federal taxes for that group.

Appendix C: for online publication: computational details

This Appendix details our simulation procedure.

1. Our initial sample of simulated individuals consists of 150,000 random draws from the first wave of our data. We use all individuals as drawn, regardless of their initial state vector.
2. We assign entire health and mortality histories to insure that we properly match how our sample composition changes with age. One issue is that our sample is fairly small, so that the medians (or 90th percentiles) of wealth or medical spending in some cohort-income groups can change with the deaths of a few individuals. While we expect these effects to average out if we forward-simulated demographic transitions, it is simpler to match the data if we base our simulations on actual life histories. A more fundamental issue is that the processes for health and mortality that we feed into the model do not depend on wealth because wealth is an endogenous variable in our model. However, we know that high wealth is a good predictor of longevity, conditional on the other state variables. Our simulation procedure captures the initial wealth/mortality gradient by construction, whereas our estimated health and mortality transition models do not.

Appendix D: for online publication: moment conditions and asymptotic distribution of parameter estimates

Recall that we estimate the parameters of our model in two steps. In the first step, we estimate the vector χ , the set of parameters than can be estimated without 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 $\nu, \omega, \beta, \underline{Y}, \underline{u}, \theta, k$, 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 $t \in \{t_0, \dots, t_T\} = \{1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010\}$, we match median assets for $Q_A = 5$ permanent income quintiles in $P = 5$ birth year cohorts.¹² 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

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

The preceding equation can be rewritten as a moment condition (Manski [48], Powell [63] and Buchinsky [12]). In particular, applying the indicator function produces

$$E(1\{a_{it} \leq a_{pqt}(\Delta_0, \chi_0)\} - 1/2 \mid p, q, t, \text{individual } i \text{ observed at } t) = 0. \quad (20)$$

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 [14]):

$$\begin{aligned} E \left([1\{a_{it} \leq a_{pqt}(\Delta_0, \chi_0)\} - 1/2] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \right. \\ \left. \times 1\{\text{individual } i \text{ observed at } t\} \mid t \right) = 0 \end{aligned} \quad (21)$$

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

We also include several moment conditions relating to medical expenses. Recall that within the model medical expenses are chosen annually and are forward-looking (i.e., for the calendar year in which they are chosen). In contrast, medical expenditures in the AHEAD are averages of spending over the preceding two years. To reconcile the two measures, we first simulate medical expenses at an annual frequency,

¹²Because we do not allow for macro shocks, in any given cohort t is used only to identify the individual’s age.

take two-year averages, and move the resulting averages back one year, to produce a measure of medical expenditures comparable to the ones contained in the AHEAD. This means that the AHEAD measure for medical spending in 2000 will be compared to averages of model-simulated spending for 1999 and 1998.

As with assets, we divide individuals into 5 cohorts and match data from 7 waves covering the period 1998-2010. (Because the model starts in 1996, while the medical expense data are averages over 1995-96, we cannot match the first wave.) 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 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:

$$E\left([1\{m_{it} \leq m_{pqt}^{50}(\Delta_0, \chi_0)\} - 0.5] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \times 1\{\text{individual } i \text{ observed at } t\} \mid t\right) = 0 \quad (22)$$

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:

$$E\left([1\{m_{it} \leq m_{pqt}^{90}(\Delta_0, \chi_0)\} - 0.9] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \times 1\{\text{individual } i \text{ observed at } t\} \mid t\right) = 0 \quad (23)$$

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:

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

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

$$\begin{aligned} E \left(\left[\frac{R_{it} R_{i,t-1}}{\sigma_{pqt} \sigma_{pq,t-1}} - AC_{pqt1}(\Delta_0, \chi_0) \right] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \right. \\ \left. \times 1\{\text{individual } i \text{ observed at } t \text{ \& } t-1\} \middle| t \right) = 0. \end{aligned} \quad (24)$$

The corresponding moment condition for the second autocorrelation is

$$\begin{aligned} E \left(\left[\frac{R_{it} R_{i,t-2}}{\sigma_{pqt} \sigma_{pq,t-2}} - AC_{pqt2}(\Delta_0, \chi_0) \right] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \right. \\ \left. \times 1\{\text{individual } i \text{ observed at } t \text{ \& } t-2\} \middle| t \right) = 0. \end{aligned} \quad (25)$$

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

$$\begin{aligned} E \left([u_{it} - \bar{u}_{pqt}(\Delta_0, \chi_0)] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \right. \\ \left. \times 1\{\text{individual } i \text{ observed at } t\} \middle| t \right) = 0 \end{aligned} \quad (26)$$

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 (21); the moments for median medical expenses described by equation (22); the moments for the 90th percentile of medical expenses described by equation (23); the

moments for the autocorrelations of logged medical expenses described by equations (24) and (25); and the moments for the Medicaid utilization rates described by equation (26). In the end, we have a total of $J = 631$ 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 [58] and Duffie and Singleton [21], 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;

$$\mathbf{D} = \frac{\partial \varphi(\Delta; \chi_0)}{\partial \Delta'} \Big|_{\Delta = \Delta_0} \quad (27)$$

is the $J \times M$ gradient matrix of the population moment vector; and $\mathbf{W} = \operatorname{plim}_{I \rightarrow \infty} \{\widehat{\mathbf{W}}_I\}$. Moreover, Newey [53] 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 [1].) We thus use a “diagonal” weighting matrix, as suggested by Pischke [61]. 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 (21). 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 [58], Newey and McFadden [54] (section 7), and Powell [63].

To find $\mathbf{D}$, it is helpful to rewrite equation (21) as

$$\Pr \left(p_i = p \ \& \ I_i \in \mathcal{I}_q \ \& \ \text{individual } i \text{ observed at } t \right) \times \left[\int_{-\infty}^{a_{pqt}(\Delta_0, \chi_0)} f(a_{it} \mid p, I_i \in \mathcal{I}_q, t) \, da_{it} - \frac{1}{2} \right] = 0. \quad (28)$$

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

$$\Pr \left(p_i = p \ \& \ I_i \in \mathcal{I}_q \ \& \ \text{individual } i \text{ observed at } t \right) \times f(a_{pqt} \mid p, I_i \in \mathcal{I}_q, t) \times \frac{\partial a_{pqt}(\Delta_0; \chi_0)}{\partial \Delta'}. \quad (29)$$

In practice, we find $f(a_{pqt} \mid p, q, t)$, the conditional p.d.f. of assets evaluated at the median a_{pqt} , with a kernel density estimator written by Koning [41]. The gradients for equations (22) and (23) are found in a similar fashion.

Appendix E: for online publication: demographic transition probabilities in the 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 $i \in \{1, 2, 3\}$, $j \in \{0, 1, 2, 3\}$,

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

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

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.