

Online Appendix for "Medicaid Insurance in Old Age"

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This online appendix includes information about various robustness checks, computational methods, and other details that are not included in the main text of the paper.

Appendix A: The MCBS data

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

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

To assess the quality of the medical expenditure data in the MCBS, we benchmark it against administrative data from the Medicaid Statistical Information System (MSIS) and survey data from the AHEAD. For Medicare payments, the match is close. For example, when using population weights, the number of Medicare beneficiaries lines up almost exactly with the aggregate statistics. More

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important, Medicare expenditures per beneficiary are very close. Over the 1996 to 2006 period, MCBS Medicare expenditures per capita for the age 65 and older population are \$6,070, only 11 percent smaller than the value of \$6,820 in the official statistics.¹

Table A1—: Medicaid Enrollment and Expenditures by Enrollee Spending Percentile: MSIS versus MCBS.

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

Note: 2010 MSIS data, adjusted to 2005 dollars.

The MCBS also accurately measures the share of the population receiving Medicaid payments.² However, MCBS Medicaid payments for the age 65 and older population are on average 32 percent smaller than what administrative data from the MSIS suggest. Table A1 compares the distribution of the MSIS administrative payment data (taken from Young et al. (2012)) to data from the MCBS. We show the MCBS distribution for all dual Medicare/Medicaid beneficiaries, the set closest to the the sample in the MSIS data. 59 percent of all dual eligibles are age 65 and older, the other 41 percent being disabled individuals under age 65 who are potentially more costly than the age 65 and older dual eligibles. Table A1 shows both means and means conditional on the distribution of payments. The MSIS data show that the least costly 50 percent of all Medicaid enrollees account for only 0.9 percent of total Medicaid payments, whereas the most costly 5 percent of all beneficiaries are responsible for 41 percent of payments. Although the MCBS data match the MSIS data well across the bottom 70 percent of the distribution,

¹Medicare statistics are located at http://www.census.gov/compendia/statab/cats/health_nutrition/medicare_medicaid.html.

²According to MCBS data, there were on average 5.1 million age Medicaid beneficiaries 65 and older over the 1996-2006 period, versus 4.7 million “aged” (which mostly refers to aged 65 and older) Medicaid beneficiaries in the MSIS data. This difference potentially reflects a small number of Medicaid age 65 and older individuals who are classified as “disabled” instead of “aged” in the MSIS data. Medicaid MSIS statistics are located at <https://www.cms.gov/Research-Statistics-Data-and-Systems/Computer-Data-and-Systems/MedicaidDataSourcesGenInfo/MSIS-Tables.html>. See De Nardi et al. (2015) for further comparisons of the MCBS data to administrative data on Medicare and Medicaid beneficiaries and payments.

the top 5 percent of all payments in the MSIS average \$100,060, whereas in the MCBS they are \$69,810. Limiting the MCBS sample to our estimation sample (retired singles who meet our age selection criteria: greater than 70 in 1994, 72 in 1996, 74 in 1998, etc.) leads to higher payments: average Medicaid payments for Medicaid beneficiaries in this MCBS subsample are \$13,620.

Table A2—: Income, Out-of-pocket Spending, and Medicaid Reciprocity Rates: AHEAD versus MCBS

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

Note: 1996-2010, for those age 72 and older in 1996.

The next set of benchmarking exercises that we perform is for out-of-pocket medical spending, Medicaid reciprocity and income between the AHEAD and MCBS. We restrict the sample to singles (over the sample period) who meet the AHEAD age criteria (at least 70 in 1994, 72 in 1996, ...) and who are not working over the sample period, just as we do in the AHEAD data. We construct a measure of permanent income, which is the percentile rank of total income over the period we observe these individuals (the MCBS asks only about total income). The first four columns of Table A2 show sample statistics from the full AHEAD sample while the final three columns of the table shows sample statistics from the MCBS sample. The first statistics we compare are income. Total income in the AHEAD data (including asset and other non-annuitized income) lines up well with total income in the MCBS data, although income in the top quintile of the MCBS is higher than in the AHEAD. Next, we compare out-of-pocket medical spending in the MCBS and AHEAD. Out-of-pocket medical expenditure (including insurance payments) averages \$2,360 in the bottom PI quintile and \$6,340 in the top quintile in the AHEAD. In comparison, the same numbers in the MCBS data are \$3,540 and \$7,020. Overall, out-of-pocket medical spending in the MCBS and AHEAD are similar, which may be surprising given that the two surveys each have their own advantages in terms of survey methodology.³ The share of the population receiving Medicaid transfers is also very similar in

³There are more detailed questions underlying the out-of-pocket medical expense questions in the

the AHEAD and MCBS. 61 percent and 70 percent of those in the bottom PI quintile are on Medicaid in the the AHEAD and MCBS, respectively. In the top quintile, 3 percent of people are on Medicaid in the AHEAD whereas 5 percent are in the MCBS. The higher Medicaid reciprocity rate in the MCBS might reflect that the MCBS data has administrative information on whether individuals are on Medicaid, which eliminates underreporting problems.

We also assess the usefulness of the Medicaid-related data in MEPS. A key problem with the MEPS data, however, is that that it does not include information on nursing home stays or expenses in the last few months of life. Using data from MSIS, Young et al. (2012) report that among those aged 65 and older, 79 percent of all Medicaid expenses are for long term care (although only 14 percent of these beneficiaries are receiving long term care). The MEPS data are useful for understanding the remaining 21 percent of Medicaid payments. Consistent with this fact, mean Medicaid payments in the MEPS for elderly beneficiaries are only \$3,499, whereas they are \$8,630 in the MCBS and \$13,414 according to the administrative data from the MSIS.

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

Appendix B: Computational Details

This Appendix details our simulation procedure.

- 1) To find optimal decision rules, we solve the model backwards using value function iteration. The state variables of the model are assets, gender, health status, permanent income, and the permanent and transitory components of medical spending (ζ and ξ). At each age, we solve the model for 200 grid points for assets, two points for gender (male and female), three points for health (good, bad, and nursing home), 13 grid points for permanent income, five points for the persistent component of medical needs shocks, and four points for the idiosyncratic component of the medical needs shocks. Our approach for discretizing the medical needs shocks follows Tauchen (1986), with the grid spaced over the percentile range [0.175, 0.825], a specification we found to work well.
- 2) Our initial sample of simulated individuals is large, consisting of 150,000 random draws of individuals in the first wave of our data. Given that we randomly simulate a sample of individuals that is larger than the number of individuals observed in the data, most observations will be drawn multiple times.
- 3) The initial distribution of all the state variables are observed in the data, except for the split between the permanent and transitory components of the medical spending shifters (ζ and ξ). Regarding the final two variables, we only observe out-of-pocket medical expenses, which in our model are a function of not only the spending shifters, but all the other state variables. Recall that forward-looking retirees will respond differently to persistent and transitory shocks of the same size. Inferring the two shocks would thus involve a costly filtering procedure utilizing the model's decision rules. We instead draw the initial values of ζ and ξ from their invariant distributions.
- 4) For each draw, not only do we take the joint realization of the individual's initial state vector (excluding ζ and ξ), but we also use the observed health and mortality history experienced by that particular individual. We assign entire health and mortality histories to insure that we properly match how our sample composition changes with age. One concern is that our sample is fairly small, so that the medians (or 90th percentiles) of wealth or medical spending in some cohort-income groups can change with the deaths of a few individuals. While we expect these effects to average out if we forward-simulated demographic transitions, it is simpler to match the data if we base our simulations on actual life histories. A more fundamental issue is that the processes for health and mortality that we feed into the model do not depend on wealth, because wealth is an endogenous variable in our model. However, we know that high wealth is a good predictor of longevity,

conditional on the other state variables. Our simulation procedure captures the initial wealth/mortality gradient by construction, whereas our estimated health and mortality transition models do not.

- 5) Given the optimal decision rules and the initial conditions of the state variables, we calculate life histories for savings, consumption, Medicaid reciprocity, and medical spending.
- 6) We aggregate the simulated data in the same way we aggregate the observed data, and construct moment conditions. We describe these moments in greater detail in Appendix C. Our method of simulated moments procedure delivers the model parameters that minimize a GMM criterion function, which we also describe in Appendix C.

Appendix C: Moment Conditions and Asymptotic Distribution of Parameter Estimates

Our econometric approach is an extension of the econometric approach used to estimate the model with endogenous medical spending in De Nardi, French and Jones (2010). The notation and exposition in this appendix thus follow closely those found in Appendix A of De Nardi, French and Jones (2010).

Recall that we estimate the parameters of our model in two steps. In the first step, we estimate the vector χ , the set of parameters than can be estimated without explicitly using our model. In the second step, we use the method of simulated moments (MSM) to estimate the remaining parameters, which are contained in the $M \times 1$ vector Δ . The elements of Δ are ν , ω , β , Y , u , θ , k , and the parameters of $\ln \mu(\cdot)$. Our estimate, $\hat{\Delta}$, of the “true” parameter vector Δ_0 is the value of Δ that minimizes the (weighted) distance between the life-cycle profiles found in the data and the simulated profiles generated by the model.

For each calendar year $t \in \{t_0, \dots, t_T\} = \{1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010\}$, we match median assets for $Q_A = 5$ permanent income quintiles in $P = 5$ birth year cohorts.⁴ The 1996 (period- t_0) distribution of simulated assets, however, is bootstrapped from the 1996 data distribution, and thus we match assets to the data for 1998, ..., 2006. In addition, we require each cohort-income-age cell have at least 10 observations to be included in the GMM criterion.

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

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

The preceding equation can be rewritten as a moment condition (Manski, 1988; Powell, 1994). In particular, applying the indicator function produces

$$(C1) \quad E(1\{a_{it} \leq a_{pqt}(\Delta_0, \chi_0)\} - 1/2 \mid p, q, t, \text{individual } i \text{ observed at } t) = 0.$$

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

⁴Because we do not allow for macro shocks, in any given cohort t is used only to identify the individual's age.

Chamberlain (1992)):

$$(C2) \quad E\left([1\{a_{it} \leq a_{pqt}(\Delta_0, \chi_0)\} - 1/2] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \times 1\{\text{individual } i \text{ observed at } t\} \mid t\right) = 0,$$

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

We also include several moment conditions relating to medical expenses. Recall that within the model medical expenses are chosen annually and are forward-looking (i.e., for the calendar year in which they are chosen). In contrast, medical expenditures in the AHEAD are averages of spending over the preceding two years. To reconcile the two measures, we first simulate medical expenses at an annual frequency, take two-year averages, and move the resulting averages back one year, to produce a measure of medical expenditures comparable to the ones contained in the AHEAD. This means that the AHEAD measure for medical spending in 2000 will be compared to averages of model-simulated spending for 1998 and 1999. Using lagged values also allows us to account for people who died prior to the most current wave. This too ensures consistency with the AHEAD, which collects end-of-life medical spending data through survivor interviews.

As with assets, we divide individuals into 5 cohorts and match data from 7 waves covering the period 1998-2010. (Because the model starts in 1996, while the medical expense data are averages over 1995-96, we cannot match the first wave.) The moment conditions for medical expenses are split by permanent income as well. However, we combine the bottom two income quintiles, as there is very little variation in out-of-pocket medical expenses in the bottom quintile until very late in life; $Q_M = 4$.

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

$$(C3) \quad E\left([1\{m_{it} \leq m_{pqt}^{50}(\Delta_0, \chi_0)\} - 0.5] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \times 1\{\text{individual } i \text{ observed at } t\} \mid t\right) = 0,$$

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

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

we have the following moment condition:

$$(C4) \quad E\left([1\{m_{it} \leq m_{pqt}^{90}(\Delta_0, \chi_0)\} - 0.9] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \times 1\{\text{individual } i \text{ observed at } t\} \mid t\right) = 0,$$

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

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

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

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

and define the standard deviation σ_{pqt} as

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

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

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

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

$$(C5) \quad E\left(\left[\frac{R_{it}R_{i,t-1}}{\sigma_{pqt} \sigma_{pq,t-1}} - AC_{pqt1}(\Delta_0, \chi_0)\right] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \times 1\{\text{individual } i \text{ observed at } t \ \& \ t-1\} \mid t\right) = 0.$$

The corresponding moment condition for the second autocorrelation is

$$(C6) \quad E\left(\left[\frac{R_{it}R_{i,t-2}}{\sigma_{pqt} \sigma_{pq,t-2}} - AC_{pqt2}(\Delta_0, \chi_0)\right] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \times 1\{\text{individual } i \text{ observed at } t \ \& \ t-2\} \mid t\right) = 0.$$

Finally, we match Medicaid utilization (take-up) rates. Once again, we divide

individuals into 5 cohorts, match data from 5 waves, and stratify the data by permanent income. We combine the top two quintiles because in many cases no one in the top permanent income quintile is on Medicaid: $Q_U = 4$.

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

$$(C7) \quad E\left([u_{it} - \bar{u}_{pqt}(\Delta_0, \chi_0)] \times 1\{p_i = p\} \times 1\{I_i \in \mathcal{I}_q\} \times 1\{\text{individual } i \text{ observed at } t\} \mid t \right) = 0$$

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

To summarize, the moment conditions used to estimate model with endogenous medical expenses consist of: the moments for asset medians described by equation (C2); the moments for median medical expenses described by equation (C3); the moments for the 90th percentile of medical expenses described by equation (C4); the moments for the autocorrelations of logged medical expenses described by equations (C5) and (C6); and the moments for the Medicaid utilization rates described by equation (C7). In the end, we have a total of $J = 633$ moment conditions.

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

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

where τ is the ratio of the number of observations to the number of simulated observations.

In practice, we estimate χ_0 as well, using the approach described in the main text. Computational concerns, however, compel us to treat χ_0 as known in the analysis that follows. Under regularity conditions stated in Pakes and Pollard (1989) and Duffie and Singleton (1993), the MSM estimator $\hat{\Delta}$ is both consistent and asymptotically normally distributed:

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

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

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

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

$$(C8) \quad \mathbf{D} = \left. \frac{\partial \varphi(\Delta; \chi_0)}{\partial \Delta'} \right|_{\Delta=\Delta_0}$$

is the $J \times M$ gradient matrix of the population moment vector; and $\mathbf{W} = \text{plim}_{I \rightarrow \infty} \{\widehat{\mathbf{W}}_I\}$. Moreover, Newey (1985) shows that if the model is properly specified,

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

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

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

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

But even though the optimal weighting matrix is asymptotically efficient, it can be biased in small samples. (See, for example, Altonji and Segal (1996).) We thus use a “diagonal” weighting matrix, as suggested by Pischke (1995). This diagonal weighting scheme uses the inverse of the matrix that is the same as \mathbf{S} along the diagonal and has zeros off the diagonal of the matrix.

An additional problem is that in cells with small numbers of observations, a moment condition will occasionally have a variance of zero. In one particular cell of the current specification, every person receives Medicaid. Rather than exclude these cells from the moment criterion, we add a small amount of measurement error to the moment condition, so that the weight on the moment (the inverse of the variance) is large but finite.

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

One complication in estimating the gradient matrix \mathbf{D} is that the functions inside the moment condition $\varphi(\Delta; \chi)$ are non-differentiable at certain data points; see equation (C2). This means that we cannot consistently estimate \mathbf{D} as the numerical derivative of $\hat{\varphi}_I(\cdot)$. Our asymptotic results therefore do not follow from the standard GMM approach, but rather the approach for non-smooth functions described in Pakes and Pollard (1989), Newey and McFadden (1994) (section 7), and Powell (1994).

To find \mathbf{D} , it is helpful to rewrite equation (C2) as

$$(C9) \quad \Pr \left(p_i = p \ \& \ I_i \in \mathcal{I}_q \ \& \ \text{individual } i \text{ observed at } t \right) \times \left[\int_{-\infty}^{a_{pqt}(\Delta_0, \chi_0)} f(a_{it} \mid p, I_i \in \mathcal{I}_q, t) \, da_{it} - \frac{1}{2} \right] = 0.$$

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

$$(C10) \quad \Pr \left(p_i = p \ \& \ I_i \in \mathcal{I}_q \ \& \ \text{individual } i \text{ observed at } t \right) \times f \left(a_{pqt} \mid p, I_i \in \mathcal{I}_q, t \right) \times \frac{\partial a_{pqt}(\Delta_0; \chi_0)}{\partial \Delta'}.$$

In practice, we find $f(a_{pqt} \mid p, q, t)$, the conditional p.d.f. of assets evaluated at the median a_{pqt} , with a kernel density estimator written by Koning (1996). The gradients for equations (C3) and (C4) are found in a similar fashion.

Appendix D: Demographic Transition Probabilities in the AHEAD

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

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

$$\begin{aligned}\pi_{ij,t} &= \Pr(h_{t+1} = j | h_t = i) \\ &= \gamma_{ij} / \sum_{k \in \{0,1,2,3\}} \gamma_{ik}, \\ \gamma_{i0} &\equiv 1, \quad \forall i, \\ \gamma_{1k} &= \exp(x_1 \beta_k), \quad k \in \{1, 2, 3\}, \\ \gamma_{2k} &= \exp(x_2 \beta_k), \quad k \in \{1, 2, 3\}, \\ \gamma_{3k} &= \exp(x_3 \beta_k), \quad k \in \{1, 2, 3\},\end{aligned}$$

where $\{\beta_k\}_{k=1}^3$ are coefficient vectors for each future state k and x_i , $i \in \{1, 2, 3\}$, is the explanatory variable vector evaluated at current state i .

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

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

imposing $\pi_{00,t+1} = 1$. This allows us to estimate $\{\beta_k\}$ directly from the data using maximum likelihood.

Appendix E: Identification and Sensitivity to Parameter Values

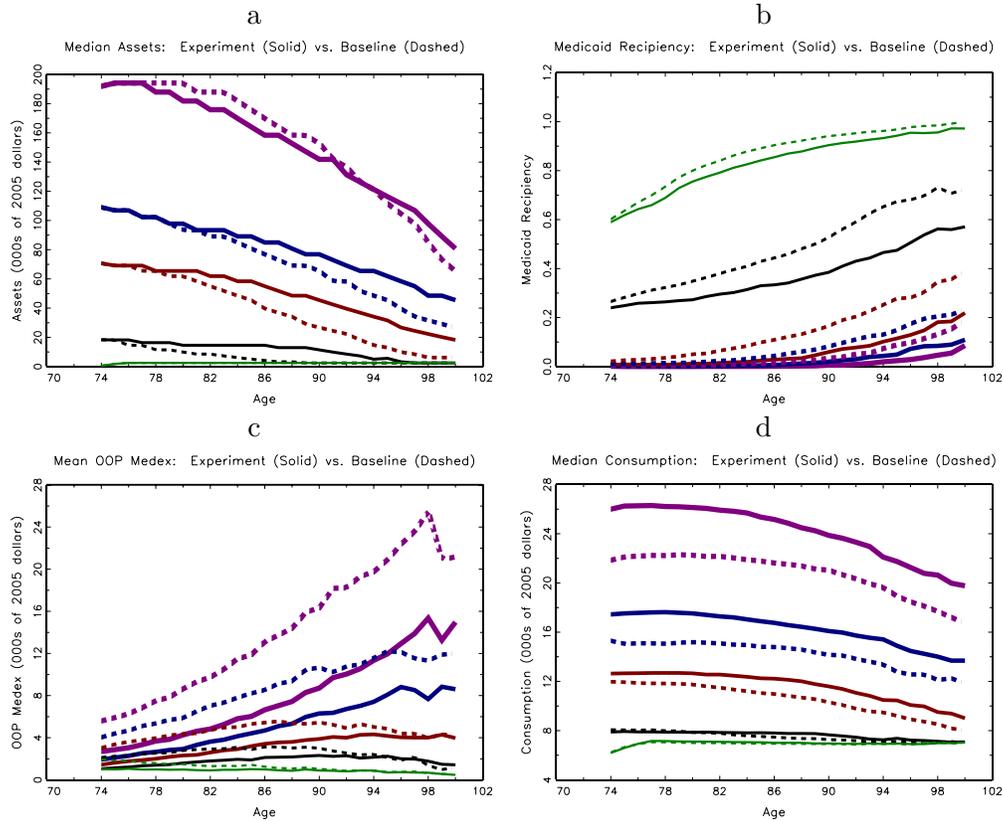
In this appendix, we consider how changes in key parameters affect the model's implications for outcomes such as savings, out-of-pocket medical spending, and Medicaid reciprocity. We change one parameter at a time, holding all other parameters at their baseline values. Table E1 shows how the parameter changes affect the asset, out-of-pocket medical spending, and Medicaid reciprocity moments, as well as the total GMM criterion (the sum of all the moments). Figures E1-E5 show how the parameter changes affect the life-cycle profiles of assets, out-of-pocket medical spending, Medicaid reciprocity, and non-medical consumption. This appendix also includes Figure E6, which shows the same profiles for the version of the model where medical spending is exogenous.

The top row of Table E1 shows the moment contributions for our baseline model. The second row shows the moment contributions that result when we reduce the consumption curvature parameter ν by 10 percent. This specification fits the data much worse: the GMM criterion in the baseline model is 1,217, whereas it is 3,513 when we reduce ν by 10 percent. Figure E1 reveals that this specification produces much lower medical spending and Medicaid reciprocity, and Table E1 shows that this leads to a much worse model fit.

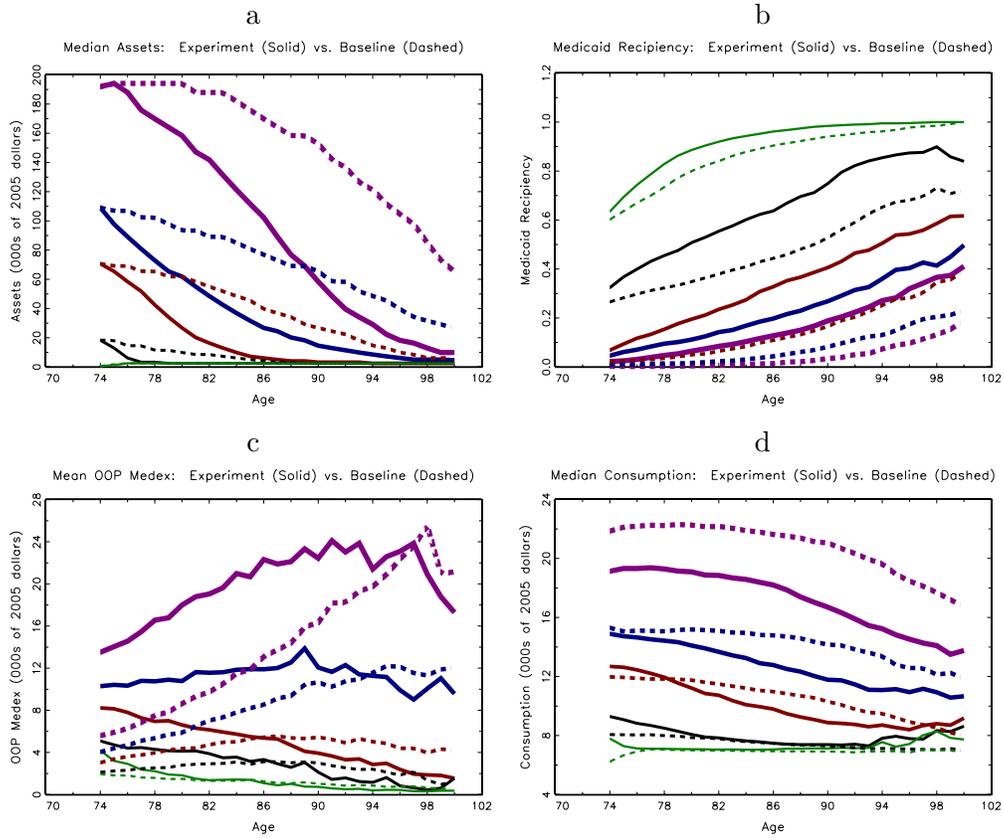
Decreasing the curvature parameter ω by 10 percent leads the model to over-predict medical spending and Medicaid reciprocity. Reducing the discount factor β by 10 percent leads to much more rapid asset decumulation, which is not consistent with the data. The next two rows of Table E1 show the effects of changing the bequest motive parameters, that is the marginal propensity to consume out of wealth in the final period before certain death (MPC) and the threshold where the bequest motive becomes operative. Both of these objects are functions of the bequest parameters θ and k . Changing the bequest parameters does not necessarily make the model fit the asset moments less well, but it does make the model fit the medical spending and Medicaid reciprocity moments less well. Next, we decrease the utility floor and the Medicaid income threshold by 10 percent. Reducing these parameters worsens the model's fit of the Medicaid moments. Finally, reducing either the mean or the variance of the medical needs shocks causes the model to fit the data less well.

Table E1—: Effects of Parameter Changes on GMM Criteria

Specification	Asset Quantiles	Medical Spending		Medicaid Reciprocity	Total
		Quantiles	Autocor- relations		
Baseline	166	543	174	335	1,217
ν Decreased 10 Percent	202	2,355	189	767	3,513
ω Decreased 10 Percent	424	1,853	252	1,207	3,736
β Decreased 10 Percent	213	696	169	316	1,394
MPC Decreased 10 Percent	179	541	174	351	1,246
Bequest Threshold Doubled	146	718	182	372	1,418
Utility Floors Decreased 10 Percent	175	532	201	364	1,271
Medicaid Income Threshold Decreased 10 Percent	165	595	150	345	1,254
Medical Shocks Decreased 10 Percent	175	580	174	378	1,308
Variance of Shocks Decreased 10 Percent	163	581	173	321	1,238

Figure E1. : ν Decreased 10 Percent

Note: Assets (panel a), Medicaid reciprocity (panel b), out-of-pocket medical spending (panel c), and non-medical consumption (d) by age and permanent income. Dashed line: benchmark, solid line: ν decreased 10 percent.

Figure E2. : ω Decreased 10 Percent

Note: Assets (panel a), Medicaid reciprocity (panel b), out-of-pocket medical spending (panel c), and non-medical consumption (d) by age and permanent income. Dashed line: benchmark, solid line: ω decreased 10 percent.

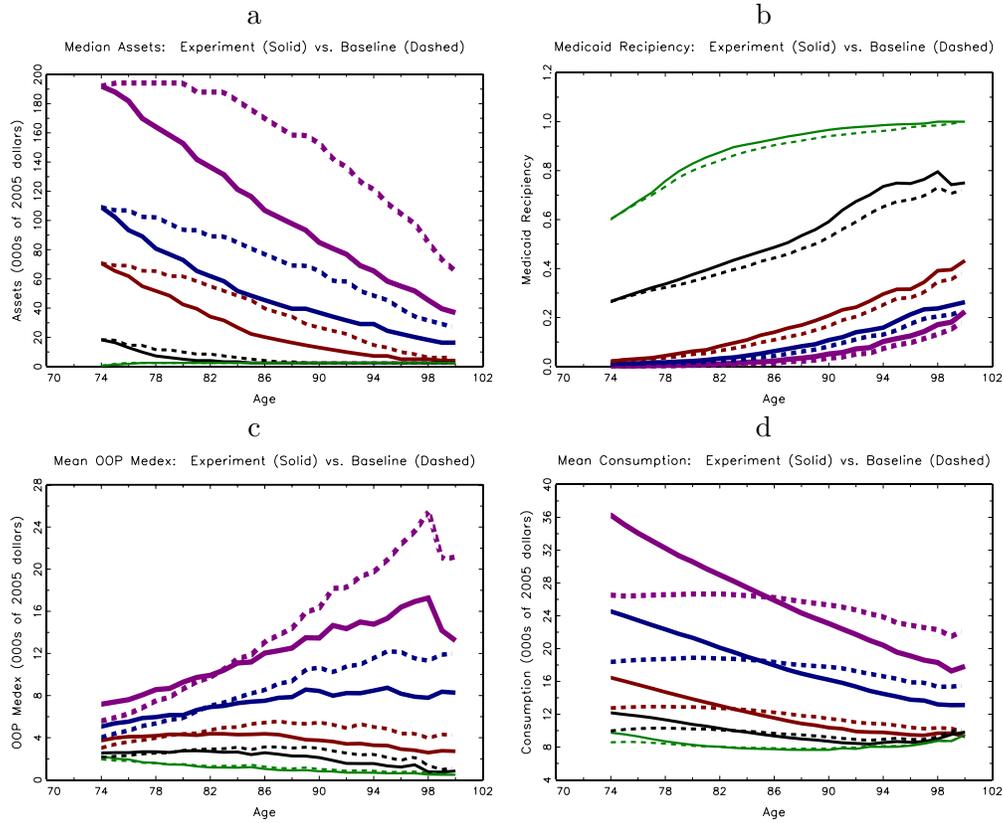


Figure E3. : β Decreased 10 Percent

Note: Assets (panel a), Medicaid reciprocity (panel b), out-of-pocket medical spending (panel c), and non-medical consumption (d) by age and permanent income. Dashed line: benchmark, solid line: β decreased 10 percent.

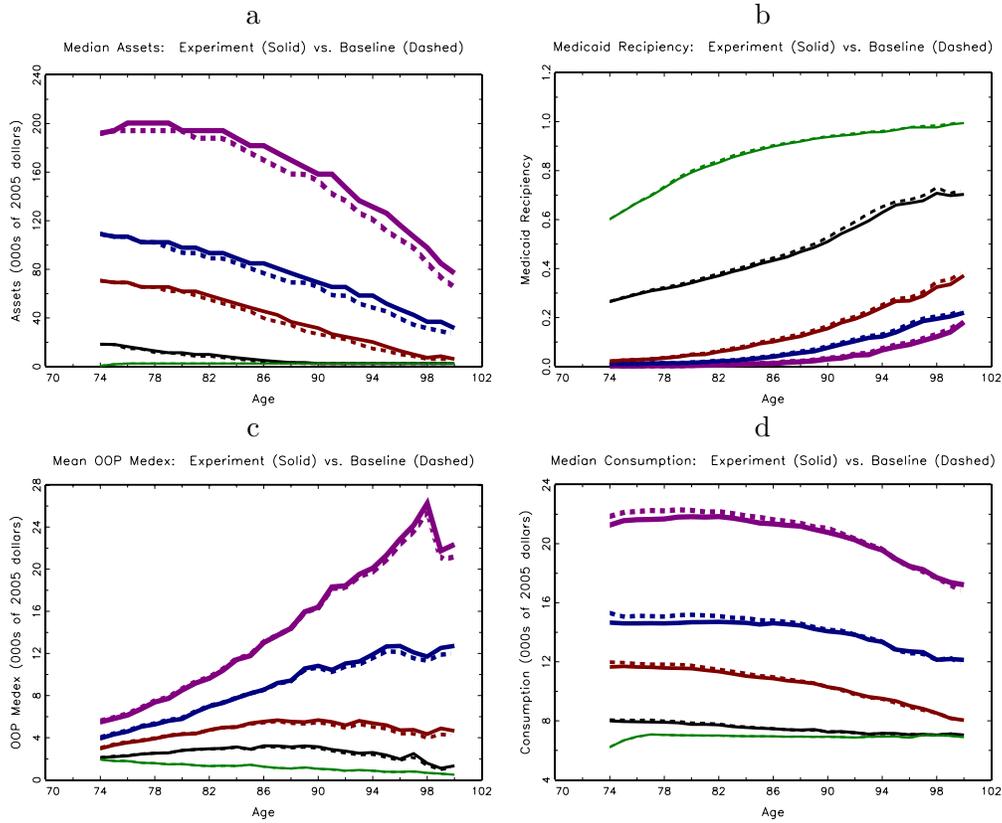


Figure E4. : MPC Decreased 10 Percent

Note: Assets (panel a), Medicaid reciprocity (panel b), out-of-pocket medical spending (panel c), and non-medical consumption (d) by age and permanent income. Dashed line: benchmark, solid line: MPC decreased 10 percent.

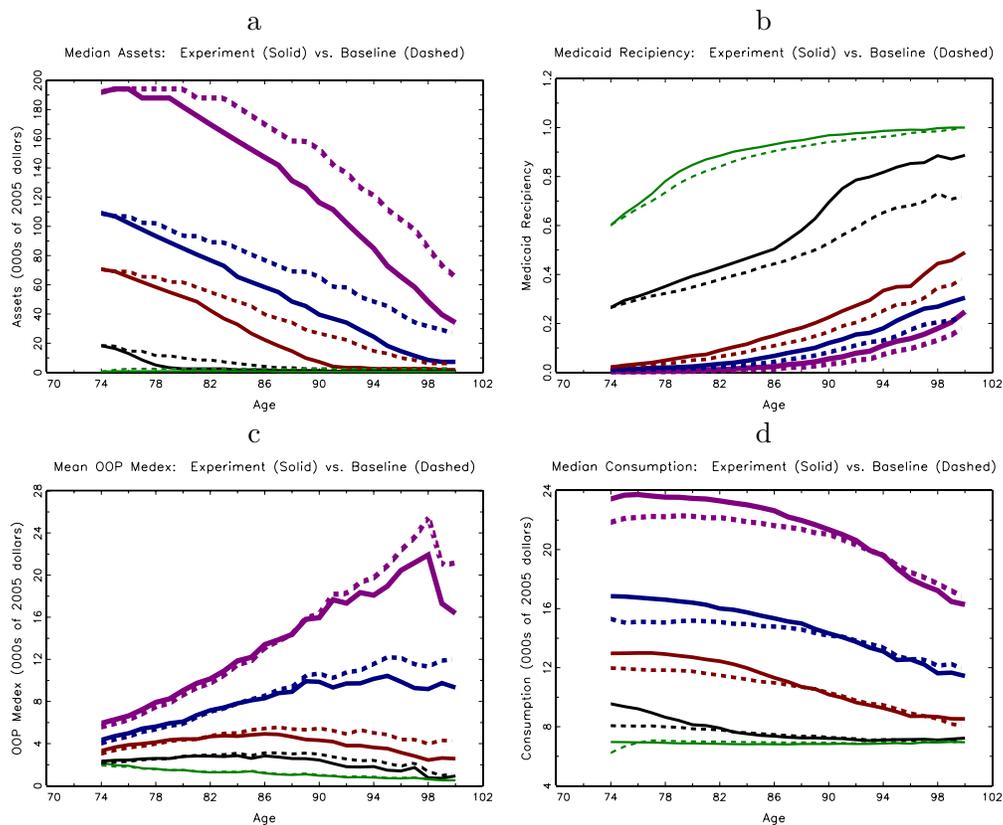


Figure E5. : Bequest Threshold Doubled

Note: Assets (panel a), Medicaid reciprocity (panel b), out-of-pocket medical spending (panel c), and non-medical consumption (d) by age and permanent income. Dashed line: benchmark, solid line: Bequest threshold doubled.

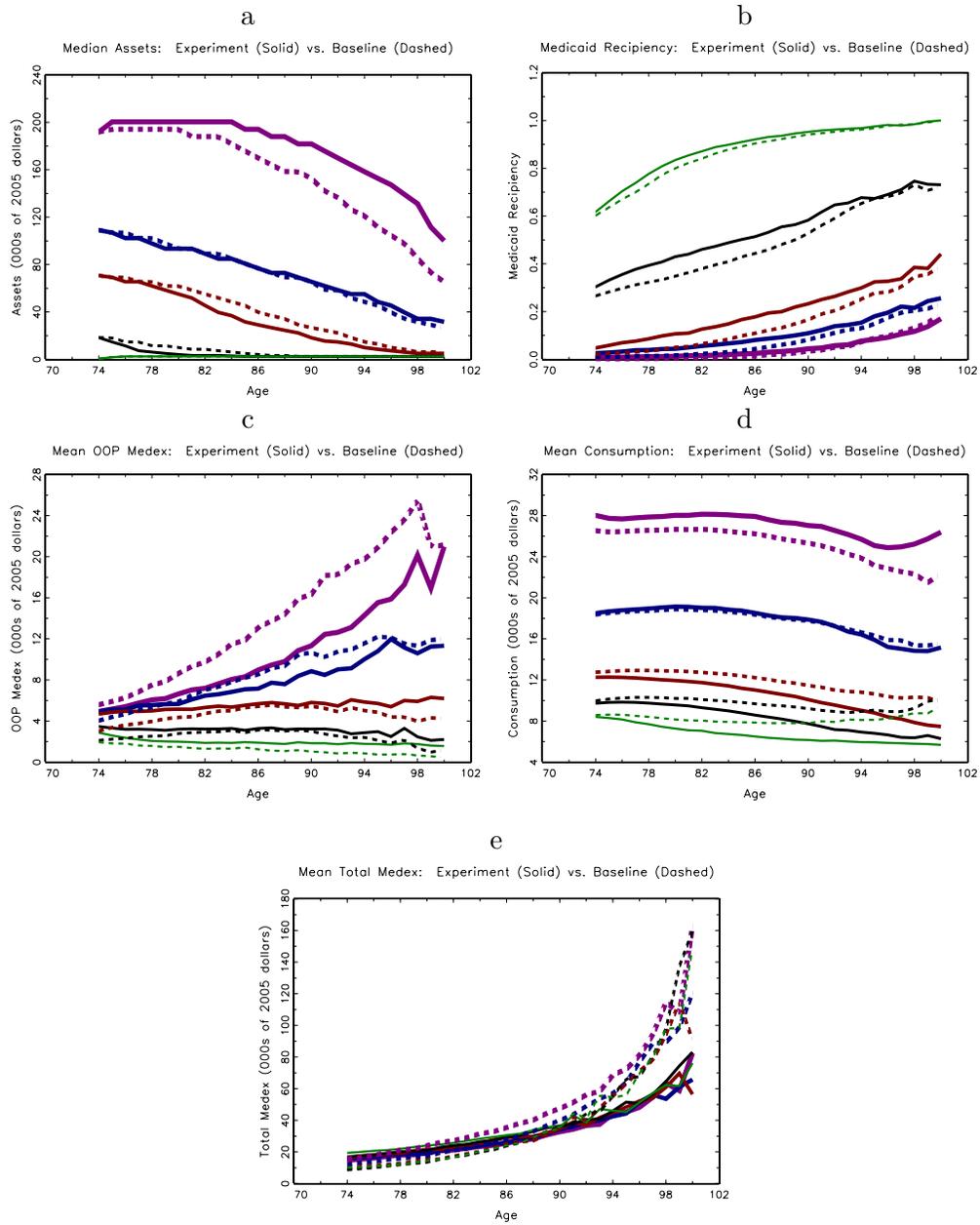


Figure E6. : Exogenous Medical Spending

Note: Assets (panel a), Medicaid reciprocity (panel b), out-of-pocket medical spending (panel c), non-medical consumption (d), and total medical spending (e) by age and permanent income. Dashed line: benchmark, solid line: exogenous medical spending.

Appendix F: Additional Parameter Estimates and Model Fits

Table F1 displays all the parameters that were estimated via our MSM procedure, along with standard errors. The first panel of this table reproduces the preference parameter estimates that were shown in Table 4 in the main text.

The next panel shows the parameters associated with the medical needs shock $\mu(h_t, \zeta_t, \xi_t, t)$. The persistent shock ζ_t has an autocorrelation coefficient (ρ_m) of 0.93 and generates 49% of the total shock variance. Although a significant portion of the (conditional) uncertainty in medical needs is short-lived, a significant portion is quite persistent. This risk exists over and above the uncertainty induced by variation in health and longevity. Continuing, Table F1 shows the level parameters and the volatility parameters for $\mu(\cdot)$. Although the multiple polynomial terms and interactions make the estimates difficult to interpret, some conclusions can be drawn. The level and volatility of the shocks are both increasing in age. People in good health have lower and less volatile shocks.

The final panel shows the overidentification statistic. The model has 633 moments and 24 parameters, leading to numerous overidentifying restrictions. The test statistic value of 1,799 implies that the model is formally rejected. Nonetheless, the model does well in matching the life-cycle profiles found in the data. This can be seen in Figures F1-F2, which compare the model-generated profiles with the data profiles. Figures 6-9 in the main text showed that the model matched the data for the bottom, middle and top PI quintiles. Figures F1-F2 show that the model performs equally well in matching data profiles for the second and fourth PI quintiles.

Table F1—: Estimated Parameters

Preference Parameters			
β : Discount Factor	0.994 (0.013)	$\underline{u}_c = \underline{u}_m$: Utility Floor ^a	\$4,600 (144)
ν : RRA, Consumption	2.825 (0.025)	θ : Bequest Intensity	39.71 (2.53)
ω : RRA, Medical Expenditures	2.986 (0.030)	k : Bequest Curvature (in 000s)	13.0 (0.655)
\underline{Y} : SSI Income Level	\$6,670 (208)		
Medical Needs Shifter (μ) Parameters			
ρ_m : Persistence of ζ	0.9274 (0.00465)	$\sigma_\epsilon^2/(1 - \rho_m^2)$: ζ 's Share of Total Shock Variance	0.4867 (0.0105)
Level Coefficients (Equation 4)		Variance Coefficients (Equation 5)	
α_0 : Intercept	-13.57 (0.110)	κ_0 : Intercept	42.07 (1.818)
α_1 : Age	0.2589 (0.00135)	κ_1 : Age	-0.0980 (0.00925)
α_2 : Age ² /100	-0.3035 (0.00212)	κ_2 : Age ² /100	0.3679 (0.0167)
α_3 : Age ³ /10000	0.2050 (0.00251)		
α_4 : $h_t = \text{Bad}$	-0.2823 (0.0352)	κ_4 : $h_t = \text{Bad}$	-0.3487 (0.129)
α_5 : Bad Health \times Age	0.00653 (0.000849)	κ_5 : Bad Health \times Age	0.02134 (0.00623)
α_6 : $h_t = \text{Good}$	-1.970 (0.113)	κ_6 : $h_t = \text{Good}$	-0.3050 (0.157)
α_7 : Good Health \times Age	-0.00942 (0.00108)	κ_7 : Good Health \times Age	0.03003 (0.00289)
χ^2 Overidentification Test	1,799	Degrees of Freedom	609

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

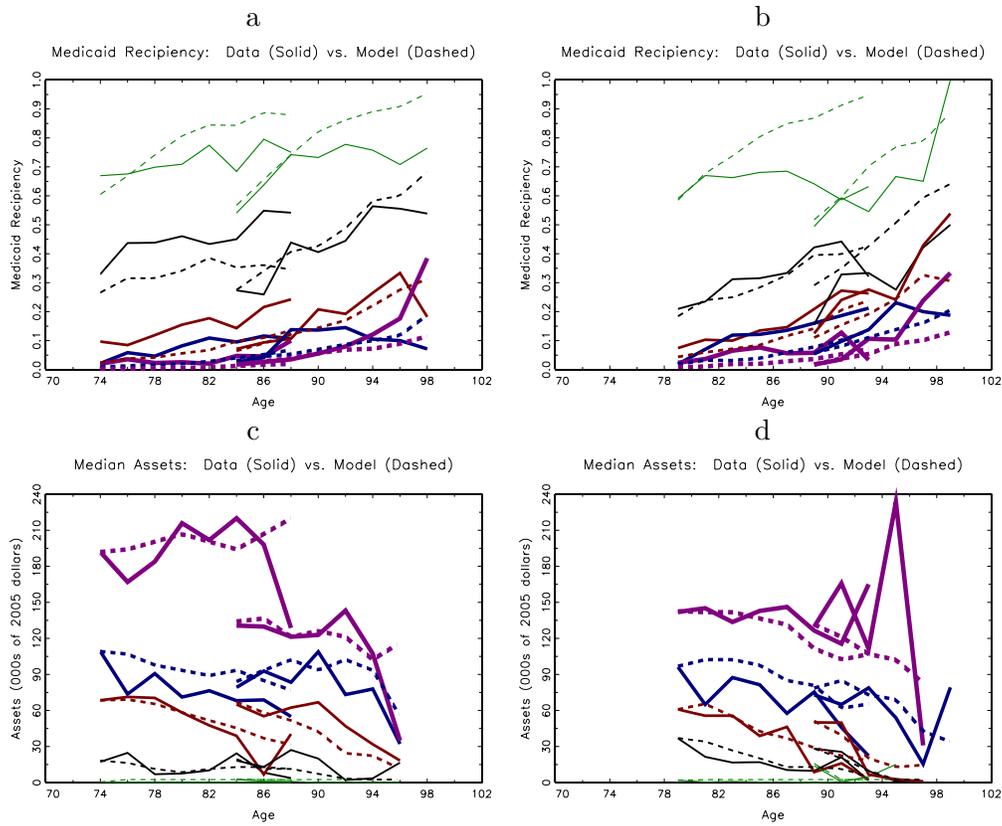


Figure F1. : Medicaid Reciprocity and Median Net Worth: Data versus Model Profiles

Note: Comparison of data (solid lines) and model (dashed lines) profiles. In panels a and b, each line represents Medicaid reciprocity for a cohort-income cell, traced over the time period 1996-2010. In panels c and d, each line represents median net worth. Thicker lines refer to higher permanent income groups. Panels a and c: cohorts aged 74 and 84 in 1996. Panels b and d: cohorts aged 79 and 89 in 1996.

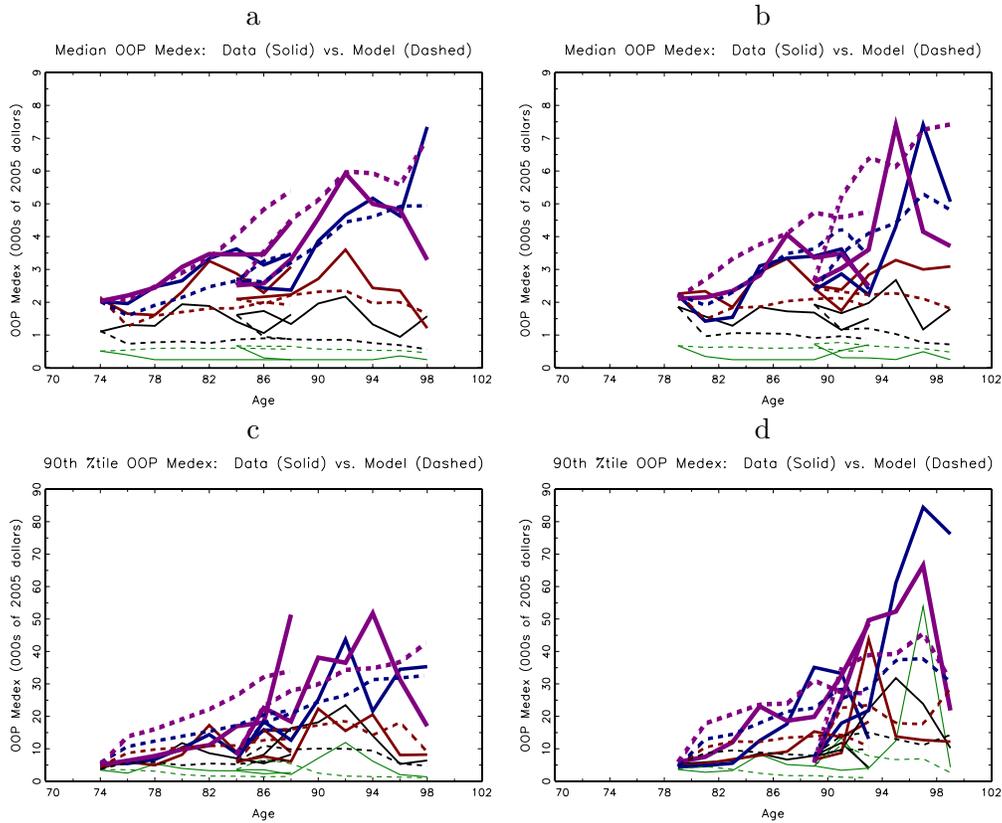


Figure F2. : Medical Expenditures: Data versus Model Profiles

Note: Each line represents median (top panels) and 90th percentile (bottom panels) of medical expenditures for a cohort-income cell, traced over 1996-2010. Left versus right panels: different cohorts. Data (solid lines) and model (dashed lines). Thicker lines: higher permanent income groups.

Appendix G: The PSID Data and Our Tax Calculations

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

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

Table G1—: Sample Size Comparison: AHEAD versus PSID, 1996 to 2010

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

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

Table G2 compares mean annuity income for each income quintile in the PSID sample and the AHEAD sample and shows that they match closely. After being sorted by income quintiles, the PDV of total household federal taxes (value in 1995, measured in 2005 dollars) is calculated for each income quintile-gender group g as follows:

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

where $w(g, t)$ is the probability that a member of group g is alive at time t ,

Table G2—: Annuity Income Comparison: AHEAD versus PSID, 1996 to 2010

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

conditional on being alive in 1967. The mortality rates behind $w(g, t)$ are taken from McClellan and Skinner (2006) until age 70 and are then updated using data from the US Life Tables for 2009. $I(g)$ is the number of people in group g , $tax(i, t)$ is the household federal taxes of individual i in year t , $r(j)$ is the nominal interest rate in year j , and $i(j)$ is the inflation rate. Since the PSID does not report taxes paid after 1990, we assume that tax payments after that year equal those paid in 1990, inflation-adjusted. We also assume a 4 percent real interest rate. We sum across all individuals to calculate the aggregate PDV of federal taxes. Given the total taxes paid for each group, we need to determine what fraction of these taxes was related to Medicaid.

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

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

Appendix H: Robustness of Compensating Variations to Medicaid Parameter Changes

To better understand what affects our estimated compensating variations, we change individual Medicaid program parameters and recompute the compensating variations associated with a 10 percent decrease in Medicaid generosity. The results in Table H1 of this appendix show that realistically small changes in Medicaid generosity and income eligibility generate relatively small changes in the compensating variations. Column (2) shows that a lower initial utility floor (for both the categorically and medically needy), which increases consumption risk, modestly increases the per-dollar valuations of Medicaid spending. Column (3) shows that increasing the Medicaid income test to its modal statutory value has virtually no effect on the compensating variations.

Table H1—: The Costs and Benefits of Reducing Medicaid by 10 Percent, Alternative Specifications

	Baseline Model (1)	Initial Floor Reduced 10% (2)	\bar{Y} (for SSI) = \$6,950 (3)
Change in Discounted Lifetime Spending			
Bottom	4,500	3,900	4,400
Fourth	4,000	3,500	4,000
Third	2,900	2,500	2,900
Second	2,200	1,900	2,200
Top	1,400	1,100	1,400
Compensating Variation			
Bottom	6,300	6,000	6,400
Fourth	5,000	4,800	5,000
Third	4,400	4,400	4,400
Second	4,100	4,600	4,100
Top	4,400	4,600	4,400
Compensating Variation / Change in Spending			
Bottom	1.40	1.54	1.45
Fourth	1.25	1.37	1.25
Third	1.52	1.76	1.52
Second	1.86	2.42	1.86
Top	3.14	4.18	3.14

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