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Medicaid Insurance in Old Age†

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The old age provisions of the Medicaid program were designed to insure retirees against medical expenses. We estimate a structural model of savings and medical spending and use it to compute the distribution of lifetime Medicaid transfers and Medicaid valuations across currently single retirees. 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. (*JEL* C51, H51, I13)

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. In this paper we seek to fill this gap.

We focus on single retirees, who comprise about 50 percent of people aged 70 or older and 70 percent of households aged 70 or older. We document new facts on Medicaid recipiency in the Assets and Health Dynamics Among the Oldest Old (AHEAD) data and show that, while the recipiency rate in the bottom income quintile is around 70 percent throughout retirement, the recipiency rate of higher-income

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retirees is initially very low, but increases with age, reaching 20 percent by age 95. Thus, even high-income people become Medicaid recipients if they live long enough and are hit by expensive medical conditions. Moreover, we document new facts from the Medicare Current Beneficiary Survey (MCBS) and show that high-income individuals, conditional on receiving Medicaid transfers, actually receive larger transfers 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 nonmedical 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 estimate the model by matching life-cycle profiles of assets, out-of-pocket medical spending, and Medicaid recipiency rates for elderly singles across different cohorts and permanent income groups. We also require our model to fit the data across the entire income distribution, rather than simply explain mean or median behavior. Matching Medicaid recipiency introduces an unexpected angle in the identification of bequest motives. To match Medicaid recipiency 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. (1987) using the RAND Health Insurance Experiment. Moreover, although our model was not required to match 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, but the transfers that they receive are on average relatively small. Households in the higher permanent income quintiles are much less likely to receive any Medicaid 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 \$3. 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 their recipients' valuations suggest 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 \$5. 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.

This 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 recipiency and payment rates.

I. Literature Review

This paper is related to previous work on savings, health risks, and social insurance. Kotlikoff (1988) stresses the importance of modeling health expenditures when studying precautionary savings, but Hubbard, Skinner, and Zeldes (1994) and Palumbo (1999) solve dynamic programming models of saving under medical expense risk and find that medical expenses have relatively small effects. However, Hubbard, Skinner, and Zeldes (1994) and Palumbo (1999) likely underestimate medical spending risk, because the datasets available at that time miss late-in-life medical spending and have poor measures of nursing home costs. As a result, the data understate the extent to which medical expenses rise with age and income.

Using newer and more comprehensive data, De Nardi, French, and Jones (2010) and Marshall, McGarry, and Skinner (2011) find that late-in-life medical expenses are large and generate powerful savings incentives. Furthermore, Poterba, Venti, and Wise (2010) show that those in poor health have considerably lower assets than similar individuals in good health. Lockwood (2014), Nakajima and Telyukova (2012), and Yogo (2009) add to the literature by estimating life-cycle models that include additional insurance choices, housing, and portfolio choices, respectively. Laitner, Silverman, and Stolyarov (2014) derive analytic expressions which provide intuition for how uncertain longevity and medical expense risk affect savings decisions.

In this paper, we extend the endogenous medical spending model of De Nardi, French, and Jones (2010) to measure the distribution of Medicaid transfers, the taxes used to fund the transfers, and the valuations retirees place on them. Relative to that paper, we make the following improvements. First, because nearly two-thirds of Medicaid payments to the elderly are to those in nursing homes, we model the nursing home state explicitly. Second, we extend the model of Medicaid so that, consistent with the institutions, there are two distinct ways to qualify: having low income and assets (the "categorically needy" pathway, which incorporates SSI) or becoming impoverished by high medical needs (the "medically needy" pathway). People at different points of the income distribution qualify for Medicaid benefits in different ways and thus receive different insurance. Third, we expand our set of econometric targets to include Medicaid eligibility rates, adding an important new source of identification. Fourth, we use data from the MCBS and PSID as well as the AHEAD, whereas De Nardi, French, and Jones (2010) used AHEAD data alone. We compare the Medicaid payments observed in the MCBS to those predicted by the model. We show that our model matches Medicaid payments well, although they are not matched by construction. Furthermore, we use the earnings histories in the PSID data to measure lifetime tax payments into the Medicaid system. This allows us to better consider who pays for Medicaid, in addition to who benefits from Medicaid.

Earlier studies of Medicaid include Hubbard, Skinner, and Zeldes (1995) and Scholz, Seshadri, and Khitatrakun (2006), who 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 (2006) exploit cross-state variation in Medicaid rules and find Medicaid has significant effects on savings. Brown and Finkelstein (2008) develop a dynamic model of optimal savings and long-term care purchase decisions and conclude that Medicaid crowds out private long-term care insurance for about two-thirds of the wealth distribution. Consistent with this evidence, Brown, Coe, and Finkelstein (2007) exploit cross-state variation in Medicaid rules and also find significant crowding out. We also find that Medicaid encourages spending and reduces savings.

Several new papers study the importance of medical expense risk in general equilibrium, including Hansen, Hsu, and Lee (2012), Pashchenko and Porapakkarm (2013), and Imrohoroglu and Kitao (2012). Kopecky and Koreshkova (2014) find that old-age medical expenses and the coverage of these expenses provided by Medicaid have large effects on aggregate capital accumulation. Braun, Kopecky, and Koreshkova (2015) use a model with medical expense risk to assess the incentive and welfare effects of Social Security and means-tested social insurance programs like Medicaid. They too find that Medicaid provides the elderly with valuable insurance. Compared to these papers, we focus more on valuation and redistribution at the individual level and include much more heterogeneity. We allow demographic transitions to depend on lifetime earnings, consistent with Hurd (1989) and Hurd, McFadden, and Merrill (1999), who highlight the importance of accounting for the link between wealth and mortality in life-cycle models. We estimate our model against life-cycle profiles, rather than calibrating it. Most important, in our model people can adjust medical spending, as well as consumption and saving, allowing the quality of care to vary.

Several 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. (2009) and Scholz and Seshadri (2013) assume that the consumption floor is invariant to medical needs, whereas our specification allows for more realistic links between medical needs and Medicaid transfers. Ozkan (2011) studies health investments over the life cycle, but does not focus on the role of Medicaid. Khwaja (2010) conducts a valuation exercise similar to ours, estimating the willingness of older males to pay for Medicare. He does not evaluate Medicaid, however, as very few individuals in his estimation sample receive it.

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.[1] Furthermore, we assess the valuation individuals place on their expected Medicaid transfers.[2] 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 (2006), we assume that the Medicaid tax burden is proportional to the general tax burden.

II. Data

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

A. *The AHEAD Dataset*

Our analysis of the Assets and Health Dynamics Among the Oldest Old (AHEAD) dataset builds upon the analysis in De Nardi, French, and Jones (2009) and De Nardi, French, and Jones (2010). The AHEAD is a survey of individuals who were noninstitutionalized 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 to 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

[1] Bhattacharya and Lakdawalla (2006) and McClellan and Skinner (2006) study Medicare progressivity.

[2] Using a simpler, calibrated model, Brown and Finkelstein (2008) analyze how Medicaid affects the valuation of long-term care insurance. Braun, Kopecky, and Koreshkova (2015) calculate the aggregate welfare effects of eliminating means-tested social insurance.

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 the 1994 asset or medical expense data. Assets in 1994 were underreported (Rohwedder, Haider, and Hurd 2006) 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 assign 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 five cohorts, each of which contains people born within a five-year window. The first cohort consists of individuals that were ages 72 to 76 in 1996; the second cohort contains ages 77 to 81; the third ages 82 to 86; the fourth ages 87 to 91; and the final cohort, for sample size reasons, contains ages 92 to 102. Throughout, we will refer to each of these five-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.

B. *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). Our description and treatment of the MCBS follow those of De Nardi et al. (2015), who assess the MCBS medical spending data in detail.

The MCBS is a nationally representative survey of disabled and elderly Medicare 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 four-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 online Appendix A.

As with the AHEAD data, we assign individuals a health status of "good" if their self-reported health is excellent, very good, or good, and a health status of "bad" if their 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 PI in the MCBS.

C. *Medicaid Recipiency 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, which follows that of De Nardi, French, and Jones (2009, 2010), 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 recipiency rate in each calendar year. We then construct life-cycle profiles by ordering the recipiency 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 14 years. The graphs report the Medicaid recipiency rate for each cohort and PI grouping at eight dates over time. At each sample date, we calculate the Medicaid recipiency rate for individuals alive at that date—we use an unbalanced panel. Cohort-PI-year cells with fewer than ten observations are dropped.

Unsurprisingly, Medicaid recipiency is inversely related to PI: the thin top lines show the fraction of Medicaid recipients in the bottom 20 percent of the PI distribution, while the thick bottom lines show the recipiency rate for the top 20 percent. The top left line shows that for the bottom PI quintile of the cohort aged 74 in 1996,

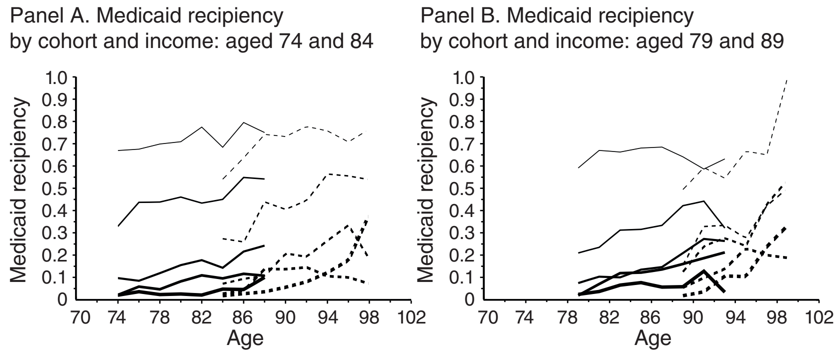

Figure 1. Medicaid Recipiency Rates by Cohort, Income, and Age

Notes: Each line represents Medicaid recipiency rates for a cohort-PI 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.

Table 1—Average Medicaid Benefits and Recipiency

Permanent income quintile	Average benefit	Recipiency rate	Average benefit per recipient
Bottom	9,080	0.70	12,990
Fourth	5,720	0.42	13,690
Third	2,850	0.16	18,350
Second	1,950	0.08	24,360
Top	1,280	0.05	23,790

Source: MCBS

about 70 percent 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 recipiency 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 percent at age 89 to over 20 percent 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.

Table 1 shows average Medicaid benefits, the recipiency rate, and benefits per recipient in the MCBS data, conditional on PI quintile. Average payments decline with PI. However, this is because recipiency 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.

D. *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

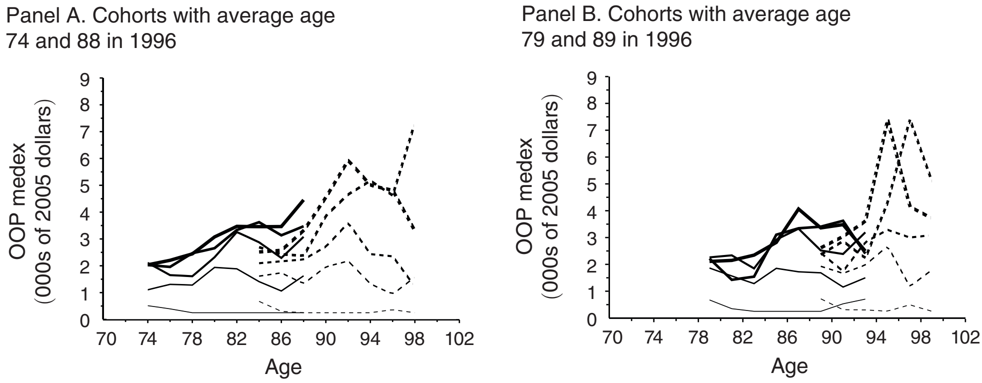

Figure 2. Median Out-of-Pocket Medical Expenses by Cohort, Income, and Age

Notes: Each line represents median out-of-pocket medical expenditures for a cohort-PI 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.

individual spends out-of-pocket on private and Medicare Part B insurance premia, drug costs, costs for hospital and nursing home care,[3] doctor visits, dental visits, and outpatient care. It does 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 children or other survivors. We annualize the data by dividing the AHEAD's spending measure by two.

French and Jones (2004) 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 ninetieth 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 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.

[3] Nursing 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 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 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.

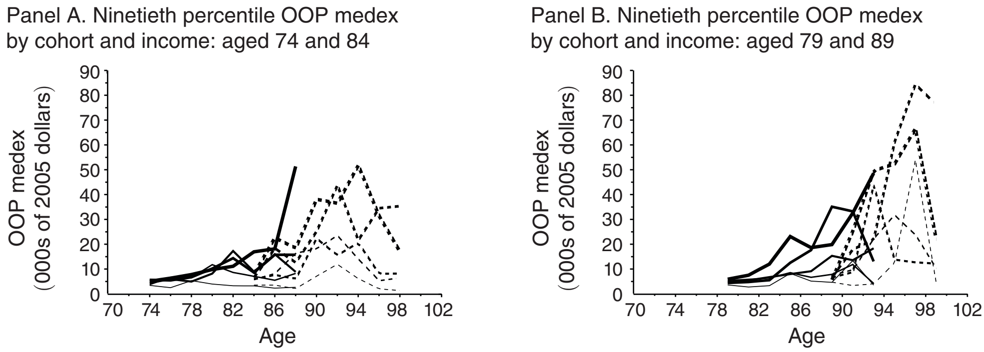

Figure 3. Ninetieth Percentile of Out-of-Pocket Medical Expenses by Cohort, Income, and Age

Notes: Each line represents the ninetieth percentile of out-of-pocket medical expenditures for a cohort-PI 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.

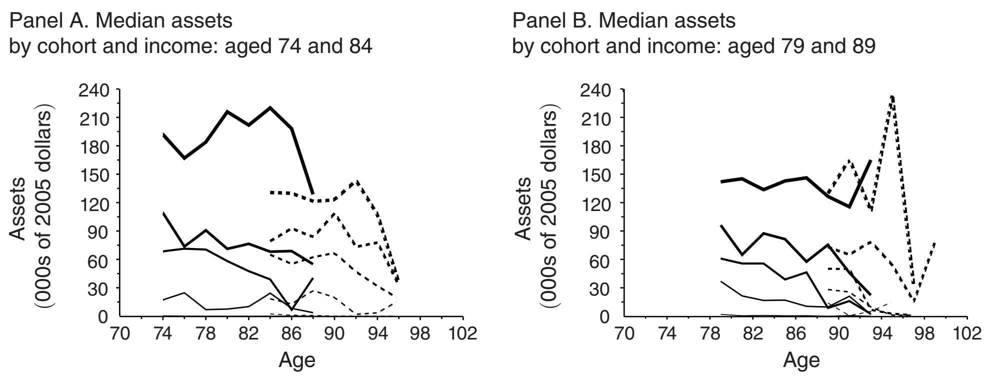

Figure 4. Median Assets by Cohort, Income, and Age

Notes: Each line represents median assets for a cohort-PI 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.

E. *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 lines show median assets in the lowest PI quintile, while the thick top lines show median assets for 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, \$210,00 at age 82, \$220,000 at age 84, \$200,00 at age 86, and \$130,000 at age 88.[4]

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 eighties, 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 1979). However, as De Nardi, French, and Jones (2010) show, the risk of medical spending rising with age and income goes a long way toward explaining this puzzle.

III. The Model

Our model is an extension of the endogenous medical spending model of De Nardi, French, and Jones (2010) that allows for richer health dynamics and a more realistic (and detailed) formulation of Medicaid. As in De Nardi, French, and Jones (2009, 2010), we consider only 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.

A. *Preferences*

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

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

where t is age, c_t is consumption of nonmedical 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.[5] One way to interpret the medical spending in the utility function formulation is that medical spending improves within-period health. This is a simple way to capture endogenous medical spending and is similar to other specifications used in the literature (Einav et al. 2013; McClellan and Skinner 2006; Bajari et al. 2014).

[4] The jumps in the profiles are due to the fact that there is dispersion in assets within a cell, and 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] We assume that preferences are separable between medical and nonmedical goods, which restricts the set of possible price and income elasticities. The parameters of our current specification are identified largely through income elasticities, by matching the way in which out-of-pocket medical spending rises with income at multiple ages. However, our specification also generates reasonable price elasticities. Given that a simpler specification matches the facts well, we decided to not estimate a more complex non-separable specification, where identification would be less transparent.

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.

As discussed in De Nardi, French, and Jones (2010), a complementary approach is that of Grossman (1972), in which medical expenses represent investments in health capital, which in turn decreases mortality (e.g., Yogo 2009) or improves health. Although a few studies find that medical expenditures have significant effects on health and/or survival (Card, Dobkin, and Maestas 2009; Doyle 2011; Chay, Kim, and Swaminathan 2010), most studies find small effects (Brook et al. 1983; Fisher et al. 2003; Finkelstein and McKnight 2008). Interestingly, Finkelstein et al. (2012) find that access to Medicaid increases total medical spending, but do not find that Medicaid reduces mortality for the under-65 population. Instead, they find that access to Medicaid reduces depression, consistent with our interpretation that health care improves utility but not longevity. These findings confirm that the effects of medical expenditures on 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 (2010) 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 percent over the life cycle if medical care was purely mitigative and had no curative or preventive components. Blau and Gilleskie (2008) 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.

B. *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

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

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, Skinner, and Zeldes 1995), 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 to the case in which people choose their medical expenditures.

C. *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.

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

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

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.

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

$$\log(\mu(\cdot)) = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \alpha_3 t^3 + \alpha_4 \cdot 1\{h_t = 2\} + \alpha_5 \cdot 1\{h_t = 2\} \cdot t + \alpha_6 \cdot 1\{h_t = 3\} + \alpha_7 \cdot 1\{h_t = 3\} \cdot t + \sigma(h, t) \times \psi_t, \tag{4}$$

$$\sigma(h,t)^2 = \kappa_0 + \kappa_1 t + \kappa_2 t^2 + \kappa_4 \cdot 1\{h_t = 2\} + \kappa_5 \cdot 1\{h_t = 2\} \cdot t + \kappa_6 \cdot 1\{h_t = 3\} + \kappa_7 \cdot 1\{h_t = 3\} \cdot t, \tag{5}$$

$$\psi_t = \zeta_t + \xi_t, \quad \xi_t \sim N\left(0, \sigma_\xi^2\right), \tag{6}$$

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

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

where $1\{\mathcal{A}\}$ is the indicator function that takes the value 1 when event $\mathcal{A}$ occurs and the value 0 otherwise. We allow the need for medical services to experience both temporary (ξ_t) and persistent (ζ_t) shocks, assuming that ξ_t and ϵ_t are serially and mutually independent. 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.

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 as a deterministic function of sex, permanent income, and age:

$$y_t = y(g, I, t). \tag{9}$$

D. *The Individual's Problem*

Consider a single person seeking to maximize his or her expected lifetime utility at age t, $t = t_{r+1}, \ldots, T$, 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,

$$y_t + ra_t - y_d \leq \underline{Y} \quad \text{and} \quad a_t \leq A_d, \tag{10}$$

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

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

recalling the restrictions on y_t and a_t in equation (10).

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

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

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

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

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,

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

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

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

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

where $b_i(\cdot) = b_c(\cdot)$ if equation (10) holds, and $b_i(\cdot) = b_m(\cdot)$ otherwise. Equations (14) and (15) both prevent the individual from borrowing against future income. Equation (16) 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 condense the dynamic programming problem, we can express 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

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

This expression can be used to eliminate m_t from the dynamic programming problem in equation (13), and to simplify the computation of $b_i(\cdot)$.

IV. Estimation Procedure

Extending the approach used by De Nardi, French, and Jones (2010), we employ a two-step estimation strategy. 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 (ν, ω, β, $\underline{u}_c$, $\underline{u}_m$, θ, k, 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:

(i) To better evaluate the effects of Medicaid insurance, we match the fraction of people on Medicaid by PI quintile, five-year birth cohort and year cell (with the top two PI quintiles merged together).

(ii) Because the effects of Medicaid depend directly on an individual's asset holdings, we match median asset holdings by PI-cohort-year cell.

(iii) We match the median and ninetieth percentile of the out-of-pocket medical expense distribution in each PI-cohort-year cell (the bottom two PI 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.

(iv) 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 II.[6]

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 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. Additional detail on our computational approach can be found in online Appendix B.

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. Online Appendix C contains a detailed description of our moment conditions, the weighting matrix in our GMM criterion function, the asymptotic distribution of our parameter estimates, and the overidentification test statistic.

V. 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, French, and Jones (2010). The procedures for estimating demographic transition probabilities and co-pay rates are new.

A. *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

[6] As was done when constructing the figures in Section II, we drop cells with less than ten 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 from 1998 to 2010.

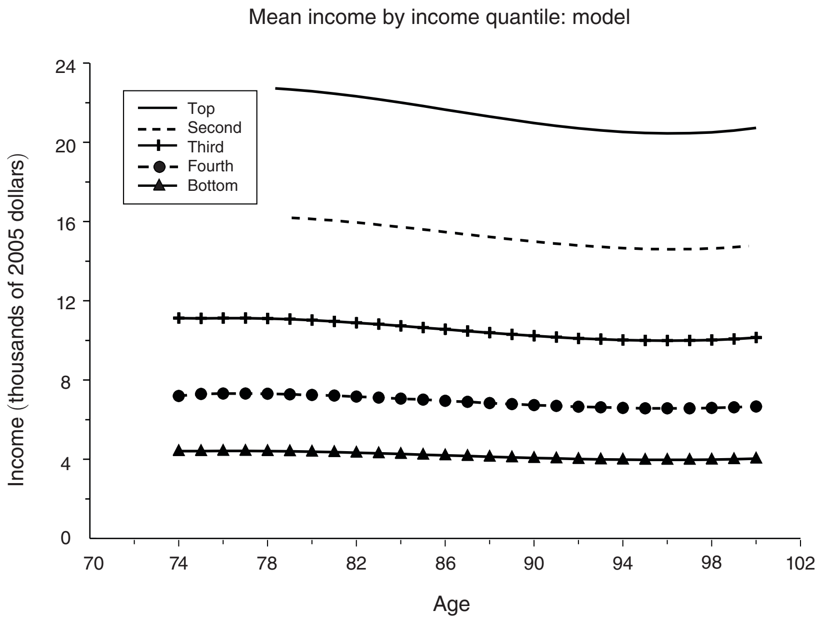

Figure 5. Average Income by PI Quintile

about $23,000 in the top quintile; median wealth holdings for the two groups are zero and just under $200,000, respectively.

B. *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. Online Appendix D 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 tenth PI percentile in a nursing home expects to live only 1.7 more years, while a female at the ninetieth PI percentile in good health expects to live 16.2 more years.[7]

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 46.0 percent of women will ultimately enter a nursing home, as opposed to 30.5 percent for men. These numbers are similar to those from the

[7] Our predicted life expectancy at age 70 is about 3 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 (2007), who finds that those in the top of the income distribution live 3 years longer than those at the bottom, conditional on being 65.

Table 2—Life Expectancy in Years

Permanent income percentile	Males: Nursing home	Males: Bad health	Males: Good health	Females: Nursing home	Females: Bad health	Females: Good health	All[a]
10	1.7	6.0	7.5	2.5	10.0	12.0	10.4
30	1.7	6.6	8.5	2.6	11.0	13.2	11.5
50	1.7	7.3	9.5	2.7	12.0	14.3	12.5
70	1.7	8.0	10.4	2.9	13.0	15.3	13.5
90	1.8	8.8	11.3	3.0	13.9	16.2	14.4
By gender[b]							
Men							9.7
Women							13.5
By health status[c]							
Bad health							10.7
Good health							14.0

Notes: Conditional on reaching age 70. Life expectancies calculated through simulations using estimated health transition and survivor functions.
[a]Using gender and health distributions for entire population.
[b]Using health and PI distributions for each gender.
[c]Using gender and PI distributions for each health status group.

Table 3—Percentage of People Ever Entering a Nursing Home

Permanent income percentile	Males: Bad health	Males: Good health	Females: Bad health	Females: Good health	All[a]
10	26.4	30.1	41.2	45.2	40.8
30	26.9	31.2	42.5	46.8	42.1
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[b]					
Men					30.5
Women					46.0
By health status[c]					
Bad health					39.9
Good health					44.9

Notes: Conditional on reaching age 70. Percentages calculated through simulations using estimated health transition and survivor functions.
[a]Using gender and health distributions for entire population.
[b]Using health and PI distributions for each gender.
[c]Using gender and PI distributions for each health status group.

Robinson model described in Brown and Finkelstein (2004), which show 27 percent of 65-year-old men and 44 percent of 65-year-old women require nursing home care.

C. *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 34 percent and does not vary much with demographics. The co-pay rate for those in nursing homes is 69 percent. For every dollar spent on nursing homes, \$0.34 come from Medicaid and \$0.35 are from out-of-pocket, with \$0.31 coming from Medicare or other sources. We cross-checked these co-pay rates with data from the 1997 to 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.

VI. Second Step Results, Identification, and Model Fit

A. *Parameter Values*

Table 4 presents our estimated preference parameters. Our estimate of β, the discount factor, is 0.994, which suggests a high level of patience. However, in our model individuals discount the future not only because of impatience, but also because they might not survive to the next period. The effective discount factor is the product $\beta s_{g,h,I,t}$. 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. (2014) 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 $\nu < \omega$, although their estimated value for ν is lower than ours.[8]

Our estimates imply that the demand for medical goods is less elastic than the demand for consumption. In a recent study, Fonseca et al. (2009) 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 percent 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 percent to find a cross-sectional distribution of ages. Combining this number with our simulations, we find an aggregate cross-sectional elasticity of -0.29.

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

[8] Einav et al. (2013) and McClellan and Skinner (2006) also study two-period problems where utility depends on medical care.

Table 4—Estimated Preference Parameters

β: discount factor	0.994 (0.013)
ν: RRA, consumption	2.83 (0.03)
ω: RRA, medical expenditures	2.99 (0.03)
$\underline{Y}$: SSI income level	\$6,670 (208)
$\underline{u}_c = \underline{u}_m$: utility floor	\$4,600 (144)
θ: bequest intensity	39.7 (2.5)
k: bequest curvature (in 000s)	13.0 (0.7)

Notes: Standard errors in parentheses. The utility floor is indexed by the consumption level that provides the floor when $\mu = 0$.

categories of recipients. The utility floor corresponds to the utility from consuming \$4,600 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 2010 for a derivation). For individuals in this group, the marginal propensity to bequeath, above the threshold level, is \$0.78 out of every additional dollar. Several other authors have recently estimated bequest motives inside structural models of old age saving.[9] Imposing a linear bequest motive, Kopczuk and Lupton (2007) 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, French, and Jones (2010) find that, depending on the specification, the bequest motive becomes active between \$31,500 and \$43,000, and generates a marginal propensity to bequeath of 88 to 89 percent. Lockwood (2014) finds a threshold of \$18,400 and a propensity to bequeath of 92 percent. 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. (2011) 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 percent. Compared to them, we find a lower threshold but a much higher marginal propensity to consume.

[9] Assembling these values requires a few derivations and inflation adjustments. Calculations are available on request.

We now turn to discussing the identification of the model's parameters and how well the model fits some key aspects of the data, and to highlighting some of the model's implications for medical and nonmedical spending at older ages.

B. *Parameter 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 $\underline{u}_c$ and $\underline{u}_m$, 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 (2002) point out that the same assets can simultaneously address both precautionary and bequest motives. Likewise, there are 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. All of these mechanics are documented in more detail in online Appendix E, which shows how changing individual parameters, one at a time, affects the components of our GMM criterion and the life-cycle profiles of several key variables.

We acquire additional identification in several ways. We require our model to match the fraction of people on Medicaid by PI, cohort, and age, which helps pin down the utility floors and the SSI threshold $\underline{Y}$. To match the observed Medicaid recipiency rates, the Medicaid insurance floors have to be substantial, in excess of \$4,600 of consumption by the healthy. A lower floor would generate too few people on Medicaid, especially at higher PI quintiles: Table E1 in online Appendix E shows that lowering the utility floor significantly worsens the model's fit of its Medicaid recipiency targets. By way of comparison, the model with endogenous medical expenses in De Nardi, French, and Jones (2010), the one most comparable with the model in this paper, is not estimated to match Medicaid recipiency rates. That model fits the asset data using a similar value of β, no bequest motives, and low utility floors. A similar specification matches the asset data very well even with our current, richer model 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 recipiency rates observed in the data, and a more generous Medicaid program reduces the need to accumulate assets. To match the same asset profiles under the more generous insurance system we need a higher discount factor and/or a stronger bequest motive. Because we restrict β to lie between 0.96 and 1.0, this implies a strong bequest motive.

Disentangling β and the bequest motive parameters is tricky. A key insight is that a higher value of β will lead both assets and medical spending to increase more rapidly over the life cycle, while stronger bequest motives will lead assets to increase more rapidly without a corresponding increase in medical spending. Requiring the model to match both asset and medical spending moments thus helps us distinguish patience from bequest motives. The intuition just described is incomplete because the medical needs shifter $\mu(h_t, \zeta_t, \xi_t, t)$ is also estimated to match the life-cycle profiles of out-of-pocket medical spending. However, the medical needs shifter is not allowed to vary by cohort or permanent income, even though our moments vary along these very dimensions. Much of the variation along these dimensions instead comes from endogenous decisions over saving and total medical spending, both of which depend on the discount factor and the bequest motive. For instance, low-permanent-income people are just as patient as richer ones, and yet they choose not to save, leading to low assets and out-of-pocket medical spending (because of Medicaid). Thus, our model is identified in many ways, because it generates heterogeneous responses to similar shocks. For example, it is in large part identified by differences in the slopes of the asset and medical expense (and Medicaid recipiency) profiles across permanent income quintiles and cohorts.

The coefficients of relative risk aversion for nonmedical and medical goods, ν and ω, also must generate reasonable asset trajectories. As shown in online Appendix E, reducing either parameter leads households to deplete their wealth more quickly by reducing their desire to smooth consumption. Further identification comes from the income gradient of medical expenditures. In particular, dividing both sides of equation (17) by consumption provides an equation for the optimal ratio of medical to nonmedical expenditures:

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

This ratio depends on the relative sizes of the coefficients ω and ν. As resources (and thus consumption) rise, $\frac{m_t}{c_t}$ will decrease when people are more risk averse over medical goods than over nonmedical goods ($\omega > \nu$). Put differently, people with higher wealth and permanent income spend a smaller share of their resources on medical goods than on consumption goods when $\omega > \nu$. Our estimates suggest this is the empirically relevant case. Figures 2, 3, and 5 show that prior to age 90, the rate at which medical expenditures increase across the permanent income quintiles is smaller than the rate of increase for annual income. It follows that the share of total expenditures devoted to medical expenditures is falling in total expenditures, and thus $\omega > \nu$. Online Appendix E shows that the two parameters are tightly identified. Reducing either ν or ω by 10 percent leads to large changes in both our GMM criteria and in the age profiles of assets, Medicaid recipiency, and the consumption of nonmedical goods and medical goods and services.

We also estimate the components of the logged medical needs shifter $\mu(h_t, \psi_t, t)$. These include the level parameters (the αs in equation (4)), the volatility parameters (the κs in equation (5)), and the process for the shocks ζ_t and ξ_t. The estimates, along with standard errors, can be found in online Appendix F. The level parameters and the volatility parameters are identified by the median and ninetieth percentile of out-of-pocket medical spending. As shown in Figures 2 and 3, both spending statistics rise rapidly with age. The last two lines in online Appendix Table E1 show the effects of first reducing the average of the medical needs shocks by 10 percent and then reducing their variance by 10 percent. Both changes worsen the fit of medical spending, but the first change also significantly worsens the fit of the Medicaid recipiency moments, showing that they too help identify $\mu(\cdot)$. The processes for ζ_t and ξ_t are identified by the first and second autocorrelations of out-of-pocket spending. Consistent with our findings, French and Jones (2004) find that, in the AHEAD data, the autocorrelation of medical spending at one lag is 0.4, but that autocorrelations at longer lags decline very slowly. They show that such a pattern implies that

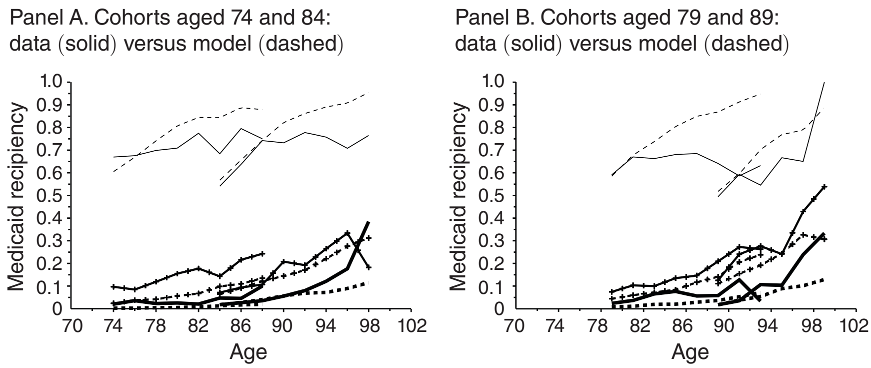

FIGURE 6. MEDICAID RECIPIENCY: DATA VERSUS MODEL

Notes: Each line represents Medicaid recipiency for a cohort-PI cell, traced over the time period 1996–2010: data (solid lines) and model (dashed lines). For each cohort we show profiles for the bottom, third, and top PI quintiles. Thicker lines refer to higher PI groups. Panel A: cohorts aged 74 and 84 in 1996. Panel B: cohorts aged 79 and 89 in 1996.

the transitory shock ξ_t has a relatively large variance and that the persistent shock ζ_t has a large autocorrelation parameter (ρ_m).

C. *Model Fit*

In our second-step we estimate 24 parameters—7 preference parameters and 17 parameters related to the medical needs shifter—to match 633 moments. The associated overidentification test statistic has a value of 1,799, implying that the model is formally rejected. Nonetheless, the model does a good job of matching its data targets, and matches other features of the data as well.

Figure 6 compares the Medicaid recipiency 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 to 76, with an average age of 74. The second set of lines are for the cohort aged 82 to 86 in 1996. Panel B displays the two other cohorts, starting at ages 79 and 89, respectively. For clarity, for each cohort we show profiles for the bottom, third and top PI quintiles. The graphs show that the model matches the general patterns of Medicaid usage. The model tends to overpredict usage by the poor, especially at older ages, and to underpredict usage by the rich, especially at younger ages. This may reflect heterogeneity along such dimensions as quality of care, or attitudes toward Medicaid, that are not captured in our parsimonious model of Medicaid.

Figure 7 plots median net worth by age, cohort, and PI. Here too the model does well, matching the way in which savings patterns differ by PI, including the tendency of higher-PI people to not run down their assets until well past age 90.

Although the model is required only to match median assets, conditional on income quintile, cohort, and age, it also matches reasonably well the unconditional cross-sectional distribution of assets. Figure 8 compares the cumulative distribution functions (CDFs) of assets both in the AHEAD data (solid line) and in the

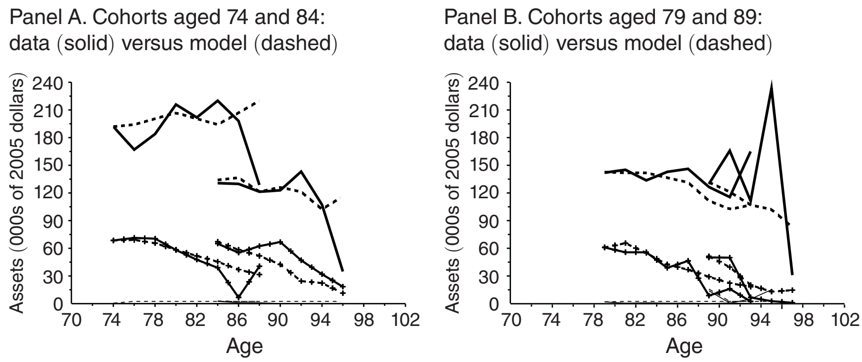

Figure 7. Median Net Worth: Data versus Model

Notes: Each line represents median net worth for a cohort-PI cell, traced over the time period 1996–2010: data (solid lines) and model (dashed lines). For each cohort we show profiles for the bottom, third, and top PI quintiles. Thicker lines refer to higher PI groups. Panel A: cohorts aged 74 and 84 in 1996. Panel B: cohorts aged 79 and 89 in 1996.

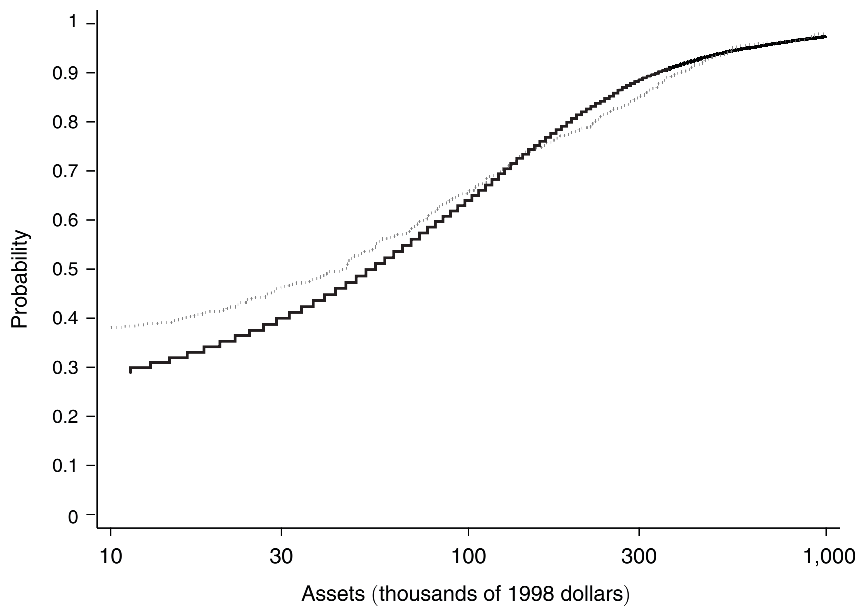

Figure 8. Cumulative Distribution Functions of Assets

Note: Model (solid line), AHEAD data (dotted line)

model simulations (dotted line).[10] Overall, the model provides a good fit of the cross-sectional distribution. The model modestly underpredicts the probability of low assets. For example, 47 percent of AHEAD households have assets below \$30,000, whereas the model predicts that 41 percent of households have assets below \$30,000. At higher asset levels the model's fit improves. For example, 67 percent of

[10] The CDF for model-predicted assets is a step function because we discretize the asset grid.

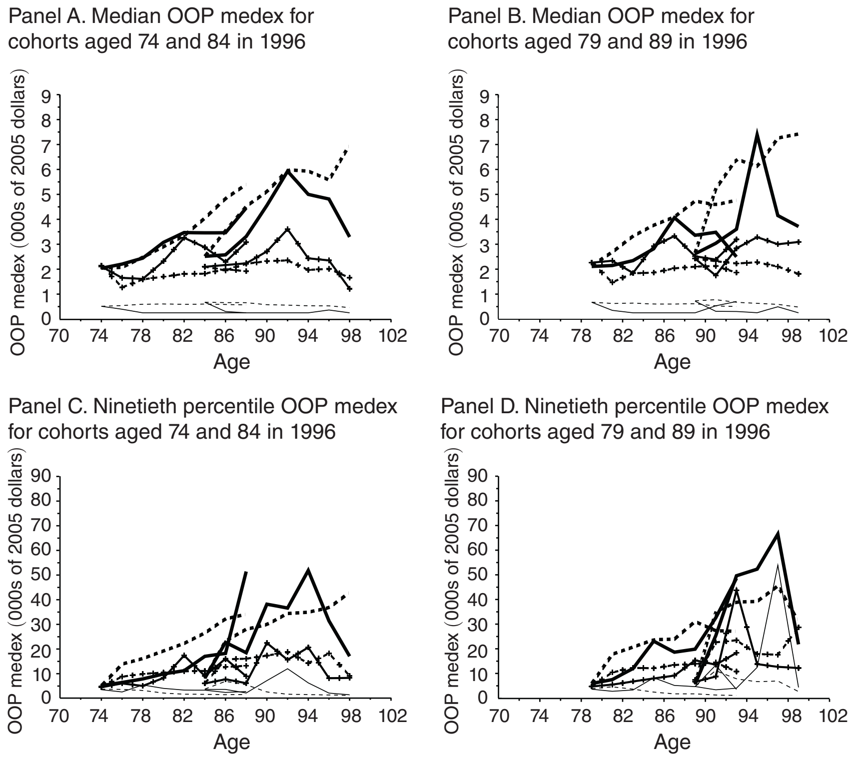

Figure 9. Out-of-Pocket Medical Expenditures by Cohort and Income

Notes: Each line represents the median (top panels) or ninetieth percentile (bottom panels) of medical expenditures for a cohort-PI cell, traced over 1996–2010: data (solid lines) and model (dashed lines). Left versus right panels: different cohorts. For each cohort we show profiles for the bottom, third, and top PI quintiles. Thicker lines refer to higher PI groups.

AHEAD households have assets below \$100,000, whereas the model predicts that 66 percent of households have assets below \$100,000.

Figure 9 displays the median and ninetieth percentile of out-of-pocket medical expenses 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 about \$2,000 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 ninetieth percentile of out-of-pocket medical expenses in the model and in the data, and thus provide a better idea of the tail risk by age and PI. Here the model reproduces the way in which the medical expenditures of lower-PI people tend to stay flat over the life cycle, but it tends to understate the medical expenditures of high-PI people in their late nineties.

Turning to the cross-sectional distribution of medical spending, Figure 10 presents three panels. Panel A, in the top left corner, presents the CDFs of out-of-pocket medical expenditures found in the AHEAD and MCBS data, as well as that

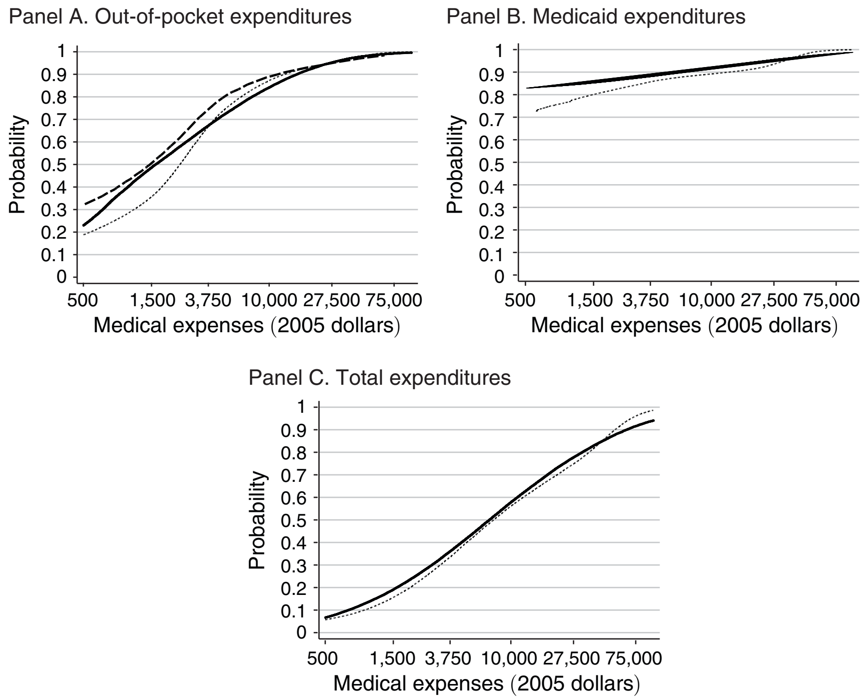

Figure 10. Cumulative Distribution Functions of Medical Spending: Data versus Model

Notes: Cumulative distribution functions of medical spending: model (solid line), AHEAD data (long dashed line, panel A only), and MCBS (short dashed line). Panel A: Out-of-pocket expenditures. Panel B: Medicaid expenditures. Panel C: Total expenditures.

produced by the model. The solid line in the figure 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-predicted ninetieth percentile of out-of-pocket spending is greater than what is observed in the AHEAD data, although it is very close to what is observed in the MCBS.

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 ninety-eighth 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 eighty-sixth percentile at \$43,000, and are lower thereafter. In summary, these differences are not large and the model fits the distribution of out-of-pocket, Medicaid, and total medical spending well. 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 it means the model is able to match the risk of catastrophic medical spending.

Table 5—Average Medicaid Payments and Out-of-Pocket Expenditures: Data versus Model

Permanent income quintile	Medicaid payments: MCBS data	Medicaid payments: Model	Out-of-pocket expenses: MCBS data	Out-of-pocket expenses: AHEAD data	Out-of-pocket expenses: Model
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

Note: 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.

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. (2015) find the administrative payments to be 24 percent 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.

The last three columns of Table 5 compare out-of-pocket expenditures from the MCBS, the AHEAD, and the model. The MCBS data show 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 $2,550 in the AHEAD data, while expenditures at the top are $8,020 in the MCBS versus $7,000 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. Because we do not allow the medical needs shocks to vary with gender, due to sample limitations, the model over-predicts spending by men. De Nardi, French, and Jones (2010), who assume medical expenditures are exogenous, find that conditional on age, health, and PI, the out-of-pocket medical expenses of men are significantly lower than the expenses of women. Details on the construction of these cross-sectional comparisons, and additional comparisons, can be found in online Appendix A.

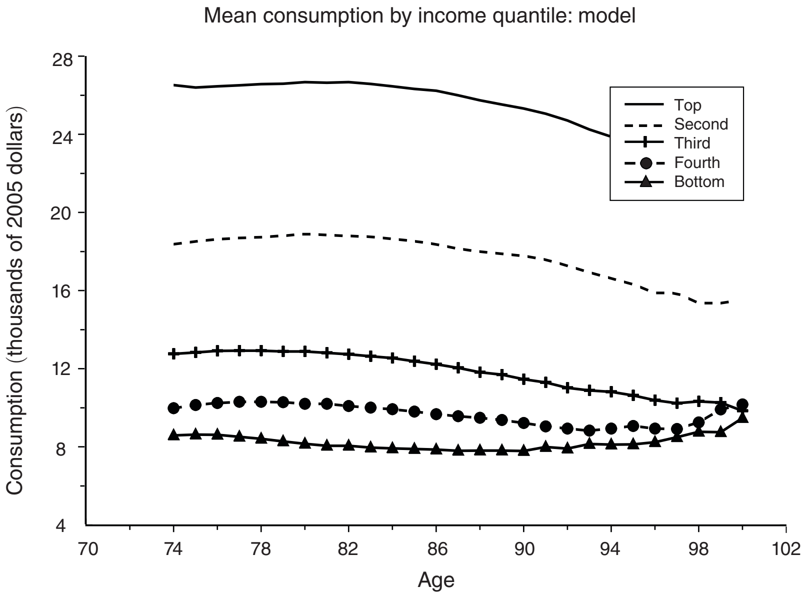

Figure 11. Simulated Consumption for the Cohort Aged 74 in 1996

D. *Medical and Nonmedical Spending in Old Age: Present Discounted Values*

To assess the effects of Medicaid from a lifetime perspective, we simulate extended life histories for the youngest cohort. 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 (potentially) age 100. Figure 11 uses these simulations to show the model's implications for nonmedical consumption, showing the trajectory of average consumption for each PI quintile. In contrast to medical expenditures, which rise rapidly with age, average nonmedical consumption expenditures decline, albeit slightly, over retirement. This pattern is quite similar to the spending profiles found in the Consumer Expenditure Survey (see, e.g., Banks et al. 2015).

After simulating life histories, we convert the expenditure streams into present discounted values, using the model's assumed pretax interest rate of 4 percent. Table 6 shows the present discounted value of both nonmedical 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 nonmedical goods at all PI levels. However, nonmedical consumption rises more quickly in PI than total medical spending, as $\nu < \omega$. Nonmedical spending for the poorest is 25 percent of nonmedical spending for the richest. In contrast, the total medical spending of the bottom PI quintile is nearly 50 percent 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 nonmedical consumption; for high-PI individuals, the opposite is true.

TABLE 6—PRESENT DISCOUNTED VALUE OF NONMEDICAL CONSUMPTION AND CONSUMPTION OF MEDICAL GOODS AND SERVICES AT AGE 74

		Medical goods and services	
Permanent income quintile	Nonmedical consumption	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 7—PRESENT DISCOUNTED VALUE OF MEDICAID PAYMENTS RECEIVED AND TAXES PAID

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

Note: 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.

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

VII. Medicaid Benefits, Taxes, and Valuations

A. *Medicaid Benefits Received and Taxes Paid*

The first column of Table 7 shows the present discounted value of Medicaid benefits, beginning at age 74. Although the payments decrease by PI quintile, they are nontrivial for all PI groups. For instance, those in the highest-PI quintile expect to receive $8,800, which is about 40 percent of their yearly income. Although the poor are more likely to 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, 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 McClellan and Skinner (2006), who calculate tax payments for Medicare. We first use data from the Panel Study of Income Dynamics (PSID) to calculate the 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.[11] See online Appendix G 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 been not 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 \$40,200 in taxes toward Medicaid, 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 right most column of Table 7 shows the ratio of taxes paid to transfers received. Those at the top of the distribution pay on average \$4.59 in taxes for every \$1 of transfers received, whereas those at the bottom of the distribution pay \$0.20 for every \$1 of transfers.

B. *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, assuming that providing an additional \$1 of Medicaid "transfers" would cost the

[11] Because of distortions, the social costs of funding Medicaid likely exceed the tax totals reported in Table 7. As surveyed by Dahlby (2008), the range of estimates for the marginal social cost of funds is large.

government exactly \$1. This is a natural benchmark, but one should keep in mind that the government can make Medicaid more or less attractive to its recipients in many ways beyond direct changes in transfers.

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 percent for those receiving Medicaid transfers, because of asset testing, which in turn distorts savings decisions.

To measure the welfare gains we compute the compensating variation; that is, the immediate payment after the Medicaid reform that would leave the retiree as well off as before the reform. This is an ex ante measure. More specifically, the compensating variation at age 74, $\lambda_{74} = \lambda(a_{74}, g, h_{74}, I, \zeta_{74}, \xi_{74})$, is computed as

$$V_{74}(a_{74}, g, h_{74}, I, \zeta_{74}, \xi_{74}; \text{current Medicaid})$$

$$= V_t(a_{74} + \lambda_{74}, g, h_{74}, I, \zeta_{74}, \xi_{74}; \text{Medicaid reform}),$$

where $V_{74}(a_{74}, g, h_{74}, I, \zeta_{74}, \xi_{74}; \cdot)$ is the value function evaluated at a given set of state variables, either in the world with current Medicaid (the 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 (2008) and McClellan and Skinner (2006) but uses a forward-looking value function, rather than a static utility function. When considering a group, we simply take averages across all its members.

To distinguish the insurance provided by the categorically and the medically needy programs, we first analyze a 10 percent 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 transfer's 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 percent 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

Table 8—The Costs and Benefits of Cutting Medicaid by 10 Percent

Permanent income quintile	Categorical floor down 10 percent: Reduction in PDV of payments (1)	Compensating variation (2)	Ratio of (2)/(1) (3)	Both floors down 10 percent: Reduction in PDV of payments (4)	Compensating variation (5)	Ratio of (5)/(4) (6)
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	N/A	2,900	4,400	1.52
Second	0.0	0.0	N/A	2,200	4,100	1.86
Top	0.0	0.0	N/A	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 percent. Right panel: both Medicaid floors are cut by 10 percent. 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.

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.[12] 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 \$4.59 of taxes (Table 7).

In Table 9, we analyze the benefits of making the Medicaid program more generous by increasing the Medicaid consumption floor by 10 percent (from \$4,610 to \$5,070). Table 9 shows that people at the bottom two 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 at twice their cost. Once again, as income increases, the insurance value of Medicaid, as opposed to its actuarial value, increases in importance. In the aggregate, taking averages over all retirees reveals that the cost increase associated with a more generous Medicaid program slightly exceeds the average valuation. Comparing the valuations to the associated tax burdens (see Table 7), however, produces different implications. Even though high-income retirees would receive the most "bang per buck" from a Medicaid expansion (\$2.00 per dollar of transfers), under the current redistributive tax system they would not support it, as their tax burden would rise (by \$4.59 per dollar of transfers) more than their valuation. In contrast, low-income retirees, who receive the least bang per buck from a Medicaid expansion, would support the

[12] Online Appendix H reports compensating variations under different Medicaid rules and shows that our estimates are robust to reasonable changes in the rules.

Table 9—The Costs and Benefits of Increasing Medicaid by 10 Percent

	Both floors up 10 percent		
Permanent income quintile	Payment increase (1)	Compensating variation (2)	Ratio (2)/(1) (3)
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.

expansion, as their tax burden would rise by even less. Only people in the middle quintile value a Medicaid expansion in excess of both its cost and their tax burden.

Put together, the results in Tables 8 and 9 indicate that under current program 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 about the right size for most currently retired singles.

C. *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 percent of elderly singles have LTCI (Lockwood 2014), and only 4 percent of LTC expenditures are paid for by LTCI (Congressional Budget Office 2004). Given that our results suggest that the elderly, and especially the high-income elderly, value Medicaid insurance heavily, it is puzzling that the market for LCTI is so small.

Brown and Finkelstein argue 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, which implies that LTCI payments for nursing home care would often crowd out 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 than small changes in generosity. 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 by a reasonable amount. These factors include:

(i) Lack of efficiency in the private market for long-term care insurance. Prices are high: Brown and Finkelstein (2008) report that imperfect competition and transaction costs result in prices that are marked up substantially above expected claims, with loads on typical policies from \$0.18 to \$0.51 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.

(ii) Limited insurance against nursing home risk. Brown and Finkelstein (2009) report that comprehensive LTCI contracts exist 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 2014). 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.

(iii) Severe adverse selection. Hendren (2013) shows that when private information problems are sufficiently large within certain subgroups, insurance markets 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 percent of 65-year-olds have health conditions that preclude them from purchasing LTCI.

(iv) Bequest motives. In a framework with exogenous medical spending, Lockwood (2014) argues that reasonably estimated bequest motives, together with medical expense risk, help explain the patterns of asset decumulation and (low) LTCI purchases seen in the data. We also estimate a significant bequest motive, which reduces the value of LTCI.

D. *Unpacking the Results: Moral Hazard and Exogenous Expenditures*

An important open question is the extent to which people impoverish themselves in order to qualify for Medicaid. Because our model includes savings and medical spending choices, it is well suited to address the quantitative importance of this form of moral hazard. 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.

TABLE 10—THE EFFECTS OF DECREASING MEDICAID PAYMENTS BY 10 PERCENT, AGE 85

		Medical expenditures		
Permanent income	Consumption	Total	OOP	Medicaid recipiency (percent)
Baseline				
Bottom	7,890	22,110	1,430	89.1
Fourth	9,810	21,280	2,860	42.9
Third	12,380	22,710	5,310	9.9
Second	18,520	25,630	8,210	3.7
Top	26,330	32,790	11,860	1.3
Medicaid floors decreased 10 percent				
Bottom	7,600	20,320	1,580	88.6
Fourth	9,600	19,870	3,010	41.0
Third	12,240	21,580	5,420	8.9
Second	18,420	24,980	8,260	3.3
Top	26,210	32,360	11,850	1.2
Difference				
Bottom	−290	−1,790	150	−0.5
Fourth	−210	−1,410	150	−2.0
Third	−140	−1,130	110	−1.0
Second	−100	−650	50	−0.4
Top	−120	−430	−10	−0.1
Percentage differences				
Bottom	−3.7	−8.1	10.5	−0.6
Fourth	−2.1	−6.6	5.2	−4.5
Third	−1.1	−5.0	2.1	−9.6
Second	−0.5	−2.5	0.6	−10.6
Top	−0.5	−1.3	−0.1	−7.1

To better understand the quantitative importance of moral hazard, we analyze further the 10 percent cut in Medicaid generosity considered in columns 4–6 of Table 8.

The cut in Medicaid generosity has two effects. First, it mechanically reduces eligibility and transfers at any given level of individual resources. Second, it changes the degree of moral hazard by changing the incentives to consume and save. To help disentangle these effects, we assess whether the benefit cut significantly affects medical and nonmedical spending and thus savings. Table 10 shows total and out-of-pocket medical spending, nonmedical spending, and Medicaid recipiency rates at age 85 for the simulated life histories used to construct Table 8. The top panel of Table 10 shows quantities for the estimated baseline model, while the second panel shows the quantities after a 10 percent reduction in the Medicaid utility floor. The bottom two panels show the differences between the two cases, in absolute and then relative (percentage) terms. Table 10 shows that a 10 percent Medicaid cut would lead nonmedical spending for 85-year-olds in the bottom PI quintile to fall by \$290, and their out-of-pocket medical spending to rise by \$150. Savings thus rise by \$140, a response that is modest relative to the decline in total medical spending of \$1,790. The changes in the other PI quintiles are similar, albeit smaller. These findings indicate that the mechanical effects of changing Medicaid are larger than the moral hazard effects.[13]

[13] Using data from a large self-insured employer, Bajari et al. (2014) find significant moral hazard. They focus on how changes in the co-insurance rate q changes the allocation of medical versus nonmedical spending, but do

An important contribution of our paper is to analyze Medicaid in a framework where medical expenditures are endogenous. To assess the importance of this feature, we build a version of the model in which medical expenses are exogenous. We do this by finding the stochastic process for exogenous medical expenses that allows the model to best fit its estimation targets. We hold preference parameters fixed, so that our experiment focuses solely on changes to medical spending. Although our process for exogenous medical spending does not depend on wealth or permanent income, the medical spending that it generates is fairly similar to that of the endogenous medical spending model. We show model predictions for the exogenous medical spending specification in Figure E6 in the online Appendix.

We then use the exogenous medical spending model to re-evaluate the 10 percent Medicaid cut considered in Tables 8 and 10. The compensating variations associated with this experiment are, from the bottom PI quintile to the top: \$5,200, \$5,300, \$5,000, \$5,700, and \$8,400. The similarity between these valuations and the valuations in the fifth column of Table 8 is not surprising. The utility floor in the endogenous spending model is indexed by consumption, as $\underline{u} = \frac{1}{1-\nu}\underline{c}^{1-\nu}$, which is identical to utility in the exogenous spending model when the consumption floor is $\underline{c}$. A 10 percent cut in $\underline{c}$ thus represents the same reduction in guaranteed utility for both medical spending specifications, and should be valued similarly under both specifications.[14] Our finding that high-income retirees often value Medicaid as much as poorer retirees is thus robust to making medical expenses exogenous.

When medical spending is endogenous, cuts to the utility floor reduce both consumption and medical expenditures; recall that the transfers are allocated optimally between consumption and out-of-pocket medical spending.[15] When medical spending is exogenous, cuts to the utility floor can only reduce consumption. The transfer reductions associated with a cut to the utility floor are thus smaller, and the valuations per unit of spending higher, when medical spending is exogenous. We still find, however, that high-PI people have the highest valuation per dollar of spending.

By way of comparison, Brown and Finkelstein (2008) measure the willingness of individuals to pay for private insurance that would top up the gaps in Medicaid coverage. Among other differences in approach, Brown and Finkelstein treat medical spending as exogenous, rather than endogenous. Consistent with our results, they find that the richest individuals place the highest insurance value on top-up policies. However, while we find that most individuals would value a Medicaid expansion at around its actuarial cost, they find that most individuals would value top-up insurance well in excess of its cost. This difference in results is consistent with the intuition that people who cannot adjust medical spending value Medicaid more relative to its cost, because they adjust to shocks along one margin (saving) rather than two (saving and medical spending).

not focus on savings. In contrast, in our Medicaid reforms the coinsurance rates remain at their baseline values—the intratemporal allocation still obeys equation (17)—and we focus on the effect of Medicaid insurance on savings.

[14] Differences in model dynamics, along with differences in the estimated spending processes, mean the valuations will not be identical.

[15] When ν and ω are close in value, as they are in our estimates, equation (17) can be approximated as $m = \left(\frac{\mu}{q}\right)^{1/\nu} c$, so that medical spending is proportional to consumption. Cuts in the utility floor thus reduce medical and nonmedical spending by similar proportions.

TABLE 11—COMPARISON OF MEDICAID AND NON-MEDICAID RECIPIENTS: SIMULATIONS

	All retirees	Medicaid recipients	Non-recipients
Mean net income	16,270	6,240	19,020
Mean 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)			
Mean	1,270	5,150	210
Percent in top 50 percent of distribution	50.0	67.9	45.1
Percent in top 10 percent of distribution	10.0	26.0	5.6
Percent in top 1 percent of distribution	1.0	4.0	0.1
Percent of population	100.0	19.7	80.3

E. *Who Selects into Medicaid*

Our model generates considerable heterogeneity in health, mortality, and medical needs. Although we model Medicaid eligibility as a strict function of financial need, individuals with expensive medical conditions are less likely to be able to afford the utility floor without assistance. This is not technically adverse selection, as individuals' medical conditions are not hidden from the "insurer" (Medicaid), but it generates similar selection dynamics. To quantify the extent to which the Medicaid population are "adversely selected" on the basis of their medical needs, Table 11 compares Medicaid recipients to other retirees along several dimensions. We construct Table 11 by simulating the baseline model over the sample period 1996 to 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.

Because medical spending in our model represents the convolution of medical needs (μ) and financial incentives, we also consider the distribution of the medical preference shifter μ. Bajari et al. (2014) measure adverse selection in a similar, if more detailed, way. Compared to non-recipients, the values of μ that confront Medicaid recipients are 4.7 times as likely to lie in the top decile and 28 times as likely to lie in the top percentile. In short, Medicaid recipients are more likely to be sick, and far more likely to be very sick, 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.

VIII. Conclusions and Future Research

In this paper we assess the effects of Medicaid insurance on single retirees. Although Medicaid payments decrease with permanent income, even higher income people can receive sizable Medicaid payments because 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 currently single retirees.

In the interest of tractability, our framework does not allow households to adjust their holdings of LTCI. Although only 9 percent of the households in our AHEAD sample hold such insurance, cuts to Medicaid may compel households to increase their coverage. Introducing this additional margin of portfolio choice to our model could lower our estimates of the value households place on Medicaid. While in Section VIIC we argue that there are many reasons to think that introducing LTCI decisions would not significantly affect our results, it is worth studying this question more formally.

By focusing on the retirement period, we are able to explicitly model many dimensions of uncertainty and heterogeneity and to treat medical expenditures as a choice variable. However, it would be valuable to model the entire life cycle, the distortions generated by the income taxes needed to finance Medicaid, and the anticipated effects of Medicaid changes at younger ages.

By concentrating on single retirees, we study the population that is most likely to receive Medicaid transfers. The data shows that couples tend to be 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 to extend our analysis to include the valuation of Medicaid insurance by couples.

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