## Online Appendix:

## Health Risk and the Welfare Effects of Social

## Security

## A The role of risk aversion

In this appendix we evaluate the importance of risk aversion in the context of our computational results. We are specifically interested in how different degrees of risk aversion affect the role of idiosyncratic health risk on welfare outcomes triggered by the discussed changes to Social Security. To do this, we consider two additional alternative versions of our baseline model with risk parameters $\sigma=3$ : one with a higher risk aversion parameter $\sigma=4$, and one with a lower risk aversion parameter $\sigma=2$. We separately calibrate both models to our original macroeconomic targets and then perform the same set of computational experiments as before with each model.

Calibrating our baseline model with a higher coefficient of relative risk aversion of $\sigma=4$ requires us to adjust the discount factor to $\beta=0.992$ and the consumption share parameter to $\eta=0.37$ so that the model matches our target capital-output ratio. Similarly, in the model with a lower coefficient of relative risk aversion of $\sigma=2$ we have to lower the discount factor to $\beta=0.975$ and increase the consumption share to $\eta=0.41$ to match the capital-output ratio.

## A. 1 Cutting Social Security

Similar to our earlier experiment we cut Social Security's payroll tax rate from 10.6 to 5.3 percent in our newly calibrated models with different degrees of risk aversion. We present the model with health risk next to the model without health risk and also show the difference in outcomes in the columns marked with $\Delta$ in Table A.1.

As we lower the degree of risk aversion $(\sigma=2)$ we can first see that the macroeconomic aggregates- $Y, K, C$ and the average hours - are not much affected by whether we allow for idiosyncratic risk or not (compare first three columns in Table A.1). With or without health risk we observe a 4 percent increase in output, a 7 percent increase in capital and a 5 percent increase in consumption as the result of the cut of Social Security. The differences between the model with idiosyncratic health risk and the model without are minor as can be seen by the numbers in column $\Delta$. We find a similar result with respect to the welfare outcomes.

Cutting Social Security leads to considerable welfare gains and these gains are not strongly affected by whether idiosyncratic health risk is present or not. What should be noted of course is that the welfare gains of cutting Social Security are much larger at 7.7 percent of CEV compared to about 5 percent of CEV in the benchmark case. In a model with smaller risk aversion $(\sigma=2)$ the precautionary savings motive is weaker than in the benchmark model. This means that Social Security leads to larger savings distortions, so that removing some of it, leads to larger welfare effects than in a model with a stronger degree of risk aversion where households react less strongly to the presence of Social Security to begin with.

We next investigate the effects in a model with a much higher degree of risk aversion and set $\sigma=4$. We again find that the macroeconomic aggregates are not much affected by the presence (or absence) of idiosyncratic health risk. However, when it comes to welfare effects we find two patterns: $(i)$ the welfare gains from cutting Social Security are smaller in the model with higher risk aversion and (ii) the welfare gains are affected by idiosyncratic health risk. Concerning the first point, we have already discussed how the precautionary savings motive becomes stronger with the degree of risk aversion. A strong precautionary savings motive mitigates the distortions caused by the Social Security program. If distortions from Social Security are small to begin with, then cuts to said program result in smaller effects, ceteris paribus. The second pattern is also fairly intuitive. If individuals care about risk (i.e., have a high degree of risk aversion $\sigma=4$ ), then the presence of additional risk from health spending (i.e., we add idiosyncratic health risk to the already present idiosyncratic income risk in our health-risk version of the model) will affect household decisions. On the other hand, in a model where individuals do not care too much about risk (i.e., have a low degree of risk aversion $\sigma=2$ ), the presence of idiosyncratic health spending risk will not matter much-qualitatively or quantitatively-for the outcome of our policy experiment.

Table A.1: Risk aversion and Social Security tax cut

|  | $\sigma=2.0$ |  |  |  | Benchmark: $\sigma=3.0$ |  |  | $\sigma=4.0$ |  |  |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
|  | H. risk | No h.r. | $\Delta$ | H. risk | No h.r. | $\Delta$ | H. risk | No h.r. | $\Delta$ |  |
|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ | $(6)$ | $(7)$ | $(8)$ | $(9)$ |  |
| Output $Y$ | 104.07 | 104.04 | 0.03 | 104.00 | 104.54 | -0.54 | 104.87 | 104.78 | 0.09 |  |
| Capital $K$ | 107.08 | 106.84 | 0.24 | 106.63 | 107.33 | -0.70 | 108.42 | 108.23 | 0.19 |  |
| Consumption $C$ | 105.30 | 105.56 | -0.26 | 105.66 | 106.33 | -0.67 | 106.13 | 106.15 | -.02 |  |
| Avge hours/week workers | 40.78 | 40.62 | 0.16 | 37.30 | 37.16 | 0.14 | 35.26 | 35.25 | 0.01 |  |
| Social Security | 52.37 | 52.37 | 0.00 | 52.29 | 52.48 | -0.19 | 52.47 | 52.40 | 0.07 |  |
| Medicaid | 112.27 | 112.11 | 0.16 | 115.37 | 112.52 | 2.85 | 114.18 | 114.94 | -0.76 |  |
| Welfare All \%C | 7.73 | 7.63 | 0.10 | 5.13 | 4.73 | 0.40 | 3.62 | 4.49 | -0.87 |  |
| Welf. No HiSchool | 7.17 | 7.30 | -0.13 | 3.74 | 3.27 | 0.47 | 2.17 | 3.87 | -1.70 |  |
| Welf. HiSchool | 7.31 | 7.09 | 0.22 | 5.15 | 4.65 | 0.50 | 3.30 | 4.59 | -1.29 |  |
| Welf. College | 9.30 | 9.31 | -0.01 | 6.84 | 6.94 | -0.10 | 7.60 | 4.84 | 2.76 |  |

Notes: We simulate a 50 percent reduction of the size of Social Security in models with different degrees of risk aversion. We again distinguish between a Health risk model with idiosyncratic health spending shocks and a No-health-risk model with deterministic age dependent medical spending. [back to 53]

## A. 2 Changing the progressivity of Social Security

In this section we repeat the experiments from Section 5.2 where we modified the progressivity of Social Security's benefit-earnings rule, holding the payroll tax rate and the taxable maximum income threshold constant, in models with $\sigma=2, \sigma=3$ (Benchmark) and $\sigma=4$. The results of these experiments are summarized in Table A.2.

Low risk aversion. As we lower the degree of risk aversion $(\sigma=2)$ we first see that the macroeconomic aggregates- $Y, K, C$ and the average hours-are not much affected by whether we allow for idiosyncratic risk or not (compare first three columns in Table A.2). With or without health risk we observe a 2 percent drop in output, a 4 percent decrease in capital and a 1 percent decrease in consumption as the result of moving to a lump sump Social Security benefits formula. The differences between the model with idiosyncratic health risk and the model without are minor as can be seen by the numbers in column $\Delta$. Welfare effects follow a similar pattern. The switch to lump-sum payments triggers a 3 percent increase in CEV which is slightly larger than in the benchmark economy. However, the welfare differences between the model with idiosyncratic health risk and the model without are very small as can be seen in column 3 of Table A.2.

When we change the benefits formula to a linear payout scheme ( $a_{1}=1$ ) we again observe that the macroeconomic aggregates show a modest increase similar to the benchmark economy and that the difference between the model with idiosyncratic health risk and the model without are very small (see columns 4-6 in Table A.2). The change in the welfare effects is different from the benchmark case as we now observe overall welfare gains compared to the benchmark economy (compare columns 4-6 to columns 10-12 in Table A.2).

At low levels of risk aversion, the switch to a linear payout formula can generate welfare gains. We do not observe this in models with higher levels of risk aversion.

High risk aversion. In the model with high risk aversion of $\sigma=4$ we again observe that the differences in outcomes between the models with idiosyncratic health risk and the model without this type of risk become larger. This is similar to the results of cutting Social Security in Section 53. First, moving to a lump-sum transfer system generates output gains in the model with health risk (column 13 in Table A.2) but output losses in the model without health risk (column 14 in Table A.2). The difference in macroeconomic variables under this policy change is much larger as can be seen from the $\Delta$ column 15 . If individuals care about risk, then a policy switch that affects this risk triggers differential responses in environments where idiosyncratic health risk is present. In other words, modeling idiosyncratic health risk as additional source of risk matters for policy experiments that make the Social Security formula more progressive and thereby remove some of this risk.

Table A.2: Risk aversion and PIA progressivity with health risk


 individual with respect to consumption levels in the benchmark. [back to 55]

## B Medical Expenditure Panel Survey (MEPS)

We primarily use data from the Medical Expenditure Panel Survey (MEPS) from the years 1999-2009 for our estimation and calibration. MEPS provides a nationally representative survey about health care use, health expenditures, health insurance coverage as well as demographic data on income, health status, and other socioeconomic characteristics. The original household component of MEPS was initiated in 1996. Each year about 15,000 households are selected and interviewed five times over two full calendar years. MEPS groups individuals into Health Insurance Eligibility Units (HIEU) which are subsets of households. We do abstract from family size effects and concentrate on adults aged $20-85$ who are the head of the HIEU.

## B. 1 Health care expenditure data

MEPS provides high quality health expenditure and health care utilization data. The MEPS Household Component (HC) collects data in each round on use and expenditures for office- and hospital-based care, home health care, dental services, vision aids, and prescribed medicines. In addition, the MEPS Medical Provider Component (MPC) is a follow-back survey that collects data from a sample of medical providers and pharmacies that were used by sample persons in a given year. Expenditure data collected in the MPC are generally regarded as more accurate than information collected in the HC and are used to improve the overall quality of MEPS expenditure data. Expenditures in MEPS refer to what is paid for health care services. Expenditures are defined as the sum of direct payments for care provided during the year, including out-ofpocket payments and payments by private insurance, Medicaid, Medicare, and other sources. Payments for over-the-counter drugs are not included in MEPS and neither are payments for long-term care. Similarly payments not related to specific medical events, such as Medicaid Disproportionate Share and Medicare Direct Medical Education subsidies, are also not included. MEPS records actual payments made and not original charges which tend to be much higher. However, it has become customary to apply discounts. In addition charges associated with uncollected liabilities, bad debt and charitable care do not constitute actual health care expenses and are therefore not counted.

## B. 2 Cohort effects

Panel data variables over the lifecycle of an individual are determined by age, time and cohort effects. Since our model only explicitly accounts for age effects, we should ideally remove time and cohort effects from the data in order to make lifecycle observations from the data consistent with lifecycle statistics generated
by the model. Since age, time and cohort effects are perfectly collinear it is difficult to estimate all three simultaneously (e.g., Jung and Tran 2014). The literature (e.g., Kaplan 2012) often suggests to conduct separate analyses once controlling for the cohort effect and in a repeat exercise controlling for the time effect. In this work we explicitly control for cohort effects of wages, income and health expenditures by regressing the $\log$ of the output variable on a set of age and cohort dummies. We focus on controlling for cohort effects because according to Jung and Tran (2014) they seem to be large in health expenditure data and time effects can be somewhat mitigated by deflating with the CPI index. We then use predictions of these regressions to generate a cohort-adjusted variable by predicting for a base cohort, that is we leave out the cohort dummies in the prediction.

Summary statistics of the unweighted sample are presented in Table B. 1 and a histogram of the age distribution is presented in Figure B.1. All dollar values are denominated in 2009 dollars using the OECD CPI for the US for all monetary measures. ${ }^{28}$
${ }^{28}$ OECD (2018), Inflation (CPI) (indicator). doi: 10.1787/eee82e6e-en (Accessed on 29 June 2018) at https://data.oecd.org/price/inflation-cpi.htm

Table B.1: Summary statistics MEPS 1999-2009

|  | All | LaborIncome $>$ \$400 |
| :---: | :---: | :---: |
| Year | 2004.249 | 2004.216 |
|  | (3.074) | (3.090) |
| Age of head of HIEU | 46.815 | 41.863 |
|  | (17.711) | (14.204) |
| Five-year age groups | 5.978 | 4.982 |
|  | (3.559) | (2.848) |
| Female | 0.442 | 0.396 |
|  | (0.497) | (0.489) |
| Married/Partnered | 0.417 | 0.444 |
|  | (0.493) | (0.497) |
| Black | $0.145$ | $0.134$ |
|  | $(0.352)$ | $(0.341)$ |
| Years of education | 12.003 | 12.487 |
|  | (4.017) | (3.740) |
| Avge hourly wage over 3 waves | 19.958 | 20.017 |
|  | (13.985) | (14.006) |
| Labor income (in \$1,000) | 28.503 | 39.382 |
|  | (34.946) | (35.482) |
| Labor income of HH (in \$1,000) | 52.333 | 65.426 |
|  | (54.126) | (54.360) |
| Pre-government HH income (in \$1,000) | 63.369 | 72.724 |
|  | (55.915) | (57.887) |
| Pre-government HIEU income (in \$1,000) | 49.194 | $58.336$ |
|  | (51.264) | $(53.921)$ |
| Health Status | 2.456 | 2.256 |
|  | (1.011) | (0.897) |
| Indicator for Healthy | 0.851 | 0.919 |
|  | (0.356) | (0.274) |
| Total health expenditures (in $\$ 1,000$ ) | 4.222 | 2.797 |
|  | (9.368) | (6.892) |
| healthExpenditureHIEU | 6.862 | 5.431 |
|  | (14.174) | (12.283) |
| Total health expenditures HIEU (in \$1,000) | 9.063 | 7.454 |
|  | (17.379) | (15.781) |
| Out-of-pocket health exp | 0.758 | 0.589 |
|  | (1.831) | (1.438) |
| OOPExpenditureHIEU | 1.240 | 1.095 |
|  | (2.445) | (2.178) |
| Total OOP expenditure HIEU (\$1,000) | 1.583 | 1.423 |
|  | (2.840) | (2.583) |
| No high school degree | 0.286 | 0.231 |
|  | (0.452) | (0.421) |
| High school degree | 0.511 | 0.537 |
|  | (0.500) | (0.499) |
| College or higher degree | $0.193$ | $0.224$ |
|  | (0.395) | (0.417) |
| Insured | 0.797 | 0.778 |
|  | (0.402) | (0.415) |
| Public health insurance | 0.207 | 0.098 |
|  | (0.405) | (0.298) |
| Private health insurance | 0.590 | 0.680 |
|  | (0.492) | (0.466) |
| d__head | 0.642 | 0.638 |
|  | (0.479) | (0.481) |
| d_head_HIEU | 1.000 | 1.000 |
|  | (0.000) | (0.000) |
| numAdultsInHH | 2.048 | 2.071 |
|  | (1.013) | (0.999) |
| numAdultsInHIEU | 1.453 | 1.491 |
|  | (0.590) | (0.611) |
| Observations | 169423 | 122694 |
| Note: MEPS 1999-2009. Unweighted sam | ple statist |  |

Notes: The table shows unweighted summary statistics (mean and standard errors in parenthesis) of heads of Health Insurance Eligibility Units (HIEU) based on MEPS 1999-2009. All dollar values are denominated in 2009 dollars using the OECD CPI for the US for all monetary measures.


Source: MEPS 1999-2009, Head of HIEU

Figure B.1: Age distribution
Notes: Data source is MEPS 1999-2009, heads of HIEU, population weighted.

## B. 3 Bias adjusted wage profiles

We follow Rupert and Zanella (2015) and Casanova (2013) and estimate a selection model to remove biases in self reported wages. Rupert and Zanella (2015) use PSID and CPS data and then employ a Tobit 2-step procedure based on Wooldridge (1995) to estimate selection corrected wage profiles. They find that once wage profiles are bias corrected they tend to be very flat which contradicts the often used hump-shaped wage profiles. Similarly, Casanova (2013) uses HRS data and finds evidence of flat wage profiles but no selection bias.

In our selection model we include fourth order polynomials in age, a control for health status, whether someone lives with a partner, family size, schooling, gender, and an indicator for part-time work. We use indicator variables for whether an individual is older than 62 and a second indicator variable for whether an individual is older 65 in the selection equation as is customary in this literature (see Rupert and Zanella, 2015). These two indicator variables are exclusion restrictions and not included in the outcome equation of the selection model. Table B. 3 shows the estimation results and Figure B. 2 shows the e wage profiles for healthy and unhealthy types and the three educational groups based on predictions from the selection model. The coefficient indicating whether an individual is healthy is highly significant and the wage profiles indicate that a healthy individual earn wages that are about 5 dollars above wages of unhealthy individuals.

French and Jones (2017) report that wages of individuals who report being in bad health are approximately 10 percent lower based on estimates of a fixed effects model in French (2005). Since the fixed effects model does not completely overcome the selection problem of self reported wages, French (2005) uses a structural model that incorporates selection and shows that fixed effects models underestimate the wage gap between health and unhealthy individuals by about 2 percentage points. Capatina (2015) uses a similar procedure and finds a consistent wage gap of 3 to 5 USD across all age groups.


Figure B.2: Selection bias adjusted wage profiles of heads of HIEUs
Notes: Data source is MEPS 1999-2009, heads of HIEU, population weighted. All dollar values are denominated in 2009 dollars using the OECD CPI for the US for all monetary measures.

Table B.3: Heckman Selection Model

|  | Log hourly wage | d__working |
| :---: | :---: | :---: |
| Age of HIEU | $\begin{gathered} 0.024 \\ (0.017) \end{gathered}$ | $\begin{gathered} -0.116^{* * *} \\ (0.040) \end{gathered}$ |
| Age ${ }^{2}$ /100 | $\begin{gathered} 0.059 \\ (0.058) \end{gathered}$ | $\begin{gathered} 0.207 \\ (0.131) \end{gathered}$ |
| Age ${ }^{3} / 1000$ | $\begin{gathered} -0.019^{* *} \\ (0.009) \end{gathered}$ | $\begin{aligned} & -0.015 \\ & (0.018) \end{aligned}$ |
| Age ${ }^{4} / 10000$ | $\begin{gathered} 0.001^{* * *} \\ (0.000) \end{gathered}$ | $\begin{gathered} 0.000 \\ (0.001) \end{gathered}$ |
| famSize | $\begin{gathered} -0.017^{* * *} \\ (0.001) \end{gathered}$ | $\begin{aligned} & -0.005 \\ & (0.003) \end{aligned}$ |
| Healthy | $\begin{gathered} 0.132^{* * *} \\ (0.007) \end{gathered}$ | $\begin{aligned} & -0.002 \\ & (0.019) \end{aligned}$ |
| High School | $\begin{gathered} 0.290^{* * *} \\ (0.005) \end{gathered}$ | $\begin{gathered} 0.041^{* * *} \\ (0.013) \end{gathered}$ |
| College | $\begin{gathered} 0.802^{* * *} \\ (0.006) \end{gathered}$ | $\begin{gathered} 0.006 \\ (0.015) \end{gathered}$ |
| Female | $\begin{gathered} -0.226^{* * *} \\ (0.004) \end{gathered}$ | $\begin{gathered} 0.272^{* * *} \\ (0.012) \end{gathered}$ |
| Married/Partnered | $\begin{gathered} 0.135^{* * *} \\ (0.005) \end{gathered}$ | $\begin{gathered} -0.086^{* * *} \\ (0.012) \end{gathered}$ |
| Works part-time | $\begin{gathered} -0.218^{* * *} \\ (0.006) \end{gathered}$ | $\begin{gathered} -0.294^{* * *} \\ (0.015) \end{gathered}$ |
| Older than 62 |  | $\begin{gathered} -0.059^{*} \\ (0.031) \end{gathered}$ |
| Older than 65 |  | $\begin{aligned} & -0.049 \\ & (0.036) \end{aligned}$ |
| Observations | 115606 |  |
| Standard errors in parentheses${ }^{*} p<0.10,{ }^{* *} p<0.05,{ }^{* * *} p<0.01$ |  |  |

Notes: Estimation results of average wages are based on a selection model-following Rupert and Zanella (2015) and Casanova (2013). This method removes biases in self reported wages. We control for cohort effects based on 5 year birth cohorts. Data source: MEPS 1999-2009.

## B. 4 Health status and health shocks

As explained in Section 3.3, we model health expenditure $m\left(\varepsilon_{j}^{h}, j, \vartheta\right)$ as a function of an exogenous health status $\varepsilon_{j}^{h}$ process that follows a Markov structure with transition probability matrix $\operatorname{Pr}\left(\varepsilon_{j+1}^{h} \mid \varepsilon_{j}^{h}, j, \vartheta\right)$. The probabilities to next period's health status $\varepsilon_{j+1}^{h}$ depend on the current health status $\varepsilon_{j}^{h}$ but also on current age $j$ and the individuals permanent income group $\vartheta$, so that an element of transition matrix $\Pi_{j, \vartheta}^{h}$ is defined as the conditional probability $\operatorname{Pr}\left(\varepsilon_{j+1}^{h} \mid \varepsilon_{j}^{h}, j, \vartheta\right)$. Health expenditures $m\left(\varepsilon_{j}^{h}, j, \vartheta\right)$ at a certain age $j$ depend on the current health status $\varepsilon_{j}^{h}$, age $j$ itself, and the permanent income group $\vartheta$.

Figure B. 3 shows health expenditures by age based on self reported health status and education level. The permanent income groups are defined as individuals with (i) no high school degree, (ii) a high school degree only, or (iii) college degree. We use these profiles directly in the model to determine medical spending magnitudes $m\left(\varepsilon_{j}^{h}, j, \vartheta\right)$ in the household problem of Section 3.8.


Figure B.3: Average Health Spending by Health State
Notes: Data source is MEPS 1999-2009, heads of HIEU, population weighted. Cohort adjusted average health spending by self-reported health state, age, and education status in 2009 USD.

We next estimate an ordered logit model to determine the conditional probability of moving to a specific health group $\varepsilon_{j+1}^{h}$ in year $t+1$ conditional on being a member of health group $\varepsilon_{j}^{h}$ at time $t$ of a $j$ year old individual using a fourth order age polynomial. The estimated health status Markov transition probabilities
are shown in Figure B.4.


Figure B.4: Conditional Health Status Markov Transition Probabilities
Notes: Data source is MEPS 1999-2009, heads of HIEU, population weighted.

The resulting health state distributions per 5-year age group are shown in Figure B.5.


Figure B.5: Health state distribution
Notes: The 5 health states are "1. excellent health", "2. very good health", "3. good health", "4. fair health" and " 5 . poor health".
Data source is MEPS 1999-2009, heads of HIEU, population weighted.

The resulting medical spending distribution is shown in Figure B.6.


Figure B.6: Medical spending distribution
Notes: The distribution is based on a simulation of 75 periods of a Markov process of 5 health states and their associated state dependent health care spending. Data source is MEPS 1999-2009, heads of HIEU, population weighted. All dollar values are denominated in 2009 dollars.

## C Panel Study of Income Dynamics (PSID)

The PSID started in 1968 with more than 5,000 US households. Participants were then re-interviewed annually until 1997. This includes people who "split off" from their original families to form new families as well as people born into these families. Other members of new families are interviewed while they are in these families but not followed if the family dissolved. In 1997 the core sample was reduced, a refresher sample of immigrant families was added and the survey frequency changed to biennial interviews. Wealth survey data is available for the years 1984, 1989, 1994, 1999, 2001, 2003, 2005, 2007, and 2009. A Summary statistics of the unweighted sample are presented in Table C. 1 and a histogram of the age distribution is presented in Figure C.1. All dollar values are denominated in 2009 dollars using the OECD CPI for the US for all monetary measures. ${ }^{29}$

We use variable SX17 from PSID, which is the sum of values of seven asset types, net of debt value plus home equity (X refers to wave). Values above USD 1,000,000 are removed. Wealth is converted to 2016 dollars using the CPI. In addition we use variable i11108 from the CNEF version of PSID which measures household pension income.


Source: PSID 1999-2009 at Household level

Figure C.1: Age distribution in PSID 1999-2009
Notes: Data source is PSID 1999-2009, heads of household, population weighted.

[^0]Table C.1: Summary statistics PSID 1999-2009

|  | $\begin{gathered} (1) \\ 1999-2009 \\ \text { mean/sd } \end{gathered}$ | (2) <br> 1999-2009: HH-Heads <br> mean/sd |
| :---: | :---: | :---: |
| Calendar year | 2004.142 | 2004.142 |
|  | (3.401) | (3.401) |
| Age of head of household | 46.136 | 46.136 |
|  | (15.863) | (15.863) |
| Female | 0.289 | 0.289 |
|  | (0.453) | (0.453) |
| Married | 0.521 | 0.521 |
|  | (0.500) | (0.500) |
| Number of Years of Education | 12.751 | 12.751 |
|  | (2.549) | (2.549) |
| Individual labor earnings in \$1,000 | 39.214 | 39.214 |
|  | (49.673) | $(49.673)$ |
| Labor income HH in $\$ 1,000$ | $54.473$ | $54.473$ |
|  | $(61.441)$ | (61.441) |
| Pre-government HH income in \$1,000 | 59.727 | 59.727 |
|  | (62.503) | (62.503) |
| HH Wealth excl. equity (2016 USD 1,000) | 89.507 | 89.507 |
|  | (155.482) | (155.482) |
| HH Wealth incl. equity (2016 USD 1,000) | 102.807 | 102.807 |
|  | (177.394) | (177.394) |
| Self-Rated Health Status | 2.439 | 2.439 |
|  | (1.080) | (1.080) |
| No high school degree | 0.186 | 0.186 |
|  | (0.389) | (0.389) |
| High school degree | $0.367$ | 0.367 |
|  | $(0.482)$ | (0.482) |
| College | 0.198 | 0.198 |
|  | (0.399) | (0.399) |
| Insured | 0.917 | 0.917 |
|  | (0.276) | (0.276) |
| Head of HH | 1.000 | 1.000 |
|  | (0.000) | (0.000) |
| Observations | 36890 | 36890 |

Note: Unweighted sample statistics.

Notes: Unweighted summary statistics of heads of households based on PSID 1999-2009. All dollar values are denominated in 2009 dollars using the OECD CPI for the US for all monetary measures.

## D Model performance: Additional graphs and tables

D. 1 Lifecycle labor income by type


Figure D.1: Model Performance II: Lifecycle labor income by type
Notes: Labor income profiles by permanent income group and health state. These are not calibration targets. Data source is MEPS 1999-2009, heads of HIEU, population weighted. [back to 21]

## D. 2 Benefits distributions and lifecycle correlations



Figure D.2: Model Performance III: Benefits distributions and lifecycle correlations
Notes: These are not calibration targets. Data source for Panel [1] is SSA (2010) and the data source for Panels [2]-[3] is MEPS 1999-2009, heads of HIEU, population weighted. [back to 21]

## D. 3 Size of permanent income groups by health status

Given the exogenous health status process and the associated definition of healthy (i.e., being in either excellent, very good, or good health) and sick (i.e., being in fair or poor health) together with the exogenous (health state dependent) survival probabilities from Panel [6] in Figure 1, the model composition of healthy/sick types by permanent income group (i.e., no high school degree, high school degree (only), and college degree) is shown in Table D.1. ${ }^{30}$ We also show the composition of these types (heads of household eligibility units) based on MEPS data from 1999-2009 using population weights.

[^1]Table D.1: Model Performance: Exogenous group sizes

| Individual type | Model | Data |
| :--- | ---: | ---: |
| Sick-No High School | $2.28 \%$ | $5.5 \%$ |
| Sick-High School | $5.35 \%$ | $6.3 \%$ |
| Sick-College | $1.69 \%$ | $1.43 \%$ |
| Healthy-No High School | $15.44 \%$ | $16.18 \%$ |
| Healthy-High School | $49.56 \%$ | $47.88 \%$ |
| Healthy-College | $25.68 \%$ | $23.42 \%$ |

Notes: The health shock and the definition of sick/healthy state results in the above cohort sizes in our model. Data Source: MEPS 1999-2009. [back to 18, 30]


[^0]:    ${ }^{29} \mathrm{OECD}(2018)$, Inflation (CPI) (indicator). doi: 10.1787/eee82e6e-en (Accessed on 29 June 2018) at https://data.oecd. org/price/inflation-cpi.htm

[^1]:    ${ }^{30}$ Health dependent survival rates are obtain from estimates in İmrohoroğlu and Kitao (2012).

