ARC Centre of Excellence in Population Ageing Research

Working Paper 2018/9

Health Shocks and the Evolution of Consumption and Income over the Life-Cycle

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May 30, 2018

Abstract

This paper studies the effects of health on earnings dynamics and on consumption inequality over the life-cycle. We build and calibrate a life-cycle model with idiosyncratic health, earnings and survival risk where individuals make labor supply and asset accumulation decisions, adding two novel features. First, we model health as a complex multi-dimensional concept. We differentiate between functional health and underlying health risk, temporary vs. persistent health shocks, and predictable vs. unpredictable shocks. Second, we study the interactions between health and human capital accumulation (learning-by-doing). These features are important in allowing the model to capture the degree to which, and the pathways through which, health impacts earnings and consumption patterns. They are also very important in estimating the value of health insurance and social insurance. A key finding is that health shocks account for roughly half of the growth in offer wage inequality over the life cycle. Eliminating health shocks leads to a 5.5% decline in the variance of the present value of earnings across all individuals.

Keywords: Health, Income Risk, Precautionary Saving, Health Insurance, Welfare
JEL classification: D91, E21, I14, I31

1 Introduction

The aim of this paper is to extend the life-cycle labor supply framework to include not only human capital accumulation (experience) but also health capital, and to explore the implications for life-cycle outcomes. In particular, we want to better understand the

*We thank Dr Philip Haywood for excellent assistance in classifying health shocks based on the International Classification of Diseases (ICD) codes. This research has been supported by the Australian Research Council grant FL110100247 and by the ARC Centre of Excellence in Population Ageing Research (project number CE110001029). We have received useful comments from participants at various seminars and conferences including the briq Workshop 2017, UNSW, IFS 2017 Conference, SAET 2017 Conference, and WAMS 2017 Workshop.

importance of health shocks as a source of earnings risk and consumption inequality. To achieve this, we incorporate health (and health shocks) in a way that captures the complex nature in which health adds to uncertainty.

We model and estimate health as a complex multi-dimensional concept. We make a distinction between "functional health" (H) and asymptomatic "risk factors" (R). The state variable H includes aspects of health that have a direct effect on labor productivity. The state variable R captures underlying health risk factors that have no immediate effect on productivity, but that affect the evolution of health and the probabilities of adverse health outcomes in the future. For example, chronic lower back pain that limits work would be reflected in a lower value of H, whereas hypertension or high cholesterol, which do not limit current work but raise the probability of adverse outcomes in the future (like heart disease), would be reflected in a higher risk factor R.

We also develop a rich model for the distribution of health shocks over the life-cycle, aiming to capture the nature of health risk in some detail. Our model includes three types of health shocks distinguished along two dimension: (i) whether the shock is temporary or long lasting, and (ii) whether the shock is predictable. For example, a broken arm will only have a short term effect on productivity, while a broken hip will have a persistent effect. In addition, some health shocks are to a degree predictable based on H and R (e.g., hypertension predicts heart attack), while other health shocks are idiosyncratic.

Our distinction among different types of health shocks is important because different shocks will have different effects on income and consumption over the life-cycle. For instance, transitory health shocks should have negligible effects on life-cycle wealth, while persistent health shocks may reduce earning capacity for an extended period. Predictable health shocks can be planned for while unpredictable shocks cannot. Naturally this means these shocks will have different effects on life-cycle consumption profiles.[1]

The second major novelty is the study of human capital accumulation in the presence of health risk.[2] Individuals accumulate human capital in a learning-by-doing model as in Imai and Keane (2004), but health interacts with this in several ways. For instance, returns to current investments in human capital (i.e., current work hours) depend on an agent's future ability to work, which can be impeded by adverse health shocks. Thus, when anticipating poor health in the future, the incentive to work today and invest in human capital is lower. Furthermore, we can predict the dynamic effect of a health shock on wages, which incorporates both the evolution of health and human capital after the shock.

Aside from the way we build health and health shocks into the life-cycle model, three other features of our framework are notable. First, we model job offers that may or may not include employer provided health insurance, where probabilities depends on education. This is a key aspect of the US environment and an important aspect of risk, as the vast majority of insurance for those under 65 is employer linked.

Second, we take the view that if a health shock occurs then the realized cost of treatment

[1] Clearly, the nature of health shocks affects the nature of medical expenses. Whether medical expenses are mainly transitory and/or predictable versus persistent and/or unpredictable is important to how well individuals can self-insure against this risk, and to the value of health insurance.

[2] These two features have not been brought together in a combined life-cycle framework, with the notable exceptions of Hokayem and Ziliak (2014) and Hai and Heckman (2015).

must be borne by the agent.[3] In this sense medical expenditures are not a choice, but rather an exogenous realization from an expenditure distribution. To capture this distribution, we estimate the level of medical expenditures associated with each different health state (i.e., each different possible combination of functional health and health shocks). Within each health state, we also allow for the possibility of "normal" vs. "catastrophic" expenditures, based on the observed distribution of costs for that condition.

Third, we model the US tax and social insurance system in some detail. In particular, if a person has a high level of medical expenditures, these may be tax deductible, and if the person has sufficiently low financial resources then he may qualify to receive a transfer that guarantees a minimum level of consumption - a feature that approximates social insurance benefits.

A brief overview of our model is as follows. Individuals begin every period with a stock of assets, functional health (H), health risk (R), and human capital. All working age individuals receive either a part time or full time employment offer, which they accept or reject, so all unemployment is voluntary. A fraction of offers include employer provided health insurance. Wages depend on functional health and human capital, and are subject to transitory and permanent shocks. After the employment decision has been made, health shocks occur with given probabilities. These, together with functional health, age, and random shocks, determine medical expenditures and the number of sick days experienced by workers. At this point individuals make consumption/savings decisions. At the beginning of the next period, new stocks of health and human capital are revealed (based on the laws of motion for these variables). To summarize, the different pathways through which health affects labor market outcomes are through wages, sick days, dis-utility of work, and human capital accumulation.

We calibrate the model to the U.S. male population using primarily the Medical Expenditure Panel Survey (MEPS).[4] The MEPS is an ideal data set since it allows us to identify the different types of health shocks. It contains information on respondents' detailed medical conditions, coded according to the International Classification of Diseases (ICD). Based on medical expert advice, these medical conditions are categorized according to (i) whether they affect productivity (i.e., daily functioning ability) directly, (ii) whether they are risk factors for other health problems, (iii) degree of predictability and (iv) degree of persistence. We use this information together with self-reported health variables to construct our health variables of interest.[5]

Our main findings can be summarized as follows: First, health shocks have a significant negative effect on labor supply over the life-cycle. We estimate that for high school workers lifetime hours would be greater by 2.7 years or 9.3% if health shocks were eliminated. For college workers the figures are 2.2 years or 6.7%. Second, health shocks lead to lower growth in offer wages over the life-cycle. For example, for the high school group, average wage offers increase by 30% between ages 25 and 55 in the benchmark model, but they would increase

[3]This is similar to De Nardi et al. (2010), French and Jones (2011) and Capatina (2015). In effect our view is that patients in the US have little ability to know the cost of their treatment ex ante and to make a decision whether or not to bear that cost. This view contrasts with the literature that treats medical expenditures as endogenous inputs into the health production function (e.g., Hokayem and Ziliak (2014), Jung and Tran (2016)

[4]We also use the CEX, CPS and PSID to estimate various moments that are used in the calibration.

[5]We thank Dr Philip Haywood for his assistance in classifying health shocks based on the ICD codes.

34% in the absence of health shocks. For college workers, the figures are 65% and 69% respectively.

Third, health shocks contribute substantially to the growth of wage inequality over the life cycle.[6] For example, for high school workers, the variance of log wage offers increases by .050 between ages 25 and 55 in the benchmark model, but the increase is only .024 when health shocks are eliminated. For college workers the comparable figures are .064 and .035. Thus, health shocks account for roughly half of the growth in dispersion in offer wages. Note that health shocks drive dispersion in offer wages both through their effect on human capital accumulation and their effect on the evolution of functional health.

Fourth, health shocks also account for a large fraction of cross-sectional consumption inequality among working age individuals. Among high school workers, removing all health shocks lowers cross-sectional consumption inequality by 43%. For college workers, the reduction is 28%. If we remove only the medical expenditures associated with health shocks, consumption inequality is reduced by 28% and 10% for the high school and college groups, respectively. Thus, for college workers about 2/3 of the reduction in consumption inequality arises through indirect channels, such as the effect of health shocks on human capital accumulation and on future functional health which affect productivity. But for high school workers about 2/3 of the reduction in consumption inequality comes from the direct effect of eliminating medical costs. Finally, we find that eliminating health shocks leads to a 5.5% decline in the variance of the present value of earnings across all individuals.

The outline of the paper is as follows. Section 2 presents a review of the literature and Section 3 presents our model. Section 4 describes the data and Section 5 presents the estimation/calibration. Section 6 presents results and Section 7 concludes.

2 Literature Review

A vast literature studies earnings risk, trying to understand overall individual risk, income and wealth inequality, and the roles of insurance markets (e.g., Lillard and Weiss (1979), MaCurdy (1982), Gottschalk et al. (1994), Gourinchas and Parker (2002), and Guvenen (2009)). Previous literature has shown that health risk is a very important component of individual level risk, and that one of its main impacts is in fact through its effect on earnings (French (2005), Attanasio et al. (2010), French and Jones (2011) and Capatina (2015)). However, while it is well known that poor overall health is associated with lower wages and lower employment, little is understood about the causal channels behind these associations. In addition, little is known regarding the effect of health on earnings dynamics, such as the link between health shocks and the persistence of earnings innovations.

Our paper contributes to the large literature studying individual risk and cross-sectional heterogeneity by providing a detailed study of the effects of health risk. It is important to better understand what determines the structure of earnings inequality in order to better understand its implications and to evaluate policies that insure against particular types of shocks (Altonji et al. (2013)). But in addition to affecting earnings, health shocks also add to individual risk through required medical expenditures and survival effects, which have

[6] The variance of human capital grows with age due to the permanent shocks to human capital, sick days, and labor force participation effects.

direct impacts on the budget constraint and on future discounting. Thus, we also study the contribution of health to consumption inequality.[7]

We build on the growing literature of life-cycle model with health uncertainty (French (2005), Attanasio et al. (2010), De Nardi et al. (2010), French and Jones (2011), Capatina (2015), Pashchenko and Porapakkarm (2016), and Jung and Tran (2016)). Two novel features differentiate our paper in important ways from this existing literature: a detailed health process and modeling human capital accumulation in the presence of health risk.

In the existing literature, health is modeled as one-dimensional (usually categorized as either good or bad). Notable exceptions are Blundell et al. (2016) who differentiate between transitory and persistent health shocks in studying the effects of health on the employment of individuals 50-66 years of age, Yang et al. (2009) who study the elderly (65+) health dynamics in relation to supplemental health insurance, and De Nardi et al. (2017) who allow for both history-dependence and ex-ante heterogeneity. Our paper is the first to model health as a complex multi-dimensional concept over the entire life-cycle.

A detailed health process is important for capturing the effect of health on earnings dynamics, but also for the medical expenditures process. The process for medical expenditures contains predictable and unpredictable components, as well as temporary and persistent components. While previous literature has estimated stochastic processes for medical expenditures that include transitory and permanent components, we contribute to this literature by explicitly studying the implications of these components for health insurance policy.[8]

The interaction between health and human capital is another important feature that has received little attention in the literature until relatively recently. For example, although they do not model human capital, Blundell et al. (2016) discuss that human capital effects could account for the dynamic effects of health on employment. Hai and Heckman (2015) build and estimate a structural model where endogenous health and human capital formation affect each other, estimated for the early part of the life-cycle. Hokayem and Ziliak (2014) also present a model where health and human capital are modeled together over the entire life-cycle. In our framework, human capital is accumulated through learning-by-doing (e.g., Shaw (1989), Eckstein and Wolpin (1989), Keane and Wolpin (2001), Imai and Keane (2004), Keane (2011)).[9]

[7]Ultimately it is the impact on consumption and the resulting inequality in economic welfare that is important (Storesletten et al. (2004)).

[8]Previous literature has also studied the nature of medical expenditure risk by estimating stochastic processes for medical expenditures. French and Jones (2004) study the distribution and dynamics of health care costs, finding that the health costs process is well represented by the sum of a highly persistent AR(1) process and a white noise component, allowing for a low-probability catastrophic event. French and Jones (2011) have also estimated a medical expenditures process where the person-specific component includes both transitory and persistent components.

[9]While education, work experience and health can all be viewed as being part of a general stock of "human capital," each one of these plays a very different role, so we distinguish between these aspects. We define *human capital* here as the stock of accumulated work experience as in a standard learning-by-doing model. It is not the general broadly defined "human capital" that might comprise education and health. The distinction between health and human capital was first made by Grossman (1972). Grossman (1972) defined human capital as the stock of knowledge and measured it by education, and one of the main motivations of the paper was to distinguish its effects from health. In the paper's framework, a person's stock of knowledge (human capital) affects market and non-market productivity and the stock of health determines the total amount of time the person can spend in various activities. While our modeling is different, we also stress

Our paper is important for several reasons. First, it is the first to build and estimate a structural life-cycle model of labor supply and saving where we incorporate a detailed health process, which is estimated using data on specific medical conditions at the 3-digit ICD-9 level. We argue that the nature of health risk is important for policy, and we estimate the effects of different types of health shocks. In particular, the properties of the health process are important in evaluating the insurability of health risk, and evaluating how well current institutions function in insuring individuals. Modeling both the persistence and the predictability of health shocks is crucial in such analysis. Second, we contribute to the literature on earnings and consumption inequality, evaluating the role of health. Specifically, we shed light on the pathways through which health affects earnings and evaluate the effect of health on earnings dynamics. Third, our paper contributes to the literature shedding light on the pathways leading to the well known health-socioeconomic status gradient.[10] In particular, we show that education plays a very important role, and in addition, it is important to model how health and human capital evolve in relation to one another over the life-cycle.

3 Model

The model is a standard life cycle model with idiosyncratic risk in survival, earnings and health. In every period before the age of 65, individuals receive an employment offer which they accept or reject. They also make a continuous consumption/savings decision. They accumulate human capital through hours worked. Borrowing is not allowed. The model is solved in partial equilibrium, assuming a small open economy with a fixed interest rate. The model period is one year.

Individuals enter the economy at the age of 25 and face survival risk every period. The maximum age to which they can live is 100. Retirement is exogenous at the age of 65. There are four education groups: less than high school, high school graduates, some college and college graduates.[11] Education is exogenous and taken as given at the age of entry into the labor force.[12] The model is calibrated separately for the four education groups.[13]

the different ways in which knowledge (in our case education and experience) and health impact outcomes in the model.

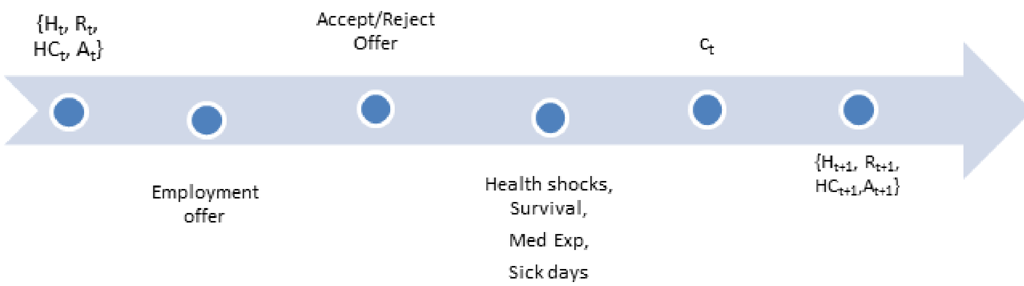
[10] It is well known that there is a strong positive correlation between all measures of socioeconomic status (education, income, wealth) and health (e.g. Adams et al. (2003), Stowasser et al. (2011), Smith (1999), Currie and Madrian (1999), Hall and Jones (2007), Galama (2011)).

[11] Education plays a key role since higher educational attainment leads to both higher productivity and earnings (Card (1999)) and greater efficiency in health production (e.g., Lleras-Muney (2006), Oreopoulos (2007), Grossman (2000), Grossman (2006)). More educated groups are also on average healthier at the time of entry in the labor force.

[12] We abstract from modeling the effect of health on formal education choices. Grossman (2006) provides a survey of the literature on the relationship between health and education. Hai and Heckman (2015) addresses the issue of causality from schooling to health and from health to schooling.

[13] The current version of this paper presents results for HS and College groups only.

3.1 Timing



At the beginning of each period, individuals start with a stock of assets A_t, a stock of human capital HC_t (for those under 65), and two different stocks of health H_t and R_t. These capture different aspects of health and are described in section 3.2. Immediately after the beginning of the period, working age individuals receive an employment offer, which can be either full time or part time, and with or without employer health insurance, which they either accept or reject. Wage offers are determined by health and human capital and are subject to temporary and permanent shocks. Health shocks and mortality shocks are then realized. Together with functional health, these health shocks determine the probabilities of medical expenditures and sick days shocks. Sick days restrict work hours and reduce the accumulation of human capital. Next, individuals make a continuous consumption/saving decision. Finally, next period state variables become known, and the next period begins. t represents the time period and also the age of the individual.

3.2 Health

3.2.1 Overview of Health

An important feature of our model is a realistic process of health over the life-cycle, that distinguishes between the different components that contribute to overall health. There are two stocks of health: functional health (H_t) and underlying health risk (R_t). In addition, every period individuals can experience health shocks that are of three types: predictable and long lasting (d_t^p), unpredictable and long lasting (d_t^u), and unpredictable short lasting (s_t). These are described in detail further below.

The two stocks of health, H_t and R_t capture two different aspects of health. Functional health status H_t measures the ability to perform daily activities and function in a work environment. Therefore, it has an impact on productivity. It is discrete and can take one of three values: poor, average and good ($H_t \in \{P, A, G\}$). On the other hand, the stock of underlying health risk R_t has no impact on the ability of perform activities or productivity. R_t captures underlying aspects of health whose only effect is to increase the probability of predictable health shocks (d_t^p) in the future. Examples are obesity and high cholesterol that increase the probability of many types of heart disease. R_t is also discrete and can take one of three values: low, medium, and high ($R_t \in \{L, M, H\}$). H_t and R_t evolve from period to period with given transition probabilities that are described further below.

There are three different types of health shocks that occur in every period with some probability. These shocks always affect the ability to function in the current period.[14] They are categorized according to two dimensions: predictability and persistence of effects. Unpredictable shocks are those that are independent of risk factors R_t, for example autoimmune disease. Predictable shocks are those that are caused (to a considerable extent) by risk factors R_t, for example stroke and lung cancer.

The persistence of the shocks is categorized as short or long term. A broken arm bone is an example of a short term shock that affects the individual in the current period only (assuming treatment). We assume that all short lasting shocks are unpredictable.[15] Long term persistent shocks are those that last for multiple periods, such as damage to the spinal column. The model captures this long term effect by allowing the transition probability of H_t to depend on these shocks. Note that the history of shocks is not a state variables in the model. This classification results in three types of shocks: predictable and long lasting (d_t^p), unpredictable and long lasting (d_t^u), and unpredictable short lasting (s_t). In each period, each shock is either present or absent. We let $\Upsilon_t = (d_t^p, d_t^u, s_t)$ summarize health shocks.

3.2.2 H and R Transition Probabilities and Health Shock Probabilities

The following table lists the transition probabilities of H_t and R_t and the probabilities of health shocks d_t^p, d_t^u and s_t. Functional health next period evolves according to a transition matrix that depends on current health, age, long lasting health shocks, employment and health insurance status (summarized by the categorical variable O), education, and income group (inc). Risk factors evolve according to a transition matrix that depends on current risk factors, age, functional health, employment and insurance status, education, and income group. Predictable health shocks are long lasting and depend on functional health, risk factors, age and education. Unpredictable shocks depend only on age.

Variable	Transition Probability Matrix / Probability
H_t	$\Lambda_H(H', H, t, d^p, d^u, O, educ, inc)$
R_t	$\Lambda_R(R', R, t, H, O, educ, inc)$
d_t^p	$\Gamma^{dp}(R, H, t, educ)$
d_t^u	$\Gamma^{du}(t)$
s_t	$\Gamma^s(t)$

3.3 Survival Probabilities

The probability of surviving to the next period depends on functional health, age, and long lasting health shocks and is given by $\varphi(H_t, t, d_t^p, d_t^u)$. Note that risk factors R affect this probability only indirectly, by affecting the probability of the predictable shocks d_t^p.

[14]Health shocks that do not affect the current period ability to function and that are predictors of future health shocks are not explicitly modeled. However, they are implicitly captured by the transition probability of R_t.

[15]In the data section, we show evidence that there are very few medical conditions that are predictable but short lasting.

3.4 Medical Expenditures

Medical expenditures are exogenous income shocks. They are a function of health, health shocks, age, and a random shock ε^{ME}, and are given by $ME(H_t, \Upsilon_t, t, \varepsilon^{ME})$. The random shock determines whether the individual experiences catastrophic medical expenditures or not. The shock ε^{ME} takes the value of either 0 or 1, with a value of 1 indicating catastrophic expenditures. The probability of catastrophic shocks is uniform across health states (H_t, Υ_t, t), and is given by δ. However, note that the catastrophic medical expenditures vary with the health states (H_t, Υ_t, t).

We assume that all individuals must undergo the recommended treatment associated with their medical conditions. Thus, our model captures the expected medical expenditure in each state, allowing for the possibility of catastrophic shocks. Of course, in reality individuals are often given choices regarding the course of treatment and therefore they can control the cost of treatment, however, we abstract from this feature.[16]

Our model directly captures the costs of the shocks d_t^p, d_t^u and s_t only in the year in which they occur. Indirectly however, the persistent health shocks d_t^p and d_t^u lead to higher probabilities of poor functional health in future periods, and hence they are associated with higher expected future medical expenditures in future periods.

3.5 Health Insurance

Health insurance is of three types: (1) employer health insurance, (2) Medicare, and (3) all other forms of social health insurance including Medicaid. The employer health insurance is available to a fraction of workers, as described in the next section. Workers whose employers provide health insurance pay an out-of-pocket premium p^{EI}.[17] The insurance pays for a fraction q^{EI} of their total medical expenditures. Medicare is available to all those 65 and older and covers a fraction q^{Med} of medical expenditures. The Medicare premium is p^{Med} is paid by those 65 and over, and a payroll tax τ^{Med} is paid by workers.

We assume the presence of a consumption floor guaranteed by the government, described in section 3.7. Since medical expenditures are income shocks, individuals may not be able to afford them given their resources, or they might have too little resources left to afford the minimum consumption floor. In these cases, we assume that other social health insurance programs cover medical expenditures up to the threshold where the individual can consume

[16] Clearly, individuals might not seek treatment or refuse treatment and have very low medical expenditures. We abstract from such scenarios. Others might spend much more than what an average treatment would cost. An important question for us is whether such extra expenditures relative to the average lead to better health transitions. As argued in De Nardi et al. (2010), the existing empirical literature suggests that medical expenses supplementing Medicaid, Medicare, and private insurance policies have only very small effects (if any) on the health capital of the U.S. elderly. In fact, Finkelstein and McKnight (2008) found that even programs such as Medicare which sometimes help pay for critical treatments, did not significantly increase life expectancy in the first 10 years after its introduction. There are only a small number of studies that find expenditures are positively correlated with survival, but the positive effect applies only to a subset of conditions, mainly related to emergency room visits (e.g., David Card (2009) and Doyle (2011)).

[17] Employers pay on average 81% of the total health insurance premium for singles (The Kaiser Family Foundation and the Health Research and Educational Trust (2010)). We only model the part paid for by the employee. The premium for employer health insurance does not vary with health status, age, or any other personal characteristics.

a minimum level of consumption. These capture programs such as Medicaid and other forms of social or family financial aid. They also indirectly capture the possibilities of simply not paying hospital bills when these are not affordable given the budget constraint and/or declaring medical bankruptcy.[18]

3.6 Employment

3.6.1 Employment Offers

At the beginning of every period and before health shocks are realized, individuals younger than 65 receive employment offers which they decide whether to accept or reject. We denote variables describing the employment offers with * superscripts. Employment offers are characterized by the wage, number of hours, and the presence/absence of employer health insurance: $\{W^*, h^*, ins^*\}$. Wage offers are continuous and are describe in detail in section 3.6.2. The number of hours h^* takes one of two values, hrs^{PT} (part time) or hrs^{FT} (full time), $h^* \in \{hrs^{PT}, hrs^{FT}\}$. The insurance offered ins^* is either present or absent, $ins^* \in \{0, 1\}$. We let the categorical variable O^* summarize employment offers based on the four possible combinations of hours and insurance $h^* \times ins^*$.

The probability of receiving each type of offer O^* depends on education, and is given by $\Pi(O^*, educ)$. Note that at the time the employment offer is accepted or rejected, medical expenditures are not known since health shocks occur after the decision is made. However, individuals know their H_t and R_t so they are able to calculate expected medical expenditures with this information.

After individuals make their employment decisions, the employment and health insurance status are summarized by the categorical variable O which takes one of five values: (1) no employment, (2) part time employment with no employer health insurance, (3) part time employment with employer health insurance, (4) full time employment with no employer health insurance, and (5) full time employment with employer health insurance. Note that unlike the variables describing employment offers which have superscripts, the actual wage, hours and insurance status of the individual in each period are denoted simply by $\{W, h, ins\}$.

3.6.2 Wages

The wage function is given by:

$$lnW^* = w(educ, HC, H, h^*) + \kappa + \varepsilon^W, \; where \tag{3.1}$$

$$w(educ, HC, H, h^*) = \beta_0 + \beta_1 HC + \beta_2 HC^2 + \beta_3 HC^3 + \beta_4 I_{H\in\{A,G\}} + \beta_5 I_{H=G} + \beta_6 I_{h^*=hrs^{PT}} \tag{3.2}$$

[18]Since we rule out borrowing, we do not explicitly model bankruptcy decisions. In particular, medical bankruptcies in the model are equivalent to qualifying for the government guaranteed consumption floor when own total financial resources are insufficient to allow this minimum consumption level due to the presence of medical expenditures. Himmelstein et al. (2009), Livshits et al. (2010) and Gross and Notowidigdo (2011) are examples of papers that specifically study medical bankruptcies.

Wage offers W^* are a function of: (1) a deterministic component $w(educ, HC_t, H, h^*)$ that depends on education, human capital, health, and hours offered, (2) a fixed productivity type κ, and (3) transitory shocks ε_t^W. The fixed productivity type κ is determined at the age of entry into the labor force and is distributed according to $\kappa \sim N(0, \sigma_\kappa^2(educ))$. The idiosyncratic transitory shocks are distributed according to $\varepsilon^W \sim N(0, \sigma_{\varepsilon^W}^2(educ))$. The variances of the fixed effect and of the transitory shocks depend on education.

Equation 3.2 describes the deterministic wage process. $I_{H\in\{A,G\}}$ is an indicator equal to 1 for individuals in average or good functional health and equal to 0 for those in poor health, and $I_{H=G}$ is an indicator equal to one for those in good health and equal to zero otherwise. $I_{h^*=PT}$ is an indicator equal to one when employment offers are part time and equal to zero otherwise. Deterministic wages depend on hours of work specified in the offer in order to capture that part time workers' wages are lower than full time workers' wages. Parameters $\beta_0 - \beta_6$ are education specific, but the notation is omitted.

3.6.3 Hours Worked

We denote the actual hours worked by an individual at time (age) t by h_t. When an individual accepts an employment offer, he commits to working h^* hours at the wage W^*. This commitment must be fulfilled unless the worker experiences sick days, denoted by sd. The actual number of hours worked by those who participate in the labor force are given by $h(h^*, H_t, d_t^p, d_t^u, s_t) = h^* - sd$. Sick days are drawn from the discrete set $sd(H) = \{sd_1^H, sd_2^H\}$, where the values depend on functional health status. The probability of each draw depends on health shocks, and is given by the probability function $\Theta(sd(H_t), H_t, d_t^p, d_t^u, s_t)$.

We assume health shocks do not affect wages within the period. Employers cannot lower wages quickly in response to an employee receiving a negative health shock. However, health shocks may force workers to reduce the number of hours worked due to having to attend doctor appointments, undergoing medical diagnostics and procedures, or simply due to the shock affecting the ability to perform daily activities in a timely manner (getting out of bed, getting dressed, getting to work). Therefore, the model captures the aspect that a worker could have a very high human capital and high wages, yet, he could have little earning capacity due to health reasons.

3.6.4 Human Capital Accumulation

Human capital evolves according to the following production function, which is a deterministic function of current human capital HC_t, current hours of labor supply h_t, along with a multiplicative shock ε_{t+1}^{HC}:

$$HC_{t+1} = (HC_t + h_t)\varepsilon_{t+1}^{HC}(1 + \delta^{HC}(t - 30)I_{t>30}) \tag{3.3}$$

where

$$\varepsilon_{t+1}^{HC} = \begin{cases} 1+\nu & \text{with probability } p^1(educ, I_{h_t>0}) \\ 1 & \text{with probability } p^2(educ, I_{h_t>0}) \\ 1-\nu & \text{with probability } 1 - p^1(educ, I_{h_t>0}) - p^2(educ, I_{h_t>0}) \end{cases} \tag{3.4}$$

The probability of the human capital shock depends on education and an indicator $I_{h_t>0}$ equal to 1 if the current period hours worked are strictly positive and equal to 0 otherwise. When hours are equal to zero, we assume that $p^1 = 0$. In effect, ε^{HC} is a permanent wage shock. In addition, human capital depreciates at a rate δ^{HC} at ages over 54 ($t = 30$). This depreciation term helps the model capture the decline in labor supply at older ages while also delivering wage age profiles that match the data.

3.7 Taxes, Social Security and Social Insurance

Retirement is exogenous at the age of 70, but all individuals start receiving social security payments $SS_t(educ)$ at the age of 65 that depend on education. ($SS_t = 0$ for $t < 65$.) We assume social security income is received regardless of employment status after the age of 65.

We follow Jeske and Kitao (2009) and Pashchenko and Porapakkarm (2016) in modeling income taxes. All individuals pay an income tax $T(y_t)$ that consists of a progressive and a proportional tax. For individuals younger than 65 and for those working past the age of 65, the taxable income y_t equals the sum of labor and capital income, minus the employee's share of the health insurance premiums p^{EI}, and minus out-of-pocket medical expenditures in excess of 7.5% of their income which are tax deductible according to the US tax code.[19] The taxable income for retirees is similar, except social security income replaces labor income. This is summarized in equation 3.5 below. The indicator function I_w is equal to one for individuals who accept the employment offer and equal to zero otherwise.

$$\begin{aligned} y &= max[0, rA + I_w(W^*h - p^{EI}ins^*) - max(0, ME(1 - q^{EI}I_w ins^*) - 0.075(rA + I_w W^*h))] \text{ if } t < 65 \text{ or } (t \\ y &= max[0, rA + SS_t - max(0, ME(1 - q^{Med}) - 0.075(rA + SS_t))] \text{ if } t \geq 65 \text{ and } I_w = 0 \end{aligned} \tag{3.5}$$

The income tax function $T(y_t)$ includes a non-linear and a linear component:

$$T(y_t) = a_0[y - (y^{-a_1} + a_2)^{-1/a_1}] + \tau_y y. \tag{3.6}$$

The non-linear component is modeled following Gouveia and Strauss (1994), and captures the progressive income tax that approximates the actual income tax schedule in the US. The linear component captures the proportional tax which includes all other taxes not explicitly modeled.

Workers also pay payroll taxes: a Medicare tax τ^{Med} (paid on labor earnings minus the premium p^{EI}) and a Social Security tax τ^{SS} (paid on earnings minus the premium p^{EI}, up to a maximum income threshold $\overline{y}_{ss}$). Total income and payroll taxes are given by:

$$Tax = T(y) + I_w[\tau^{SS} min(W^*h - p^{EI}ins^*, \overline{y}_{ss}) + \tau^{Med}(W^*h - p^{EI}ins^*)] \tag{3.7}$$

Consumption is taxed at the rate τ^c. The government also runs a social assistance program which guarantees a minimum level of consumption $\bar{c}(educ)$ to every individual.

[19] We assume that social security is not income taxed for individuals between ages 65 and 70. We make this assumption to approximate the fact that taxes paid on social security income by workers over 65 can often be recovered at older ages.

When disposable income (net of required medical expenditures) falls below $\bar{c}$, the person receives a transfer tr that compensates for the difference. The consumption floor depends on education to capture the fact that average benefits vary with education. The transfer function is given by:

$$
\begin{aligned}
tr_{t<70} &= max\{0, (1+\tau^c)\bar{c} + ME(1 - q^{EI} I_w ins^*) - (1+r)A - I_w(W^* h - p^{EI} ins^*) - SS_t + Tax\} \\
tr_{t\geq 70} &= max\{0, (1+\tau^c)\bar{c} + ME(1 - q^{Med}) + p^{Med} - (1+r)A - SS_t + Tax\}
\end{aligned}
\tag{3.8}
$$

3.8 Preferences

In each period, individuals derive utility from consumption (c) and leisure (l). The within-period utility function is given by:

$$
u(c,l) = \frac{1}{1-\sigma}[c^{\alpha} l^{(1-\alpha)}]^{(1-\sigma)}. \tag{3.9}
$$

The quantity of leisure is equal to the total time endowment (normalized to one) minus the dis-utility of work expressed in units of time given by $\phi(educ, H, h^*)$, and is summarized by:

$$
l = 1 - I_w \phi(educ, H, h^*). \tag{3.10}
$$

The time cost of work depends on education, health and hours of work (either part time of full time). For retirees, leisure is equal to 1, so preferences are only a function of consumption.

3.9 Individual's Problem:

3.9.1 Working Age Individuals

At the beginning of every period, the individual's state denoted by χ is given by age, education, fixed productivity type, health, health risk factors, human capital, assets, and employment offer.

$$
\chi = (t, educ, \kappa, H_t, R_t, HC_t, A_t, (W_t^*, h_t^*, ins_t^*)) \tag{3.11}
$$

Given χ, each individual maximizes the expected discounted lifetime utility by choosing whether to accept or reject the employment offer. This decision is summarized by the indicator function I_w. After this decision is made, health shocks are realized. Right after, the individual draws the shock ε^{ME} which determines whether medical expenditures are catastrophic or not, and also draws from the probability distribution for sick days, which can be high or low for every state. At this stage, the state of the individual is summarized by χ , I_w, the vector of health shocks $\Upsilon = (d^p, d^u, s)$, ε^{ME}, and sd. Given χ, I_w, Υ, ε^{ME} and sd, he now chooses consumption.

The individual solves the problems in two stages. First, he solves the policy function for consumption conditional on χ and all possible realizations of Υ , ε^{ME} and sd, for both $I_w = 0$ and $I_w = 1$. The expected value next period is calculated over the probabilities of all possible realizations of $\Psi \equiv (O^{*'}, H', R', \varepsilon^{HC'}, \varepsilon^{W'})$. Note that $\varepsilon^{HC'}$ determines HC' which together with $\varepsilon^{W'}$ determine $W^{*'}$.

The policy function $c(\chi, I_w, \Upsilon, \varepsilon^{ME}, sd)$ is the solution to the following problem:

$$G(\chi, I_w, \Upsilon, \varepsilon^{ME}, sd) = \max_c \{u(c,l) + \beta E_\Psi V(\chi')\} \tag{3.12}$$

subject to

$$A' = (1+r)A + I_w(W^*h - p^{EI}ins^*) + tr - (1+\tau^c)c - ME(H, \Upsilon, t, \varepsilon^{ME})(1 - q^{EI}I_w ins^*) - Tax \tag{3.13}$$

$$c \leq \frac{1}{1+\tau^c}[(1+r)A + I_w(W^*h - p^{EI}ins^*) + tr - ME(H, \Upsilon, t, \varepsilon^{ME})(1 - q^{EI}I_w) - Tax] \tag{3.14}$$

and equations 3.5 to 3.10. Equation 3.13 describes the evolution of assets. Equation 3.14 is a zero borrowing constraint.

After solving for the policy functions, the individual chooses whether to accept or reject the employment offer by solving:

$$V(\chi) = \max_{I_w} E_\Upsilon \left\{\varphi G(\chi, I_w, \Upsilon, \varepsilon^{ME}, sd)\right\}. \tag{3.15}$$

The expectation is taken over the probabilities of all possible Υ, ε^{ME} and sd.

3.9.2 Retired Individuals

After the age of 65 when retirement occurs exogenously, the individual makes decisions on consumption only. At the time these decisions are made, the state of the individual is given by age, education, health, health risk factors, assets and health shocks. He maximizes the expected discounted lifetime utility by solving the following:

$$V(t, educ, H, R, A, \Upsilon, \varepsilon^{ME}) = \max_c \{u(c) + \beta E\varphi V(t+1, educ, H', R', A', \Upsilon')\} \tag{3.16}$$

subject to

$$A' = (1+r)A + SS + tr - (1+\tau^c)c - ME(H, \Upsilon, t, \varepsilon^{ME})(1 - q^{Med}) - p^{Med} - T(y) \tag{3.17}$$

$$c \leq \frac{1}{1+\tau^c}[(1+r)A + SS + tr - ME(H, \Upsilon, t, \varepsilon^{ME})(1 - q^{Med}) - p^{Med} - T(y)] \tag{3.18}$$

and equations 3.5 to 3.10. All individuals now receive social security income $SS(educ)$, pay a Medicare premium p^{Med}, and have a fraction of medical expenditures q^{Med} covered by Medicare.

3.10 Summary of Health Effects

There are several reasons why good functional health (H) is valuable in this framework: (1) it is associated with higher wage offers, (2) it is associated with lower medical expenditures, and (3) it lowers the probability of future predictable health shocks (d^p), and therefore it indirectly raises the expected future ability to work and accumulate human capital, and lowers expected future medical expenditures associated with shocks. On the other hand, low health risk (R) is desirable only because it lowers the probability of future predictable health shocks (d^p).

The benefits of good health relative to bad health differ with age and education. For example, at very young ages, the probability of recovery from bad health is relatively high. Good health at young ages is mainly valued for the effect on wage offers and ability to accumulate human capital (through fewer sick days). In the late working life when human capital is relatively high, the main benefits of good health are fewer sick days (which imply higher incomes) and a lower dis-utility of work. Medical expenditures also become higher as the individual nears retirement, starting to play a more important role. After retirement, individuals benefit from good health through increased survival probabilities and lower medical expenditures.

The relationship between health and human capital is of particular importance. Better health is associated with higher wage offers and fewer sick days, leading to higher labor supply and more human capital accumulation, all else equal. In turn, higher levels of human capital lead to higher incomes, which contribute to good health (both H and R).

4 Data and Variable Construction

We use the Medical Expenditure Panel Survey (MEPS) which is a rotating panel in which each household is followed over the period of two and a half years. A new cohort is sampled every year. For each household, five interviews are conducted. We use panels 5 to 16 covering years 2000 to 2012. The early panels are not used because some key variables of interest are not available before 2000. Our sample consists of males 25 years of age and older as of the beginning of the survey.

4.1 Medical Conditions in MEPS

An important advantage of MEPS over other panel surveys is that it contains information on respondents' detailed medical conditions. The medical conditions and procedures reported by respondents were recorded by interviewers as verbatim text which was then coded by professional coders to fully-specified ICD-9 codes.[20] For confidentiality reasons, condition codes were collapsed from fully specified codes to 3-digit code categories in the publicly available files. The relatively high level of detail in the classification of these conditions allows us to distinguish between the different types and aspects of health shocks described in the model.

[20] The International Statistical Classification of Diseases and Related Health Problems (abbreviated ICD) is published by the World Health Organization and is used world-wide for morbidity and mortality statistics, reimbursement systems and automated decision support in medicine.

We categorize each of the 989 3-digit ICD-9 medical conditions according to the following criteria: (1) short-term productivity loss, (2) long-term productivity loss, (3) predictive power, and (4) predictability.[21] Productivity loss is not limited to a work environment, but includes limitations in daily functioning. *Short-term productivity loss* applies when a medical condition leads to limitations that last for at least 2 weeks per year for less than two years. *Long-term productivity loss* applies when a medical condition has an impact for at least 2 weeks per year for more than two years. A medical condition is classified as a *predictor* if its presence increases the probability of other medical conditions occurring in the future. Finally, a condition is classified as *predictable* if health related behavior and prior health conditions are together implicated in at least 50% of its occurrences.[22]

Table 1 lists the 16 possible combinations of these 4 characteristics and presents the number of ICD-9 codes corresponding to each one. It also shows how these combinations are then grouped for the construction of the health shocks d^p, d^u, and s, and the health risk stock R. Their construction will be discussed in more detailed below. Conditions that do not affect short or long term productivity and that are not predictors for other conditions are not used.

4.2 Constructing Health (H)

Health (H) is constructed using factor analysis combining the following information available in the MEPS: (1) perceived health status, (2) perceived mental health status, (3) ADL screener, (4) IADL screener, and (5) a score of physical functioning limitations. It is meant to capture general well-being and the ability to function.

Perceived health and mental health status take values from 1 to 5 indicating states that are poor, fair, very good, excellent and very good. The ADL and IADL screeners are binary variables that indicate the presence of any ADL and IADL limitation, respectively. Finally, we construct a score of physical functioning limitations from eight categorical variables that indicate the degree of difficulty with: (1) lifting 10 pounds, (2) walking up 10 steps, (3) walking 3 blocks, (4) walking a mile, (5) standing 20 minutes, (6) bending/stooping, (7) reaching overhead, and (8) using fingers to grasp. These five variables are then standardized using the mean and standard deviation of each variable in Round 1 of interview. Therefore, the measurement does not vary across rounds or years of interview.

We then conduct factor analysis on these five variables. Factor loadings are reported in the Appendix. The first factor is highly correlated with all variables and we interpret it as functional health. We use the factor loadings to predict this factor for all individuals in Rounds 1, 3, and 5. Because the resulting factor is continuous, we discretize it into three categories corresponding to poor, average and good functional health as in the model.[23] Table presents the distribution of H by age group. The Appendix presents the initial distribution

[21] We are very grateful to Dr. Philip Haywood, a clinician and academic who performed this classification according to our specified criteria.

[22] When an ICD code is judged to have different characteristics across ages, an age threshold was provided, and we split such conditions into separate conditions according to the provided age threshold. When we classify the observed ICD-9 conditions in the MEPS based on provided age thresholds, the age as of the beginning of the survey period is used.

[23] The discretization is based on two thresholds. The upper threshold is the median of the constructed factor in Round 1. The lower threshold is equal to the mean of the factor minus one standard deviation in the

of H by education group, revealing a very strong correlation between education and good health even at young ages.

4.3 Constructing the Health Risk Factor (R)

We use information on medical conditions together with BMI to construct the health risk variable. Table 1 lists the possible combinations of characteristics a medical condition needs to satisfy for it to be included in the construction of heath risk. There are 41 ICD-9 conditions that meet our criteria. These conditions do not affect short-term productivity but they either affect long-term productivity or predict other future health conditions. Of these 41 conditions, only 28 are present in our sample. In addition, we use 8 risk related items in the ICD-9 classification that stand for family history of disease. These total 36 ICD-9 codes used in the construction of R are listed in the Appendix.

We first construct three variables summarizing ICD-9 conditions and procedures: (1) an indicator variable for essential hypertension (the form of hypertension that has no identifiable cause), (2) an indicator variable for disorders of lipoid metabolism (e.g., high cholesterol), and (3) a variable equal to the count of all other ICD-9 conditions and procedures that are used to construct R. Hypertension and high cholesterol are by far the most commonly observed conditions among those classified as risk factors. In addition, we construct two variables based on BMI: a variable for excessive BMI equal to $(BMI - 21.75) \cdot I_{[BMI>21.75]}$ and a variable for low BMI equal to $(21.75 - BMI) \cdot I_{[BMI<21.75]}$. The resulting five variables are then standardized using the mean and standard deviation of each variable in Round 1 so that the measurement does not vary across rounds or years.

We take a weighted sum of these five variables to aggregate them for each of Rounds 1, 3, and 5, and again standardize them using the mean and standard deviation in Round 1. The weighing procedure involves determining the relative importance of each variable in predicting the health shocks d_t^p. The details are described in detail in the Appendix.

Finally, we discretize the health risk variable into three groups corresponding to those in the model: low, medium, and high.[24] The Appendix shows the distribution of the final health risk variable by age. The fraction of high risk individuals increases rapidly with age reaching 33% in the 75-79 age group.

4.4 Constructing Health Shocks (d^p, d^u, and s)

Health shock variables are constructed using the ICD-9 medical conditions satisfying the criteria presented in Table 1. Each variable d^p, d^u, and s is constructed as a binary variables equal to zero if a respondent has no medical condition that satisfies its criteria, and equal

same sample. Good health corresponds to values of the factor that are equal to or larger than the median; average health corresponds to values lower than the median but higher than the mean minus one standard deviation; and poor health corresponds to values smaller than the mean minus one standard deviation.

[24]Because the distribution of the computed continuous R is highly skewed, we use the same approach as the construction of H using the following two thresholds: the median of R in Round 1, and the mean value plus one standard deviation based on the same sample. R is "Low" if its value is equal to or smaller than the median, "Medium" if the value is larger than the median but smaller than the mean plus one standard deviation, and "High" if the value is larger than the mean plus one standard deviation.

to 1 if the respondent has one or more such conditions. Unlike variables H and R that are round specific, heath shocks are constructed at the annual level, for each of the two years of interview in each panel.

As seen in Table 1, there are only 9 conditions classified as predictable that have only short term effects on productivity. In our MEPS sample, their combined prevalence is only 0.5%. Therefore, we do not have a separate variable for such shocks, and instead we include these medical conditions in the construction of the unpredictable short lasting health shocks s_t. Because there are so few such conditions, their inclusion is unlikely to affect the results. Also, we include "unknown" conditions in the construction of the s_t shocks. The Appendix shows that these conditions are relatively expensive, so we do not want to exclude them, and they have the characteristics of short lasting, unpredictable health shocks.

5 Estimation

The benchmark model is calibrated to match the US economy during the time period 2000 to 2012, for civilian, non-institutionalized males who are not attending school. The calibration is conducted separately for the four education groups in the model. The strategy used is to estimate some of the parameters directly from the data and to simultaneously calibrate others by matching specific moments observed in the data. We estimate the following directly from the data: (1) the initial distributions of H and R and probability matrices for H, R, d^p, d^u, s;(2) survival probabilities $\varphi(H_t, t, d_t^p, d_t^u)$; (3) medical expenditures $ME(H_t, \Upsilon_t, t, \varepsilon^{ME})$; and (4) sick days that give us the actual hours worked $h(h^*, H_t, d_t^p, d_t^u, s_t)$.

The parameters that we estimate by matching moments are listed in Table 3. These include the tax function parameters a_2 and τ_y , the time discount factor β, the time costs associated with employment $\phi(educ, t, H, h^*)$, the wage function parameters, employment offers probabilities, and the education specific consumption floor $\bar{c}(educ)$.

Finally, we take several parameters from previous literature. These include the utility function parameters α and σ, interest rate, most parameters related to the tax structure, Social Security, and health insurance parameters (see Table 2 for values). The EPHI coverage rate is set to 70% and the Medicare coverage to 50% of medical expenditures, consistent with Attanasio et al. (2010), Capatina (2015) and Pashchenko and Porapakkarm (2016).[25]

We take the progressive tax function parameters a_0 and a_1 from Gouveia and Strauss (1994), but we calibrate the parameters a_2 and τ_y so that the effective tax rate for different income groups is consistent with the data.

5.1 Parameters Estimated Directly from the MEPS Data

We estimate the following transitions using our MEPS sample, using the two years of pooled data for each individual and using sampling weights.

[25] Attanasio et al. (2010) found that this coverage rate resulted in total Medicare costs as a fraction of GDP consistent with the data.

5.1.1 Transition Probabilities: Functional Health and Health Risk (H)

Since H and R are discretized to 3 states, we estimate their transition probability matrices $\Lambda_H(H', H, t, d^p, d^u, O, educ, inc)$ and $\Lambda_R(R', R, t, H, O, educ, inc)$ using ordered probit models. These models include a cubic in age, and dummies for all other relevant variable categories. Income is discretized into quintiles. These regression results are reported in the Appendix. We use the estimated coefficients to construct the transition probability matrices.

5.1.2 Probabilities of Health Shocks (d^p, d^u, and s)

The estimation of the probability functions $\Gamma^{dp}(R, H, t, educ)$, $\Gamma^{du}(t)$, and $\Gamma^{s}(t)$ is based on logit regressions. The estimation results are reported in the Appendix.

5.1.3 Survival Probabilities

The probability of surviving to the next period is given by $\varphi(H_t, t, d_t^p, d_t^u)$. We estimate φ using a logit model where the dependent variable is a dummy equal to one when an individual survives to the next year and equal to zero otherwise. The explanatory variables are functional health status, age and its squared term, and the two long lasting health shocks.[26] Probabilities for ages over 82 are predicted out of sample. The Appendix shows selected survival probabilities by age, health status and health shock.

5.1.4 Medical Expenditures

We use data on total annual medical expenditures available in MEPS to estimate the medical expenditure function $ME(H_t, \Upsilon_t, t, \varepsilon^{ME})$.[27] For each (H_t, Υ_t, t) cell, we take the 95th percentile as the cutoff between regular and catastrophic expenditures. We then calculate the mean medical expenditures among individuals below and above the 95th percentile in each cell. In order to obtain smooth age profiles, we run regressions of these mean values on age and age squared and obtain the fitted values. The estimation results and additional details are reported in the Appendix. Since we chose the 95th percentile as the cutoff, the probability of catastrophic expenditures in each (H_t, Υ_t, t) state, δ, is 5.0%.

It is well known that MEPS tends to underestimate aggregate medical expenditures (Pashchenko and Porapakkarm (2016), De Nardi et al. (2017)). Therefore, we follow De Nardi et al. (2017) and multiply the estimated medical expenses by 1.60 for people younger than 65 years old and by 1.90 for people 65 or older. This brings the aggregate medical expenses computed from the MEPS in line with the corresponding statistics in the National Health Expenditure Account (NHEA).

[26] Note that we attempted to include other variables in the regression, such as the short lasting shocks s_t, heath risk R_t and education. However, the coefficient on s_t does not have the expected sign, and the other variables do not increase the model's predictive power.

[27] Total medical expenditures in MEPS are defined as the sum of direct payments for health care services provided during the year, including out-of-pocket payments and payments by private insurance, Medicaid, Medicare, and other sources. Payments for over-the-counter drugs are not included.

5.1.5 Average Hours in Full Time and Part Time Employment

We estimate hrs^{PT} and hrs^{FT} (hours in part time and in full time employment offers) using data from the MEPS on hours worked, using only workers in good health who do not experience health shocks in the period in which hours are reported. We discretize the distribution of hours using cluster analysis. The "not employed" group contains all those with hours worked per year less than 520. The "part time" group contains all workers with annual hours between 520 and 1,500 hours, and the "full time" group contains all those with hours greater than 1,500. The median number of hours is 20 in the part time group and 40 in the full time group, when considering only workers in good health with no health shocks, so we set hrs^{PT} and hrs^{FT} equal to these values, respectively.

5.1.6 Hours Worked

Individuals who accept employment offers are not able to work the hours specified in the offer if they experience sick days. In the MEPS, we observe the number of work days lost due to illness.[28] We use the MEPS to first construct the set $sd(H) = \{sd_1^H, sd_2^H\}$, and then estimate the corresponding probabilities $\Sigma(sd(H_t), H_t, d_t^p, d_t^u, s_t)$.

Keeping only workers who work in all interview rounds belonging to each year, we run a regression of annual sick days on age, age squared, functional health interacted with each type of health shock, and all the health shocks interacted with each other.

We then predict days lost for each combination of health shocks and health status, and take an average across all ages since there is very little variation with age. The average days lost for each health shock combination are presented in the Appendix. These are converted to the time units of the model to give $sd(H_t, d_t^p, d_t^u, s_t)$.

Looking at differences across education groups, we find that those with some college and those with college education have fewer sick days than the other education groups.[29] We also estimated the regression model separately by education group to allow all coefficients to vary with education. However, the effects of education are in general very small, so we do not model sick days by education.

5.2 Calibration of Remaining Parameters

We jointly calibrate the remaining parameters listed in Table 3. The calibration targets key moments on labor supply, earnings, and savings from the data. Specifically, the calibration minimizes the sum of the squared differences between the targets in the data and their counterparts in the simulated data, weighting all targets equally. All calibrated model parameters jointly affect all the estimated moments, but some parameters are relatively more important for a subset of moments. The identification of each parameter is discussed in detail below.

[28] The variable DDNWRK tells us the number of times the respondent lost a half-day or more from work because of illness, injury, or mental or emotional problems during each round of interview. We take the sum of this variable across all interview rounds belonging in a year, counting Round 3 in the year in which it has more than 50% of days from the start to the end date.

[29] This might be the case since higher education is usually associated with jobs that rely less on physical ability, so educated workers can more often perform their jobs even in adverse health states.

5.2.1 Time Discounting

We calibrate the discount factor $\beta(educ)$ to match the average asset to income ratio observed in the data for working age individuals, by education.

5.2.2 Tax Structure

We calibrate the parameters a_2 and τ_y in equation 3.6 to match the effective tax rate corresponding to different income groups.

5.2.3 Employment Offer Probabilities

We calibrate the employment offer probabilities $\Pi(O^*, educ)$ so that the shares of individuals employed in full time and part time work, with and without insurance, by education status, match those observed in the MEPS data. We target the average share in each type of employment, averaging across ages 30-45 when these shares are relatively constant. At younger and older ages, these shares change considerably with age, and other model mechanisms help us achieve these patterns. Employment share profiles are shown in Figure 4. There are large differences across education groups in the shares of workers employed full time and with insurance. These shares clearly increase with education. Differences in the shares of part time workers, with and without insurance across education groups are smaller.

5.2.4 Dis-utility of Work

The time cost of employment $\phi(educ, H, h^*)$ is calibrated by targeting the share of the population working part time and full time, by age, education, and functional health status (H). The full time employment profiles are shown in Figure 6. As we can see, more education and good health are associated with higher full time employment shares. There is a sharp decline in full time employment after the age of 55, so high time costs of work are needed to match these.

Note that in fact the offer probabilities $\Pi(O^*, educ)$ and the time costs $\phi(educ, H, h^*)$ are both crucial for these profiles. The targets for identifying the offer probabilities are more aggregate. Offers $\Pi(O^*, educ)$ need to be reasonable enough such that after individuals make their employment decisions, the levels of the employment profiles match the data. On the other hand, the time costs drive mainly the shape of these employment age profiles.

5.2.5 Wages

Due to selection bias in the data, all wage function parameters need to be estimated in the model. In the data, we observe only the earnings of those who choose to work. There is a strong selection effect into employment since on average, the higher educated groups, those with more human capital, and those in good health are more likely to work. The coefficients $\beta_0 - \beta_9$ would be biased for this reason if estimated directly from the data. Therefore, we calibrate $\beta_0 - \beta_9$, iterating on them until the average wages by age, health status and education are the same for workers in the simulated data as in the MEPS data.

The remaining wage parameters to be calibrated are those determining the distribution of wages: (1) the variance of the fixed component $\sigma_\kappa^2(educ)$, (2) the variance of the transitory shocks $\sigma_{\varepsilon^W}^2(educ)$, and (3) the size and probabilities of the human capital shock which acts as a permanent wage shock (ν, $p^1(educ, t, I_{h_t>0})$, and $p^2(educ, t, I_{h_t>0})$). To identify these, we want that the structure of residual wages be the same in both the real and simulated data. (Residual wages are obtained from estimating an OLS model of wages on age, age squared and age cubed, separately by education.) However, it is well known that data on wages is very noisy due to measurement error (Bound and Krueger (1991), Bound et al. (2001), Gottschalk (2005)). Therefore, before constructing any distributional moments on wages using the simulated data, we add noise to the simulated wages. Specifically, we add a random normal term ε^N to equation 3.1, where $\varepsilon^N \sim N(0, \sigma_N^2(educ))$. We identify $\sigma_N^2(educ)$ by targeting the overall variance of wages by education. Clearly, parameters σ_κ^2, $\sigma_{\varepsilon^W}^2$, and those related to the human capital shocks ε^{HC} are also very important for the overall variance of wages, but we simultaneously calibrate these by targeting other more specific moments.

We use the residual wages, from both the simulated and real data, and estimate a random effects plus AR(1) process. This is a descriptive model of the underlying true wage process. As in indirect inference, we identify the true wage process parameters relevant to the structure of wage inequality by targeting the following estimates from this descriptive model: the variance of the individual fixed wage effect, the variance of the transitory component, and the autoregressive coefficient and variance of the innovation in the AR(1) process. The parameters $\sigma_\kappa^2(educ)$ and $\sigma_{\varepsilon^W}^2(educ)$ are identified by targeting the estimated variance of the individual fixed wage effect and the variance of the transitory component, respectively. The parameters ν, $p^1(educ, I_{h_t>0})$, and $p^2(educ, I_{h_t>0})$ are identified by targeting the estimated parameters of the AR(1) process.

Figure 7 shows the wage age profiles of different groups constructed using the MEPS data. Average wages decrease significantly with poorer health. The differences in wages between the poor and average health groups are particularly large. Figure 8 shows the variance of log wages among full time workers. Table 4 presents the estimated parameters from decomposing wage residuals, and also shows the average wages of part time workers relative to those of full time workers. We calibrate the part time wage penalty in the model to match these.

5.2.6 Consumption floor

We calibrate the education and health specific consumption floor to match the percentage of individuals who receive government transfers, by education and health (Table 4).

6 Results

6.1 Model Fit

Table 5 presents selected calibrated parameters, while the Appendix presents the remaining parameter values. The model matches the data very well in terms of part time and full time employment (Figure 5), employment age profiles by health (Figure 6), wages of full time workers by health (Figure 7), wage inequality (Figure 8) and assets (Figure 9), by education and age. It also matches quite well some untargeted moments, such as employment status transitions, for all individuals and for healthy individuals separately (Table 6). Finally, it approximates patterns in average consumption and consumption inequality over the life-cycle (Figure 10). We note that the relatively sharp drop in average consumption between the ages of 55 and 65 is due to the Cobb-Douglass preference function, so as individuals drop out of the labor force and gain more leisure, they consume less. We also note that the consumption inequality profile estimated from the CEX for the HS group displays an unusual pattern (declining from age 45 to 65), and the robustness of this results will be explored in future versions.

Also, the model is fairly successful in matching the concentration of medical spending in the population, which is an important feature of the data. Figure 11 shows the concentration of medical spending in the model compared to the MEPS data , for ages 25-64. In general, the model somewhat underestimates the concentration of expenditures, which is likely caused by the feature that only two possible expenditures (non-catastrophic and catastrophic) are allowed in each (H_t, Υ_t, t) cell.

6.2 The Nature of Health Risk - Importance of Each Dimension

To study the nature of health risk, we conduct counterfactual experiments where we eliminate one or more health risk components. In the counterfactuals, we eliminate each of the shocks s, d^u, and d^p, combinations of these, and give all individuals low health risk or good health with certainty for life. Since we are focused on working age individuals, we construct all statistics for individuals aged 25-64. Table 7 shows the resulting changes in the fractions of individuals with various shocks, the distribution of H, average medical expenditures, average sick days, and life expectancy at age 25.[30]

There are two main findings. First, the unpredictable shocks s and d^u together account for 64% of medical expenditures, while predictable shocks d^p account for only 14%. (Approximately 24% of medical expenditures are not due to any shocks.) Unpredictable persistent shocks are also more important relative to predictable shocks in determining the distribution of functional health in the population. However, d^u and d^p shocks are roughly equally important for life expectancy: eliminating d^u leads to 6.2 and 5.2 additional years of life, and eliminating d^p leads to 6.8 and 4.7 extra years, for the HS and college, respectively.

Second, health risk R accounts for approximately 45% of d^p shocks, but since these have relatively small effects on H and ME, the effects of R on these variables are relatively small during working ages. Therefore, while lowering underlying health risk in the working age population is clearly desirable (lowering the incidence of d^p shocks and increasing life expectancy), the overall benefits in terms of lowering medical expenditure risk are small. Since individual actions to lower underlying health risk would go only a short way towards lowering the overall medical expenditure risk, it is important to have a well functioning health insurance system.[31]

[30] Sick days are endogenous in the model because they depend on selection into the labor force.

[31] However, R could be found to play a small role due to data limitations. Underlying health risk could be under reported, especially at young ages. Young individuals may be unaware of underlying conditions such as high cholesterol until they experience a major health shock, when they have these risks diagnosed. Since major health shocks occur mainly in old age, young individuals are more likely to be unaware of their underlying heath risks.

It is well known that education is the most important determinant of health, and consistent with the data, the percentage of working age college graduates in good health is 17.8 percentage points higher than for HS (e.g., Grossman and Kaestner (1997), Grossman (2000), Smith (2007), Cutler and Lleras-Muney (2008) and Cutler and Lleras-Muney (2010a)). Using our model, we find that health risk R accounts for very little of this difference. The most important contributor is the difference in the transition for H: even conditional on income, health insurance, age, risk factors and medical conditions, this transition process is much more favorable for college graduates. Better H transition probabilities for the college could be due to factors that are not captured in the model, such as differences in cognitive ability or social interactions (Cutler and Lleras-Muney (2010b)).

6.3 Health and Employment

In this section, we study counterfactuals where various health components are eliminated, looking at the effects on employment. The results are summarized in Tables 8 and 9.

We observe very large increases in employment in response to the elimination of persistent health shocks d^u and d^p, and smaller but still substantial increases in response to the elimination of transitory shocks s. For example, in the absence of unpredictable persistent health shocks, the average employment rate increases by 4.4 percentage points. Persistent shocks negatively affect future functional health, lowering expected future productivity and increasing the dis-utility associated with work.

Eliminating persistent shocks significantly raises employment mainly among those in poor and average functional health, but also among those in good health (Table 9). This is because eliminating persistent health shocks raises the returns to learning-by-doing, and in general, raises the marginal benefit of labor force participation because lower expected sick days imply higher earning capacity.

Functional health is the most important health aspect for employment. If all individuals had good health with certainty throughout their lives, employment would increase to 91% and 95% in the two education groups respectively, despite the presence of unpredictable shocks d^u and s, and positive (although smaller) probabilities of predictable shocks d^p. The presence of underlying health risk is relatively unimportant for employment. The elimination of health risk R increases labor supply by approximately 2.2%.

6.3.1 Mechanisms

To study the relative importance of the mechanisms through which heath affects employment, we conduct counterfactuals shutting down the following channels: the effect of H on wages, the effect of health on the dis-utility of work, removing the effect of sick days on human capital accumulation, and finally removing all sick days (so they no longer affect earnings either) (Table 10). In all cases, the marginal benefits associated with employment increase, and this is partly due to higher returns to learning-by-doing.

We find that the direct effect of functional health on wage offers is by far the most important for labor supply. The effect of functional health on the dis-utility associated with work is the second most important for the HS group, but plays only a negligible effect for the College.

Sick days restrict human capital accumulation and also lead to lower earnings by restricting working hours. We note that the great majority of workers in poor functional health who are most likely to experience sick days are in fact not employed. Since they stay out of the labor force, the average number of sick days experienced by workers is lower than 5 full time working days per year per person, which is consistent with aggregate statistics for the US (Research (2013)). So if sick days have a significant effect, we anticipate it to be through a labor force participation margin rather then the effects of actual observed sick days for workers.

We conduct an experiment where we only remove the effect of sick days on human capital accumulation. Here, we assume that human capital is accumulated by workers according to the number of hours specified in the employment offer (h^*) instead of actual hours worked after sick days (h). We find that the resulting increase in employment is very small. We then remove sick days entirely, so that in addition to not affecting human capital accumulation, they no longer affect earnings. Labor supply increases by 1.8 and 2.3 percentage points for the high school and college groups respectively, which is significant. This finding highlights the importance of adequate paid sick leave.

Looking at the welfare effects in Table 10, measured in consumption equivalent variation (CEV), we observe that the direct effect of H on productivity has a large welfare cost: when all individuals receive the wages of those in good H, welfare increases by 3.2% and 1.7% for the HS and College groups, respectively. Removing sick days leads to welfare changes of 1.0% and 0.8% for the two groups.

6.3.2 The persistence of d^u and d^p

The health shocks s, d^u and d^p have an immediate effect in the period in which they occur only because they affect medical expenditures and sick days. But the risk of medical expenditures and sick days has relatively small effects on employment compared to the larger effects associated with d^u and d^p shown in Table 8.[32] These persistent shocks matter for employment mainly because they affect future functional health, H, and because this in turn directly affects productivity. Here we explore the persistence of these shocks through H.

The shocks d^u and d^p affect the transition probability of H only in the period in which they first occur. From Table 7, we know that d^u has the largest effect on H, while d^p has a smaller but still significant effect. To see more clearly the persistence of shocks, Figure 12 plots the responses in functional health, employment, consumption, and wage offers, comparing HS individuals who had a d^u shock at age 45 with those who did not, conditional on having average H and medium R at the age of 45. There are large differences in these profiles in the 2 years following the shock, but the profiles become almost identical after approximately 5 years.

Since poor and average H states become more persistent with age, the persistence of d^u and d^p shocks also increase with age. Figure 13 show that d^p shocks at age 45 have smaller overall effects on all variables because these affect H less on average.

[32] The effect of medical expenditures will be discussed in detail in Section 6.6.

6.4 Health Effects on Wages

Health affects wage offers through the following channels: (1) a direct effect since wage offers depend on H, and (2) an indirect effect through human capital accumulation. The latter arises because health affects labor force participation and because sick days reduce human capital accumulation for those employed.

Figure 14 shows how wage offers (the mean and variance) change in response to the elimination of various health effects. Table 11 summarizes the growth in the mean and the variance of wage offers over the life-cycle. We find that the growth in average wage offers over the life-cycle is reduced significantly by the presence of health shocks and by adverse functional health. For example, for the HS group, average wage offers increase by 30% between ages 25 and 55 in the Benchmark, compared to 34% in the absence of health shocks, and 36% when all individuals have good functional health.

We also observe that for the HS (College) group, the variance of log wage offers increases by 0.05 (0.06) in the Benchmark, driven by the growing dispersion of human capital and of functional health with age.[33] However, this growth is only 0.024 (0.035) in the absence of health shocks, and 0.013 (0.034) when all have good functional health. So, health shocks account for a very large fraction of the increase in wage offers inequality over the life-cycle.

However, looking at moments on actual wages, post selection in the labor force, the effects look very different (Table 12).[34] In general, those who accept employment offers are more likely to be in good functional health, with higher than average human capital, and with better than average transitory wage shocks. When we eliminate health shocks, it is individuals at the bottom of the wage distribution who enter the labor force, acting to increase wage inequality and lower average wages. For the HS group, this effect is so big that overall, average wage growth in fact declines when health shocks are removed, and wage inequality growth over the life-cycle becomes *steeper*.[35] For the College group, the effects go in the opposite direction, but are quantitatively very small.

These results are interesting because they highlight how better population health in the future could lead to higher employment, higher wage offers, and lower inequality in wage offers, but at the same time, lead to lower average observed wages and higher wage dispersion among low educated workers.

6.5 Health and Inequality in Earnings and Consumption

Figure 15 shows how average consumption increases in various counterfactuals where health shocks are eliminated. It also shows how the variance of consumption decreases in these counterfactuals. The figure reveals that in the absence of health shocks, or when all are in good H states, consumption growth is steeper over the life-cycle, and the age at which consumption peaks is greater. In addition, the variance of consumption at each age decreases, declining more at older ages relative to the benchmark. Table 13 summarizes this

[33] The variance of human capital grows with age due to the permanent shocks to human capital ε_t^{HC}, sick days, and labor force participation effects.

[34] Note that in this table, wages include added measurement error.

[35] Looking in absolute terms, we find that average wages are lower and wage inequality is higher for the HS in experiments where health shocks are removed, compared to the Benchmark.

information. The effect of unpredictable persistent shocks d^u stands out: in their absence, consumption growth between age 25 and 50 would be 35% for the HS and 63% for the College, compared with 31% and 58% in the benchmark. Also notable is that the removal of sick days also leads to significantly greater consumption growth for the College (62%).

We now ask how much of the cross-sectional variance in consumption can be attributed to health effects? Table 13 shows that the variance of log consumption calculated keeping all working age individuals decreases dramatically when health shocks are eliminated. For the HS group, the cross-sectional variance falls from 0.4 to 0.23 when all health shocks are eliminated (the d^u shocks have the largest effect), and for the college, the variance falls from 0.29 to 0.21. Removing only the medical expenditures associated with health shocks lowers the variance to 0.29 for HS and to 0.26 for the College group. When we combine the two education groups, the cross-sectional variance falls from 0.44 to 0.32 with the removal of health shocks.

Finally, we study how the variances of the present value of consumption and earnings change in different counterfactuals. We find that the removal of health shocks leads to a 2.5% drop in the variance of the present value of consumption (calculated for working ages only) and a 5.5% drop in the variance of the present value of earnings (Table 14). Tables 15 and 16 show that it is the low initial productivity types that drive this result.

6.6 Medical Expenditure Risk and Health Insurance Counterfactuals

We use our model to isolate the importance of medical expenditures risk arising from different health components. Table 18 shows the welfare effects of eliminating the medical expenditures associated with s, d^u, d^p, poor and average H, catastrophic shocks, and all medical expenditures.

The medical expenditures associated with unpredictable shocks s and d^u have the largest welfare costs: eliminating each of these leads to 1.9% higher welfare in terms of CEV. This is expected given that unpredictable health shocks alone (d^u and s) account for 57% of medical expenditures among working age individuals (Table 7). Eliminating medical expenditures associated with d^p shocks or with poor and average H states leads to welfare gains of approximately 1.1% in each case. In general, catastrophic medical expenditures are important: eliminating them leads to welfare gains of 1.7%, which is relatively large considering that only 3.1% of individuals across all ages have medical expenditures higher than $20,000. Interestingly, labor supply increases by 1.6 percentage points for both education groups in the absence of catastrophic expenditures. This is because catastrophic medical shocks very often lead to reliance on social insurance, so the benefits of working and saving are lower in their presence (Hubbard et al. (1995)). Finally, eliminating all medical expenditures leads to a welfare gain of 7.9%.

Finally, we conduct counterfactual experiments that illustrate the value of insuring medical expenditures for working age individuals. However, we note that these experiments are *naive* in the sense that neither wages nor EPHI insurance premiums are allowed to adjust, and our model does not capture moral hazard or general equilibrium effects.

First we consider two counterfactuals related to employer provided health insurance:

removing EPHI and giving EPHI to all workers. When EPHI is removed, welfare decreases on average by 1.4%. Providing EPHI to all workers increases welfare by 0.6% for the high school group, but only 0.1% for the college group.

We evaluate a public health insurance option for working age individuals, financed by revenue neutral consumption taxes (imposed on working age individuals only), considering co-insurance rates of 70%, 50%, 30% and 10%. We leave EPHI unchanged, assuming that the public insurance covers a fraction of any remaining medical expenditures for those who have EPHI. The results are presented at the bottom of Table 18. We see that the overall welfare changes are negative. The high school group experiences welfare gains, but these are more than offset by the welfare losses of the college educated group. Public insurance represents a transfer from high income individuals (mainly full time workers who already have EPHI) to low income individuals with low labor supply, who have higher medical expenditure risk and are less likely to have EPHI.

Finally, we introduce a public insurance option that covers 100% of medical expenditures, when these are higher than a given threshold. We consider two thresholds, $20,000 and $30,000, which affect 2.12% and 1.34% of the working age population, respectively. For both thresholds, only the low educated benefit, and the overall welfare change is negative.

7 Conclusion

In this paper, we study how health contributes to earnings and consumption inequality. We construct a rich life-cycle framework of labor supply and asset accumulation decisions, with two novel features: (1) a detailed health process over the life cycle that includes several dimensions of health: functional health, underlying health risk, and health shocks that are predictable/unpredictable and temporary/persistent, and (2) interactions between health risk and human capital accumulation (learning-by-doing). We show that both of these features are important in allowing the model to capture the degree to which, and the pathways through which health impacts earning and ultimately consumption patterns. They are also very important in evaluating the role of insurance.

Here we summarize some of the key preliminary findings, focusing on the working age population. 1. *Unpredictable health shocks* (i.e., not significantly predicted by underlying health risk such as obesity, smoking or HBP) account for a large share of medical expenditures experienced by workers. 2. *Persistent health shocks* have very large effects on employment. They lower labor supply not only for those in poor health who are likely to experience such shocks, but also for those in good health. 3. In terms of the pathways though which health affects employment, the *direct effect of functional health on productivity* is the most important. Dis-utility of work, sick days, and human capital accumulation effects are also significant in size, but are smaller in relative terms. 4. The risk associated with *unpredictable persistent health shocks* generates large welfare losses. Individuals rely heavily on government social insurance in the presence of these shocks, so for example, the fraction of people receiving transfers falls by approximately a third in the absence of these shocks. 5. Health shocks and functional health account for very large fractions of the increase in inequality in wage offers over the life-cycle. 6. Eliminating health shocks leads to a 5.5% decline in the variance of the present value of earnings across all individuals.

Tables

Table 1: Classifying Medical Conditions

Assignment	Short-Term Productivity	Long-Term Productivity	Predictor	Predictable	The Number of ICD codes
d^p	YES	YES	YES	YES	27
d^u	YES	YES	YES	NO	18
d^p	YES	YES	NO	YES	38
d^u	YES	YES	NO	NO	272
s	YES	NO	YES	YES	3
s	YES	NO	YES	NO	8
s	YES	NO	NO	YES	6
s	YES	NO	NO	NO	298
s	Condition details missing ("unknown" conditions)				
R	NO	YES	YES	YES	5
R	NO	YES	YES	NO	6
R	NO	YES	NO	YES	1
R	NO	YES	NO	NO	0
R	NO	NO	YES	YES	6
R	NO	NO	YES	NO	23
Not used	NO	NO	NO	YES	9
Not used	NO	NO	NO	NO	269

Table 2: Model Parameters

Parameter	Value
Preferences	
α	0.4
σ	2.8
Interest rate r	0.04
Taxes (%)	
Consumption tax	5.70
Social Security tax τ^{SS}	6.2
Medicare tax τ^{Med}	1.45
Income threshold $\overline{y}_{ss}$	98,000
a_0 (Gouveia and Strauss (1994))	0.258
a_1 (Gouveia and Strauss (1994))	0.768
Social Security and Insurance	
Social Security income, HS	$14,179
Social Security income, College	$15,540
Health Insurance	
Fraction of ME paid by Medicare q^{Med}	50%
Fraction of ME paid by Employer Insurance q^{EI}	70%
Medicare premium p^{Med}	$900
Employer Insurance Premium (Employee's Share) p^{EI}	$700

Table 3: Calibration

Parameter	Description	Target
Utility		
$\beta(educ)$	Time discount factor	Mean asset to income ratio
$\phi(educ, H, h^*)$	Time cost of employment	Employment age profiles, by health
Offer Probabilities		
$\Pi(O^*, educ)$	Probs of the 4 employment offers	Mean shares by O, ages 30-50
Wages		
$\beta_0(educ) - \beta_6(educ)$	Deterministic component	Wage age profiles, by H and O
$\sigma^2_\kappa(educ)$	Variance of fixed effect	Moments on decomposition of residual wages
$\sigma^2_{\varepsilon^W}(educ)$	Variance of transitory shocks	Moments on decomposition of residual wages
$p^1(educ, I_{h_t})$, $p^2(educ, I_{h_t})$	Probability of HC shock	Moments on decomposition of residual wages
δ^{HC}	HC depreciation	Employment profiles at ages>54
Social Insurance		
$\bar{c}(educ)$	Consumption floor	% 30-50 yo in good health receiving gov. tr.

Note: All targets are constructed by education. When a single value is presented, it is used for all education groups.

Table 4: Calibration Targets: Moments on Government Transfers, Employment and Wages

	HS	College
Parameters of the descriptive wage model (random effects plus AR1)		
Var fixed effect		
Model	.05	.10
Data	.10	.08
Var transitory shock		
Model	.08	.09
Data	.07	.08
Permanent shock persistence		
Model	.88	.95
Data	.90	.93
Var of innovation		
Model	.02	.01
Data	.02	.03
Other:		
Average PT/FT wages, 30-50 yo		
Model	0.93	0.91
Data	0.92	0.91
% Receiving Gov. Tr. (30-50)		
Model	12.1	6.1
Data	10.6	4.0

Notes: 1. Government transfers are calculated from CPS data for the 30-50 age group. Individuals in the CPS are classified as government transfer recipients if they receive strictly positive income amounts from any of the following: welfare, SSI, disability insurance, workers' compensation or if they are covered by any public health insurance. 2. The estimated wage process moments were calculated using the PSID, with data from 1968-1997, keeping only full time workers aged 25-61, with wages greater than half of the minimum age in each year.

Table 5: Selected Calibrated Parameters

Parameter	HS	College
Preferences		
β	0.975	0.99
Wages		
PT Penalty (PT/FT wages)	0.89	
ν	0.3	
σ^2_κ	0.13	0.115
$\sigma^2_{\varepsilon^W}$	0.11	0.1
σ^2_N	0.19	
Average Disutility of work		
FT, H=Poor	0.145	0.16
FT, H=Avg	0.108	0.138
FT, H=Good	0.089	0.138
Disutility PT/FT	0.33	
Other		
$\bar{c}$	5,460	9,516
a_2 (tax parameter)	0.08	
τ_y	0.0	

Table 6: Calibration: Other Moments not Targeted

	HS		**College**	
	Model	**Data**	**Model**	**Data**
Employment Transitions				
All				
E to NE	8.1	5.1	3.1	3.2
E to E	77.4	76.3	90.2	89.1
NE to NE	6.4	12.6	3.1	4.1
E to E	8.0	6.0	3.6	3.6
Employment Transitions				
H=**Good in Both Yrs**				
E to NE	3.7	3.4	2.1	2.3
E to E	90.5	88.8	94.2	93.1
NE to NE	1.9	4.5	1.4	2.7
E to E	4.0	3.3	2.4	1.8

Notes: Employment transitions are calculated using MEPS, for the 30-50 age group. Employed is abbreviated as "E" and not employed as "NE."

Table 7: Counterfactual Experiments: Effect on Individuals 25-64

	Health Shocks			Health (H)				Sick	△ Life
HS	s	du	dp	**Poor**	**Avg**	**Good**	ME	**days**	**Expect.**
Benchmark	38.6	21.2	13.3	5.5	40.3	54.3	2.88	3.3	0.0
No s shocks	0.0	21.2	13.3	5.4	40.2	54.4	1.89	2.4	0.2
No du shocks	38.8	0.0	12.5	3.8	36.9	59.3	1.99	2.7	6.2
No dp shocks	38.7	21.3	0.0	4.1	39.0	56.9	2.42	3.1	6.8
No s and du	0.0	0.0	12.6	3.8	37.0	59.2	1.05	1.9	6.3
No s, d^u, d^p	0.0	0.0	0.0	2.9	35.6	61.5	0.64	1.7	11.1
All have Low R	38.6	21.2	7.4	4.8	39.7	55.5	2.67	3.2	2.6
All have Good H	38.9	21.3	7.9	0.0	0.0	100.0	2.36	2.5	10.9
College									
Benchmark	38.8	21.2	9.2	1.6	26.3	72.1	2.59	2.9	0.0
No s shocks	0.0	21.2	9.2	1.6	26.3	72.1	1.72	2.2	0.1
No du shocks	38.8	0.0	8.6	0.9	22.3	76.8	1.76	2.4	5.2
No dp shocks	38.8	21.3	0.0	1.1	24.4	74.5	2.28	2.8	4.7
No s and du	0.0	0.0	8.7	0.9	22.4	76.6	0.94	1.7	5.2
No s, d^u, d^p	0.0	0.0	0.0	0.7	21.3	78.0	0.67	1.5	8.3
All have Low R	38.8	21.3	4.9	1.3	25.5	73.2	2.45	2.9	2.1
All have Good H	38.8	21.3	6.4	0.0	0.0	100.0	2.32	2.5	6.8

Table 8: Counterfactual Experiments: Effect on Individuals 25-64, Employment

HS	**Emp**	**Emp (PT)**	**Emp (FT)**	**Yrs Experience**
Benchmark	78.7	6.1	72.6	29.1
No s shocks	80.0	6.4	73.6	29.7
No d^u shocks	82.6	6.6	76.0	30.9
No d^p shocks	82.3	6.5	75.8	30.7
No s and d^u	82.7	6.9	75.9	31.0
No s, d^u, d^p shocks	84.6	7.1	77.5	31.8
Good initial H and low R	79.4	6.2	73.2	29.4
All have Low R	80.3	6.3	74.1	29.8
All have Good H	91.0	7.3	83.6	34.2
College	**Emp**	**Emp (PT)**	**Emp (FT)**	**Yrs Experience**
Benchmark	86.3	3.9	82.4	32.8
No s shocks	86.5	4.0	82.5	33.0
No d^u shocks	91.0	4.2	86.8	34.8
No d^p shocks	91.4	4.2	87.2	34.9
No s and d^u	89.9	4.2	85.7	34.5
No s, d^u, d^p shocks	91.0	4.3	86.8	35.0
Good initial H and low R	86.7	3.9	82.8	32.9
All have Low R	89.1	4.1	85.0	33.9
All have Good H	94.8	4.3	90.4	36.3

Notes: The column "Emp" presents the overall employment as a fraction of all individuals aged 25-64. The next two columns give the part time and full time employment per individuals aged 25-64. The last column presents the average number of full time equivalent years worked over the lifetime per individual, so it is the average accumulated experience at retirement age. (For example, if a worker worked 20 hours per week one year, and 20 hours the next year, these together add up to one year of FT equivalent employment.)

Table 9: Counterfactual Experiments: Effect on Individuals 25-64, Employment by Health

	Employment by H		
HS	**Poor**	**Average**	**Good**
Benchmark	17.5	72.9	89.2
No s shocks	14.7	74.9	90.2
No d^u shocks	16.5	76.4	90.8
No d^p shocks	18.9	77.3	90.3
No s and d^u	14.5	76.0	91.4
No s, d^u, d^p shocks	17.0	77.6	91.8
Good initial H and low R	17.1	73.6	89.3
All have Low R	18.0	75.0	89.6
All have Good H	-	-	91.0
College	**Poor**	**Average**	**Good**
Benchmark	25.0	76.9	91.1
No s shocks	22.3	77.1	91.4
No d^u shocks	34.0	84.9	93.5
No d^p shocks	39.5	86.2	93.8
No s and d^u	27.6	82.5	92.8
No s, d^u, d^p shocks	32.8	85.1	93.2
Good initial H and low R	25.3	77.6	91.2
All have Low R	31.9	81.7	92.6
All have Good H	-	-	94.8

Table 10: Mechanisms Through Which Health Affects Employment, and Welfare Effects

HS	**Emp**	**Avg. FT Yrs**	**CEV**
Benchmark	78.7	29.1	-
No effect of sd on HC	78.9	29.2	0.08
No sd	80.5	30.2	0.96
No effect of H on $W*$	84.1	31.1	3.21
No effect of H on time cost of work	81.6	30.2	2.10
College	**Emp**	**Avg. FT Yrs**	**CEV**
Benchmark	86.3	32.8	-
No effect of sd on HC	86.9	33.1	0.11
No sd	88.6	34.1	0.76
No effect of H on $W*$	90.5	34.4	1.65
No effect of H on time cost of work	86.6	32.9	0.02

Table 11: Health Effects on Wage Offers: Growth in Mean and Growth in Inequality from age 25 to 55

	% $\triangle$ Mean W^*		**$\triangle$ Var log(W^*)**	
	from age 25 to 55		**from age 25 to 55**	
	HS	**College**	**HS**	**College**
Benchmark	29.9	64.9	0.050	0.064
No s shocks	30.6	65.1	0.045	0.054
No d^u shocks	33.3	67.7	0.035	0.043
No d^p shocks	32.1	67.6	0.036	0.043
No s, d^u, d^p shocks	34.0	68.9	0.024	0.035
All have Good H	36.2	70.6	0.013	0.034
No sd	30.6	66.6	0.045	0.052
No effect of H on $W*$	35.1	70.0	0.018	0.037
No effect of H on disutility of work	30.8	65.1	0.043	0.063
No transitory wage shocks	32.2	67.7	0.033	0.045
No human capital shocks	38.5	91.7	0.034	0.009

Table 12: Health Effects on Wages: Growth in Mean and Growth in Inequality from age 25 to 55

	% $\triangle$ Mean W		**$\triangle$ Var log(W)**	
	from age 25 to 55		**from age 25 to 55**	
	HS	**College**	**HS**	**College**
Benchmark	30.6	54.8	0.042	0.115
No s shocks	29.3	54.3	0.054	0.115
No d^u shocks	27.9	55.1	0.058	0.109
No d^p shocks	26.5	54.6	0.058	0.107
No s, d^u, d^p shocks	27.7	56.0	0.058	0.102
All have Good H	26.8	55.8	0.066	0.101
No sd	29.7	56.4	0.046	0.108
No effect of H on $W*$	33.2	57.2	0.041	0.106
No effect of H on disutility of work	33.8	54.7	0.030	0.115

Table 13: Health Effects on Consumption

	% $\triangle$ Mean Cons age 25 to 50		Peak Cons		Var log (cons) ages 25-64		
	HS	**College**	**HS**	**College**	**HS**	**College**	**All**
Benchmark	31.3	58.0	50	53	0.40	0.29	0.44
No s shocks	33.0	63.8	53	53	0.34	0.26	0.40
No d^u shocks	34.6	62.9	54	54	0.31	0.22	0.37
No d^p shocks	33.7	61.4	54	54	0.33	0.23	0.39
No s, d^u, d^p	35.5	66.8	54	54	0.23	0.21	0.32
All have Good H	34.8	66.0	55	56	0.20	0.20	0.28
No sd	32.9	61.9	53	53	0.37	0.25	0.41
No effect of H on $W*$	30.8	64.7	54	53	0.31	0.22	0.36
No effect of H on disutility of work	30.9	60.6	50	53	0.35	0.28	0.41
No ME of health shocks	31.8	64.2	53	52	0.29	0.26	0.36
No ME	31.0	65.2	50	50	0.27	0.25	0.35
No transitory wage shocks	29.7	43.6	52	56	0.28	0.16	0.31
No permanent wage (HK) shocks	40.1	78.1	53	59	0.31	0.21	0.38

Notes: The cross-sectional variance of log consumption is calculated including government transfer recipients. In the calibration, this group was excluded.

Table 14: The Variance of Present Value of Consumption and Earnings

Both Education Groups	**% Change from Benchmark**	
	Variance PV Consumption	**Variance PV Earnings**
No s shocks	-2.95	-5.46
No d^u shocks	-2.69	-3.69
No d^p shocks	-1.95	-2.12
No s, d^u, d^p shocks	-2.53	-5.51
No ME of s, d^u, d^p shocks	-4.36	-9.98
No transitory wage shocks	-20.78	-19.98

Table 15: The Variance of Present Value of Earnings

High School	**Low Productivity**		**High Productivity**	
	Ln Var(PV Earnings)	**% change**	**Ln Var (PV Earnings)**	**% change**
Benchmark	22.64		23.00	
No s, d^u, d^p shocks	22.13	-39.9	22.75	-22.5
All in good H	22.13	-39.7	22.79	-19.3
No s, d^u, d^p shocks + good H	21.68	-61.5	22.61	-32.8
No transitory wage shocks	22.15	-38.6	22.94	-6.5
College	**Low Productivity**		**High Productivity**	
	Ln Var(PV Earnings)	**% change**	**Ln Var (PV Earnings)**	**% change**
Benchmark	24.20		24.53	
No s, d^u, d^p shocks	23.51	-49.8	24.46	-6.1
All in good H	23.45	-53.1	24.48	-4.3
No s, d^u, d^p shocks + good H	23.38	-56.1	24.44	-8.4
No transitory wage shocks	23.39	-55.9	24.31	-19.2

Table 16: The Variance of Present Value of Consumption

High School	**Low Productivity**		**High Productivity**	
	Ln Var(PV Cons)	**% change**	**Ln Var (PV Cons)**	**% change**
Benchmark	21.58		22.11	
No s, d^u, d^p shocks	21.12	-36.7	21.81	-26.4
All in good H	21.02	-42.6	21.81	-26.5
No s, d^u, d^p shocks + good H	20.69	-59.0	21.64	-38.1
No transitory wage shocks	21.26	-27.1	22.09	-2.3
College	**Low Productivity**		**High Productivity**	
	Ln Var(PV Cons)	**% change**	**Ln Var (PV Cons)**	**% change**
Benchmark	22.94		23.53	
No s, d^u, d^p shocks	22.55	-32.5	23.47	-5.6
All in good H	22.53	-34.0	23.48	-4.8
No s, d^u, d^p shocks + good H	22.47	-37.7	23.44	-7.8
No transitory wage shocks	22.31	-47.0	23.20	-28.0

Table 17: Decomposition of Variance of the Present Value of Earnings and Consumption

High School				
R-squared	**Low Productivity**		**High Productivity**	
Model includes:	**PV Earnings**	**PV Consumption**	**PV Earnings**	**PV Consumption**
Health Shocks	0.051	0.056	0.020	0.027
+ H and R shocks	0.683	0.665	0.474	0.427
+ Sick days and ME shocks	0.683	0.668	0.475	0.431
+ Employment offer shocks	0.704	0.697	0.620	0.629
+ Transitory wage shocks	0.903	0.892	0.937	0.929
College				
R-squared	**Low Productivity**		**High Productivity**	
Model includes:	**PV Earnings**	**PV Consumption**	**PV Earnings**	**PV Consumption**
Shocks s, d^u, d^p	0.024	0.023	0.015	0.013
+ H and R shocks	0.719	0.704	0.698	0.666
+ Sick days and ME shocks	0.719	0.705	0.698	0.666
+ Employment offer shocks	0.734	0.726	0.749	0.730
+ Transitory wage shocks	0.917	0.925	0.919	0.897

Table 18: Counterfactual Experiments: Medical Expenditures and Welfare (CEV)

		All	**HS**	**College**
No s shocks ME		1.93	2.03	1.84
No d^u shocks ME		1.93	1.97	1.90
No d^p shocks ME		1.07	1.13	1.02
All have ME of Good H		1.08	1.27	0.91
No catastrophic ME		1.70	1.74	1.67
No ME		7.86	7.53	8.17
All offers have EPHI		0.36	0.62	0.11
No offers have EPHI		-1.41	-1.77	-1.08
Public Health Insurance, ages 25-64				
Co-insurance	**Consumption tax**			
70%	1.37%	-0.14	0.04	-0.30
50%	2.28%	-0.20	0.09	-0.47
30%	3.19%	-0.23	0.19	-0.62
10%	4.10%	-0.21	0.36	-0.75
0% on ME>$20,000	1.34%	-0.13	0.06	-0.30
0% on ME>$30,000	1.00%	-0.11	0.02	-0.24

Table 19: Wages, Hours and Earnings Regression Results

Dependent Var	Log Wages	Weekly Hours	Annual Earnings
Mean	3.056	35.110	83.261
SD	0.563	19.284	38.747
s=1	0.002	-0.430**	-0.756**
	(0.004)	(0.174)	(0.301)
d^p=1	0.003	-1.179***	-2.492***
	(0.006)	(0.283)	(0.523)
d^u=1	0.004	-1.392***	-2.165***
	(0.005)	(0.226)	(0.406)
Lag Dependent Var	0.876***	0.677***	0.731***
	(0.006)	(0.007)	(0.000)
Education			
HS	0.026***	1.195***	2.413***
	(0.005)	(0.247)	(0.386)
Some College	0.050***	1.834***	4.213***
	(0.006)	(0.269)	(0.442)
College	0.105***	2.965***	8.724***
	(0.008)	(0.258)	(0.463)
Health (H in Round 1)			
Avg	0.020	5.131***	8.926***
	(0.020)	(0.407)	(0.764)
Good	0.035*	6.446***	11.918***
	(0.020)	(0.429)	(0.800)
R2	0.836	0.553	0.643
Observations	22,951	37,120	38,183

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: All regressions include year dummies, age, age squared and age cubed. The wage regression is estimated using only workers who have positive wages in both Rounds 1 and 5. The Weekly Hours regression is estimated including all individuals, and those who are not employed have zero hours. Restricting to those with positive hours (consisting 79.2% of the sample), the mean hours are 43.083 and sd is 10.620. The annual earnings regression also includes all individuals, and is estimated after performing a Box-Cox transformation on annual earnings. We also note that in models without controls for H and health shocks, the R-squared declines to 0.836, 0.544 and 0.636, respectively.

Figures

Figure 1: Fractions with d^u, s and d^p shocks by Age, Model and Data

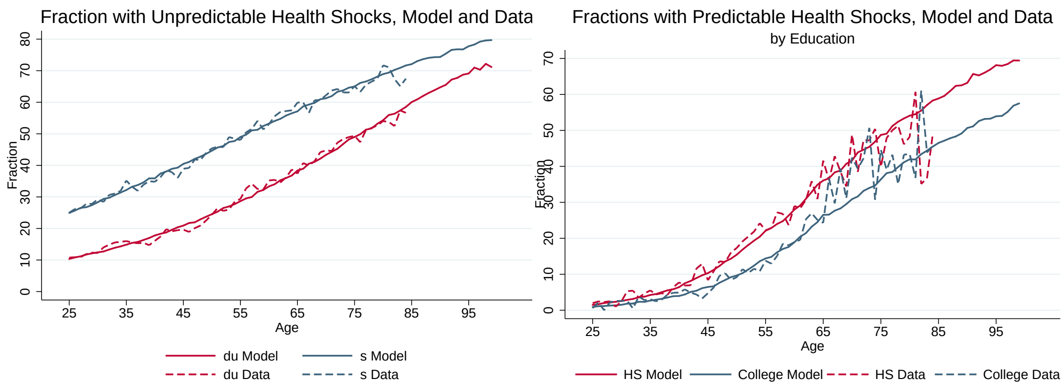


Figure 2: Distribution of H, Model and Data

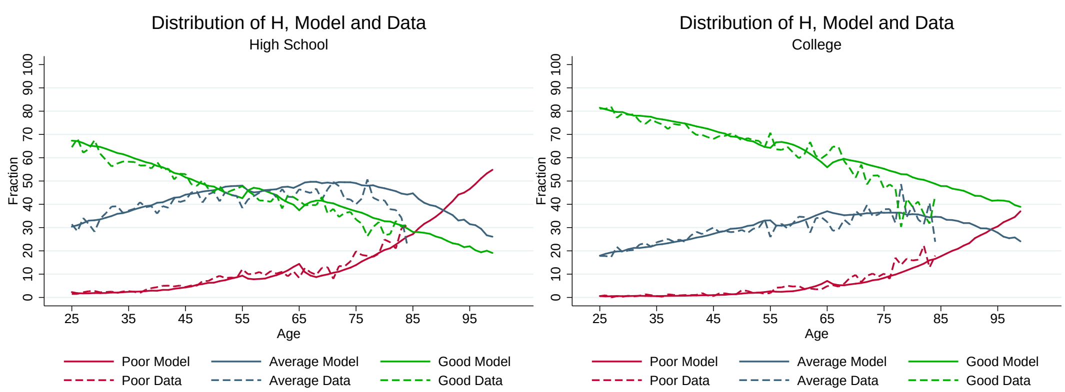


Figure 3: Distribution of Health Risk R, Model and Data

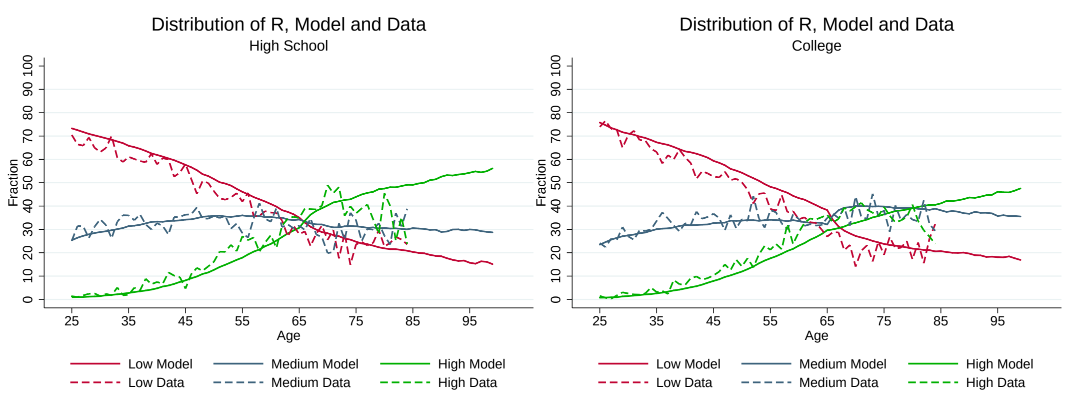


Figure 4: Distribution of Employment, Including Insurance Status, MEPS

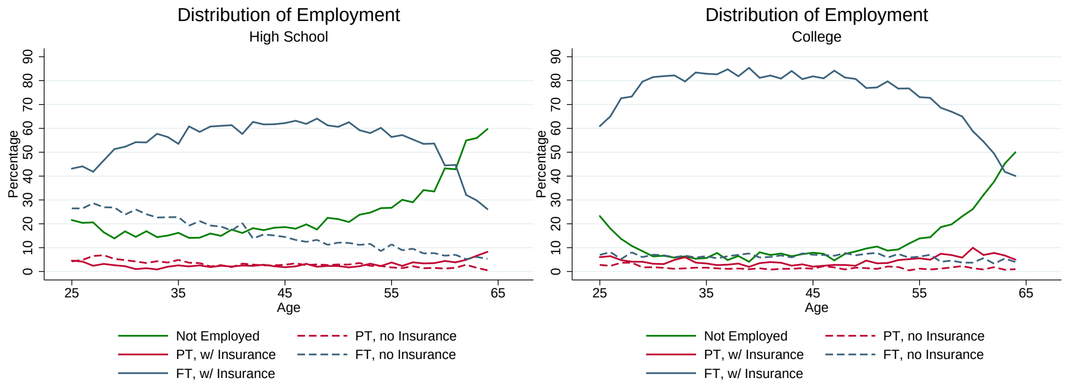


Figure 5: Percentage of Population in FT and PT Employment, Data (MEPS) and Model

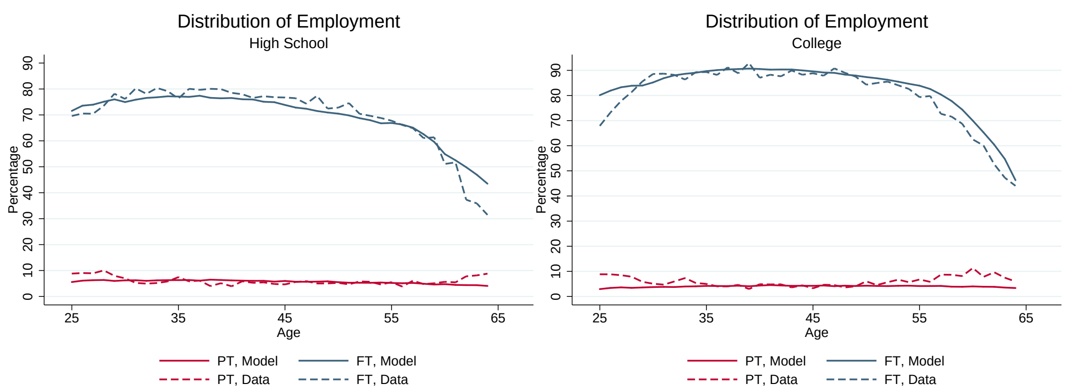


Figure 6: Distribution of FT Employment by Health and Age, Data (MEPS) and Model

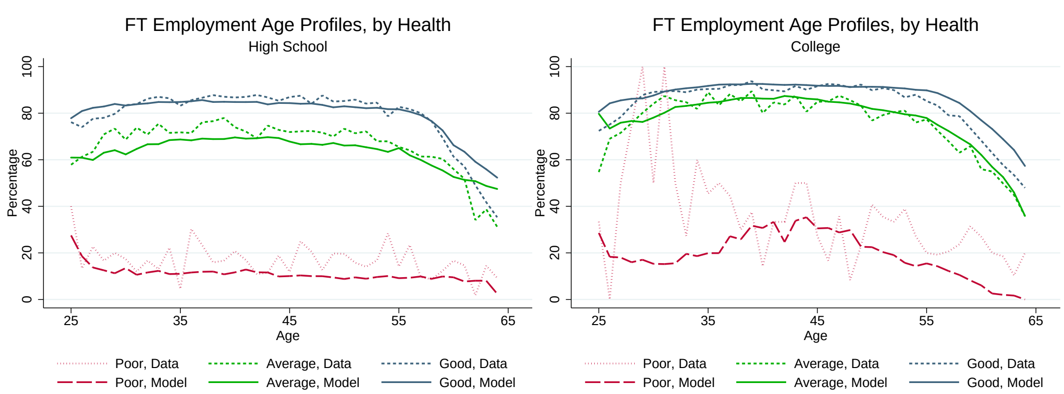


Figure 7: Wage Profiles of Full Time Workers, by Health, Model and MEPS Data

Figure 8: Variance of Log Wages, Full Time Workers, Model and MEPS Data

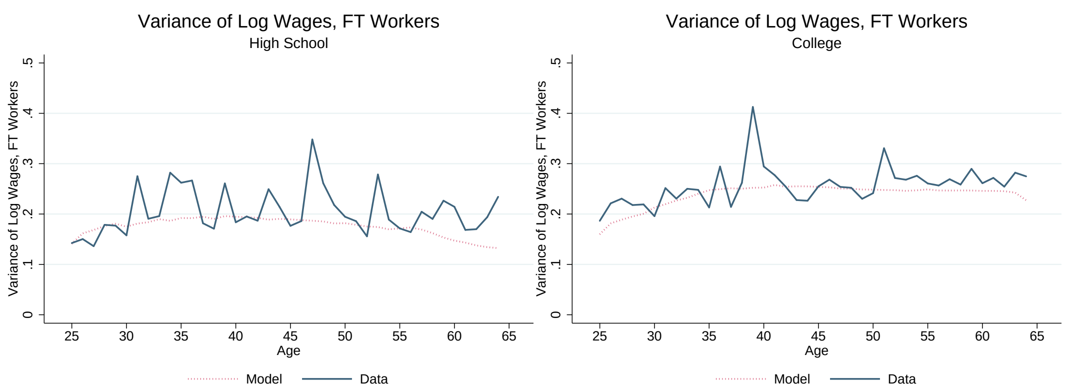
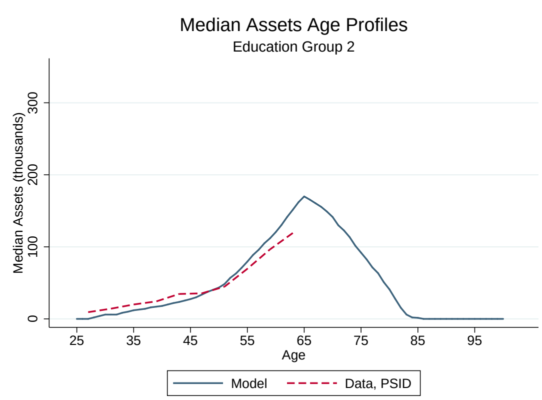
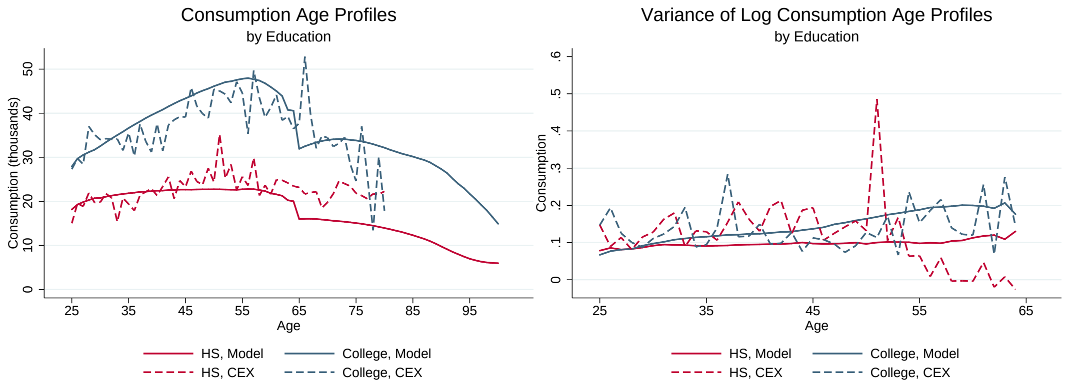


Figure 9: Median Assets Age Profiles, by Education, PSID



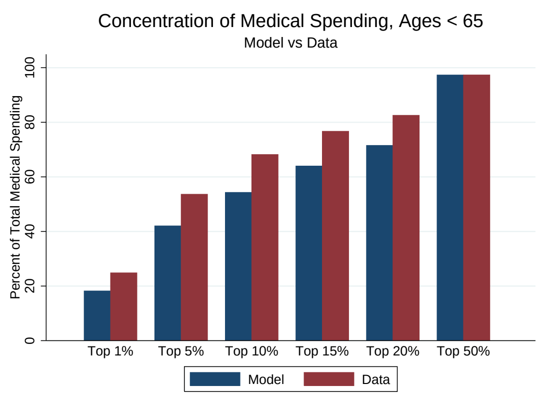
Data source: PSID Supplemental Wealth Surveys. Assets are equal to total wealth excluding home equity. Mortgages are not included. (Please see Appendix for details.)

Figure 10: Consumption, Model and CEX Data



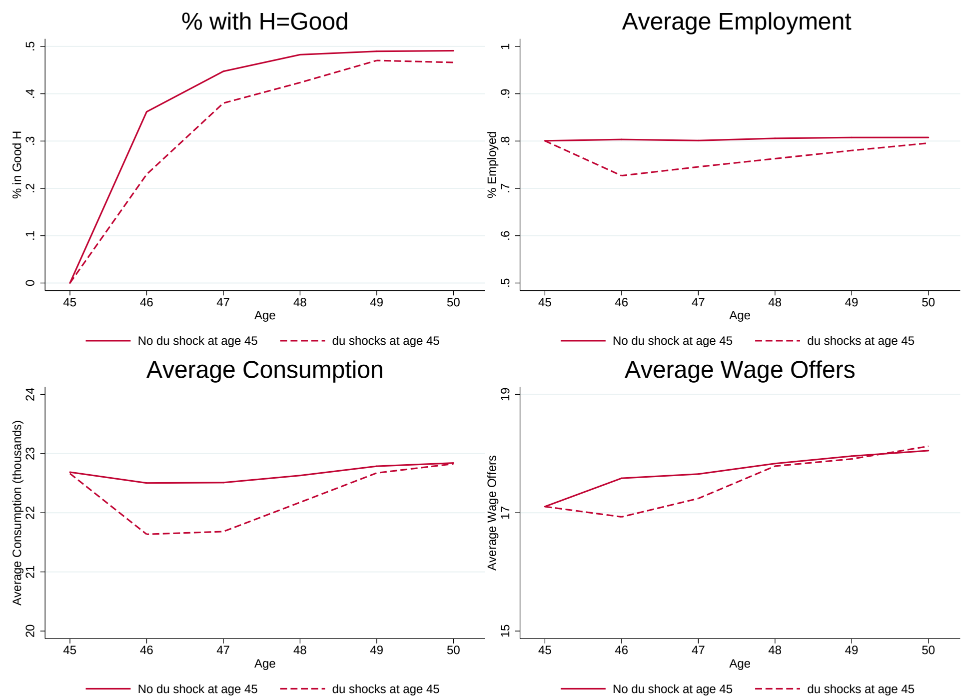
Note: In constructing the variance of log consumption profiles, we exclude those on the consumption floor in the model. We also exclude observations in the data where consumption falls below the calibrated consumption floor in the model. The data profiles show non-durable + housing consumption profiles, excluding health services, calculated using the CEX 1996-2004.

Figure 11: Distribution of Medical Spending, Ages 25-64, Model and Data



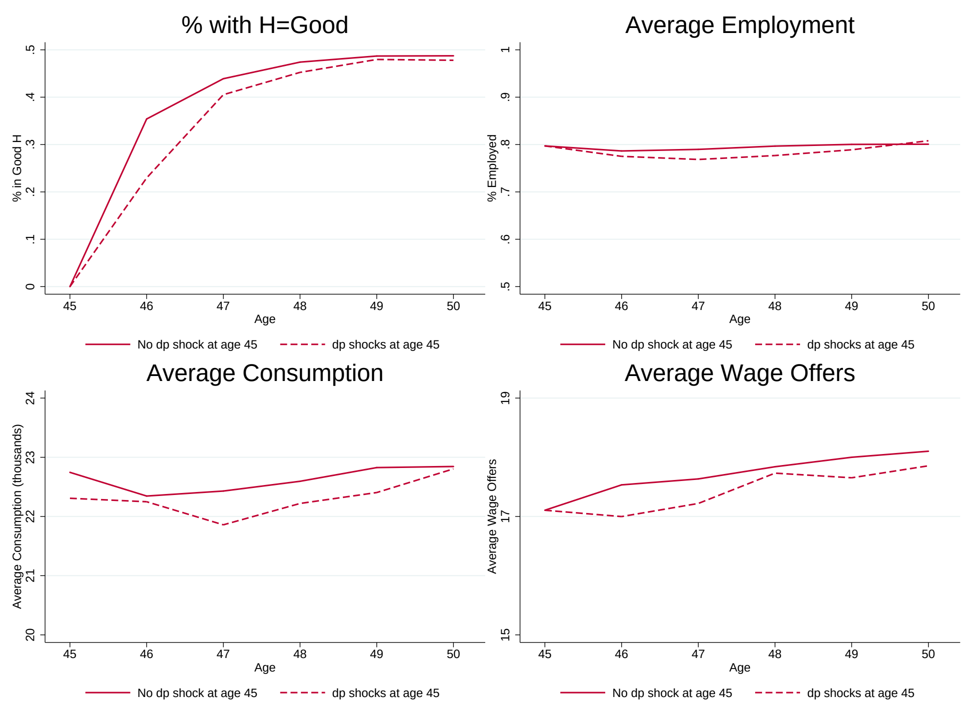
Note: The data source is MEPS, combining all education groups, and using medical expenditures from year 1 of interview for each person.

Figure 12: Selected Responses After d^u Shocks at Age 45, HS



Note: The graphs are constructed for individuals with H=Average and R=Medium at age 45.

Figure 13: Selected Responses After d^p Shocks at Age 45, HS



Note: The graphs are constructed for individuals with H=Average and R=Medium at age 45.

Figure 14: Wage Offers and Health Shocks

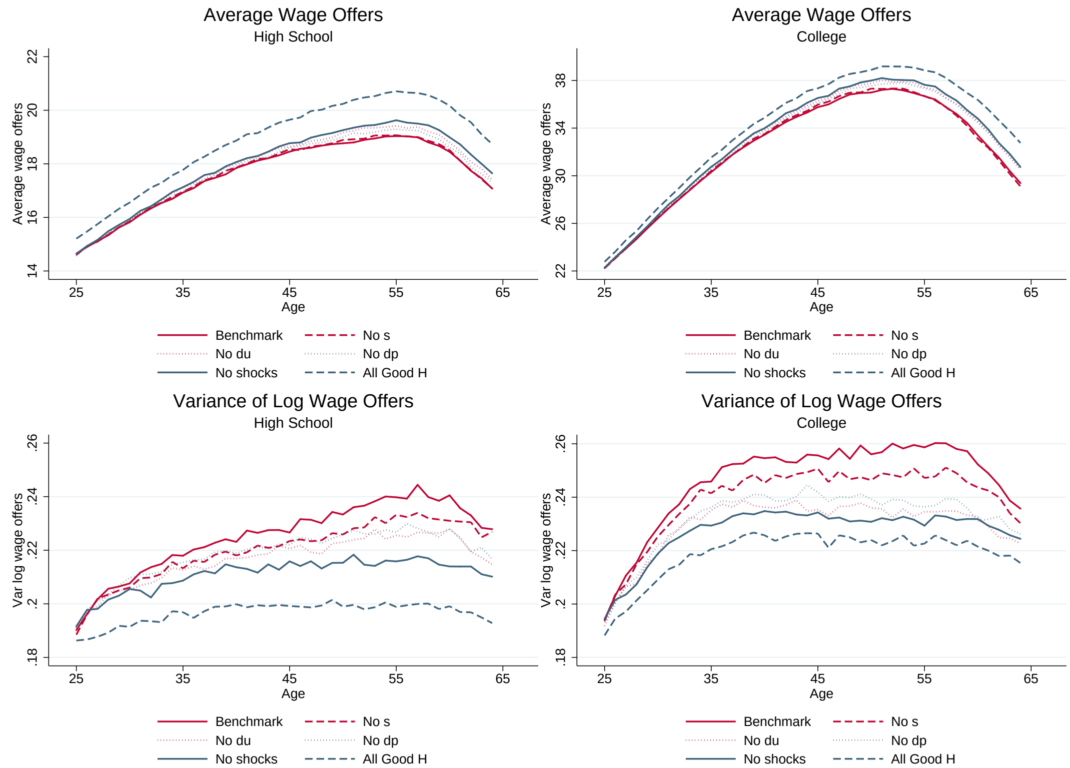
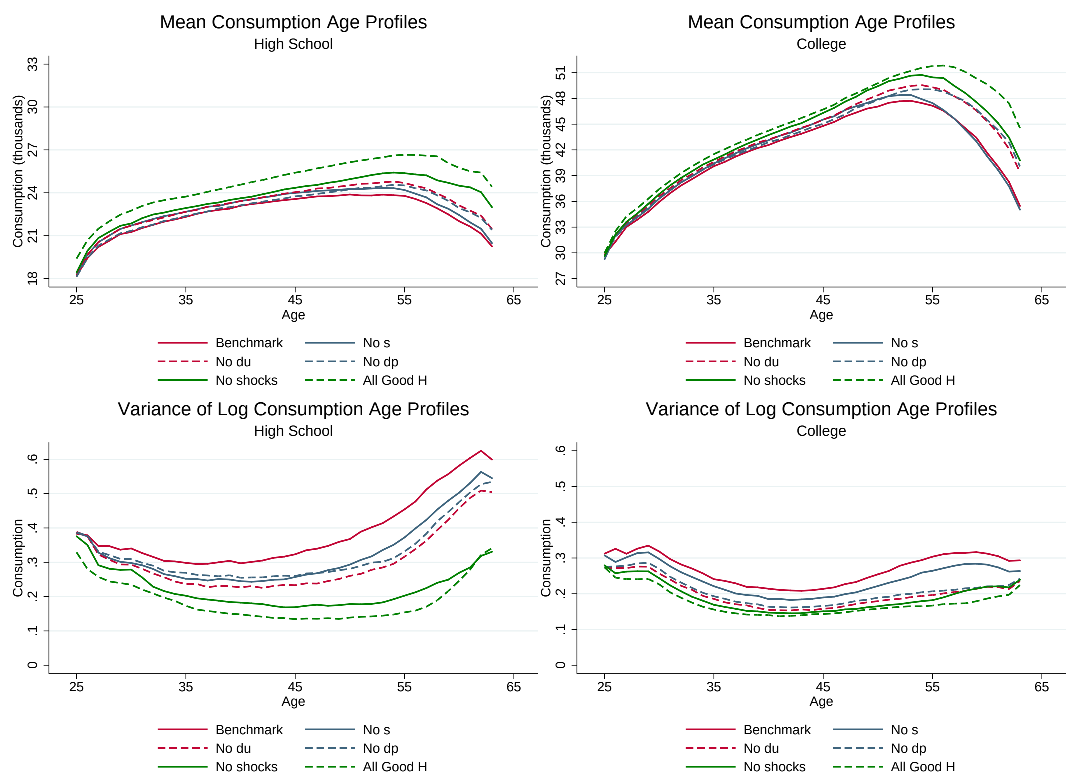


Figure 15: Consumption: Mean and Variance by Age



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