Health Shocks and the Evolution of Earnings over the Life-Cycle*

Elena Capatina, Michael Keane, Shiko Maruyama

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Abstract

We study the contribution of health shocks to earnings inequality and uncertainty in labor market outcomes. We calibrate a life-cycle model of labor supply and savings that incorporates health and health shocks. Our model features endogenous wage formation via human capital accumulation, employer sponsored health insurance, and means-tested social insurance. We find a substantial part of the impact of health shocks on earnings arises via reduced human capital accumulation. Health shocks account for 15% of lifetime earnings inequality for U.S. males, with two-thirds of this due to behavioral responses. In particular, it is optimal for low-skill workers – who often lack employer sponsored insurance – to curtail labor supply to maintain eligibility for means-tested transfers that protect them from high health care costs. This causes low-skill workers to invest less in human capital. Provision of public health insurance can alleviate this problem and enhance labor supply and human capital accumulation.

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1 Introduction

In this paper we study the impact of health shocks on earnings and life-cycle earnings inequality. Smith (2004) documents the effects of major health shocks on earnings in the Health and Retirement Study (HRS), finding large negative effects over horizons of two to ten years. We extend this work by embedding health shocks in a life-cycle labor supply framework incorporating endogenous human capital formation. Our structural estimation framework enables us to distinguish between *direct* effects of health shocks on earnings, and *indirect* effects operating through their impact on labor supply, human capital accumulation, savings and other behaviors. We find the behavioral responses to health shocks greatly amplify their impact on earnings and life-cycle earnings inequality. Our structural model also allows us to assess how changes in the economic environment, such as providing health insurance to the uninsured, would alter labor supply, earnings inequality and savings behavior.

Since its inception in work by MaCurdy (1981) and Heckman and MaCurdy (1980), the life-cycle labor supply literature has emphasized how agents respond differently to temporary vs. persistent and predictable vs. unpredictable wage shocks. In extending the life-cycle model to include health shocks, it is important to recognize that they can also be categorized in this way. Thus, in our model, people are subject to health shocks that may be temporary or persistent, and unpredictable or predictable. This lets us analyze how different types of health shocks affect the evolution of earnings over the life-cycle. We find that persistent unpredictable shocks have the greatest impact on earnings and earnings inequality.

Our framework allows us to study how health risk affects human capital accumulation. In our model individuals accumulate human capital via learning-by-doing, as in Keane and Wolpin (1997) and Imai and Keane (2004). Returns to current investments in human capital depend on expected future labor supply, which is reduced by poor health and/or adverse health shocks. Our framework allows us to predict the dynamic effect of a health shock on future earnings, incorporating the impact on the evolution of human capital after the shock.[1]

Our results imply that a large part of the impact of health shocks on earnings arises from the behavioral responses to those shocks. For example, for a 40 year-old male college graduate, our model implies that a major persistent health shock reduces the present value of remaining lifetime earnings by \$45k or 4.5%. We estimate that fully 40% of this impact is due to the knock-on effect of reduced human capital accumulation after the shock.

Turning to earnings inequality, if we simulate a counterfactual environment with health shocks eliminated, the Gini coefficient for the present value of lifetime earnings falls by 15%. But if we do the same experiment holding decision rules for labor supply and consumption fixed, the Gini falls by only 5%. Thus, two-thirds of the impact of health shocks on inequality arises through the behavioral response to health risk, as opposed to the direct effects of health shocks themselves. Much of our analysis is devoted to better understanding the direct and behavioral channels through which health shocks affect earnings inequality:

First, consider the "direct" channels through which health shocks contribute to earnings inequality in a fixed environment: Differential exposure to health shocks over the life-cycle generates increasing inequality with age in health status, which directly affects productivity

[1] We define "human capital" as skill generated by education and work experience. We distinguish this from "health." Both affect worker productivity in our model. The distinction is useful as it lets us distinguish *direct* effects of health shocks on earnings from *indirect* effects operating through human capital accumulation.

(hence wage offers) and tastes for work. Lost work time due to health shocks also generates increasing inequality with age in accumulated work experience and human capital.

Second, consider the behavioral channels: In an environment with health shocks, low-skill workers, who often lack private insurance, have an incentive to curtail their labor supply to maintain eligibility for means-tested social insurance. This reduces their rate of human capital accumulation.[2] Conversely, health risk has a positive effect on labor supply of high-skill workers, who wish to work and save more in order to self-insure against medical expenses. Thus, health risk induces low-skill workers to work less, and high-skill workers to work more. These behavioral forces can explain roughly 10% of lifetime earnings inequality.

A brief overview of our model is as follows: Individuals begin every period with stocks of health, assets and human capital. Working age individuals receive employment offers that they accept or reject. A fraction of offers include employer provided health insurance. Wage offers depend on human capital and health, which are subject to transitory and persistent shocks. The disutility of working depends on health. After the employment decision is made, health shocks (of different types) occur with probabilities that depend on health status. These health shocks determine medical expenditures and sick days suffered by workers. Finally, individuals make consumption/savings decisions. At the start of the next period, new stocks of health and human capital are revealed (based on their laws of motion).

Some aspects of the model deserve further comment: Following De Nardi et al. (2010) and French and Jones (2011), we model medical expenditures as cost shocks. If a health shock occurs, the realized cost of treatment (net of insurance) *must* be borne by the agent.[3] An alternative is to treat medical expenditures as generated by voluntary choices to invest in health, as in Grossman (1972). But we argue that most medical expenditure can be better thought of as driven by cost shocks, particularly as only a small fraction of medical expenditure is devoted to preventive medicine.[4]

To assess how health shocks impact labor supply and earnings, it is important to account for the role of social insurance. Following Hubbard et al. (1995), and numerous subsequent papers such as De Nardi et al. (2010) and French and Jones (2011), we assume workers with sufficiently low income/assets qualify for a transfer that guarantees a minimum level of consumption. This consumption floor is designed to capture, in a simple way, an array of benefits such as Foodstamps, Medicaid and Disability.

We also incorporate private and public health insurance. In our model, workers receive job offers that may or may not include employer sponsored health insurance. This is a key aspect of the US environment, with its employer-based insurance system for those under 65. Workers operating at the consumption floor receive public coverage for medical expenses, approximating the means-tested Medicaid public insurance program.

In this environment, we show how means-tested social insurance reduces incentives to supply labor and invest in human capital. Accounting for health risk (on top of wage risk)

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[2] Low-skill workers have lower labor supply from early in the life-cycle, due to low wages and the option to use means-tested insurance. Unemployment and low incomes lead to worse health as they age. This creates a vicious cycle, as worse health feeds back to further lower wages and labor supply.

[3] Our view is that patients have little ability to know the cost of their treatment *ex-ante*, or to make informed choices whether to bear that cost. Hence, they pay for whatever treatment is prescribed. Thus, medical expenditure is not a *choice*, but rather an exogenous realization from an expenditure distribution.

[4] For example, in 2015 spending on preventive as a fraction of total health spending was only 2.9% in the U.S. (www.oecd.org/els/health-systems/health-data.htm). Most spending is on treatment of specific illness.

magnifies this effect: Low-skill workers often lack private health insurance, so they face considerable consumption risk from *both* wage and health shocks. This creates a strong incentive to curtail labor supply to maintain eligibility for means-tested social insurance.[5]

We also analyze the impact of providing public health insurance to people who lack employer provided insurance. Coverage of health expense risk reduces the incentive for low skill workers to curtail labor supply to maintain eligibility for means-tested social insurance. As a result, they work more and acquire more human capital. Through this positive labor supply mechanism, public health insurance raises additional tax revenue and saves on means-tested social insurance costs – thus counteracting a large share of the cost of its provision. To our knowledge this benefit of public health insurance has not been noted previously.

We calibrate our model to the U.S. male population using the Medical Expenditure Panel Survey (MEPS). The MEPS contains detailed information on respondents' medical conditions, coded according to the International Classification of Diseases (ICD). Based on expert medical advice, we categorized medical conditions according to (i) whether they affect productivity, (ii) whether they are risk factors for other health problems, (iii) predictability, and (iv) persistence.[6] The MEPS also contains detailed measures of total and out-of-pocket medical expenditures. Using this information, we estimate stochastic processes for health, health shocks, and medical costs. These are important inputs to our model.[7]

The outline of the paper is as follows. Section 2 reviews the literature and Section 3 presents our model. Section 4 describes our MEPS data. Section 5 describes the calibration, and section 6 discusses model fit. Section 7 presents results and Section 8 concludes.

2 Relation to Literature

Our paper contributes to the literature on earnings inequality by assessing the importance of health risk as a contributing factor. We also contribute to the rapidly growing literature on life-cycle models with health uncertainty (e.g., Palumbo 1999, French 2005, Jeske and Kitao 2009, Khwaja 2010, Attanasio et al. 2010, De Nardi et al. 2010, French and Jones 2011, Kitao 2014, Capatina 2015, Pashchenko and Porapakkarm 2017, Jung and Tran 2016, De Nardi et al. 2017, Cole et al. 2018, and Hosseini et al. 2018). We extend this work by using a richer model of the health process, and by incorporating endogenous human capital.

Our work is closely related to the reduced form literature on effects of health shocks on employment and earnings. Much of that work defines health shocks as changes in the stock of self-reported or objective health (Au et al. 2005, García Gómez and López Nicolás 2006, Lenhart 2019). These papers find declining health reduces earnings and employment.

Because the stock of health and employment/earnings are jointly determined over the life-cycle, Smith (1999, 2004) argues the best way to identify the effect of health on labor market outcomes is to control for baseline health and human capital and estimate effects of the onset of specific health shocks. Adopting this approach, he finds that onset of cancer, heart and lung disease have substantial negative effects on employment and earnings. For

[5] As in Hubbard et al. (1995), low-skill workers in our model also have an incentive to accumulate less assets to maintain eligibility for means-tested social insurance, as the means test involves income and assets.

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

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

example, in the HRS he estimates a cumulative income loss of $\$37k$ over ten years (1994-2003) following a major health shock. Using a similar approach, Pelkowski and Berger (2004) find that onset of permanent health conditions reduces wages and hours.

Our work can be viewed as a structural extension of this type of analysis, where we build health shocks into a life-cycle labor supply model. As we emphasized in the introduction, our model distinguishes several mechanisms through which health shocks affect labor market outcomes. As we also discussed in the introduction, we classify health shocks as persistent vs. transitory and predictable vs. unpredictable, as these types of shocks should have different impacts on earnings, labor supply and consumption. To our knowledge, the only prior work that estimates effects of persistent vs. transitory health shocks on employment and earnings is Blundell et al. (2016), who find much larger effects of persistent shocks.

We also contribute to the literature on life-cycle models of human capital accumulation (e.g., Shaw 1989, Eckstein and Wolpin 1989, Keane and Wolpin 1997, 2001, Imai and Keane 2004) by incorporating health and health shocks into a model of learning-by-doing. A prior paper that incorporates both health and learning-by-doing in a life-cycle model is Hokayem and Ziliak (2014). We substantially extend their work by adopting a full solution approach, so we can do policy experiments. We also model the participation margin of labor supply, adopt a richer specification of the health process, and treat health spending very differently: They assume a Grossman (1972) model where medical expenditures are voluntary choices to invest in health. We instead follow De Nardi et al. (2010) and French and Jones (2011) and model medical spending as a cost of treatment for health shocks (and hence a risk) rather than an investment. We argue most medical expenditure is better thought of as due to cost shocks, as only a small fraction of medical expenditure is devoted to preventive medicine.

Our paper is also related to the literature studying how means-tested social insurance affects labor supply (see Hubbard et al. 1995, Moffitt 1992). We extend recent papers that study how means-tested insurance interacts with health risk: French and Jones (2011) study the effects of employer-based health insurance, Medicare and Social Security on labor supply and retirement behavior. Benıtez-Silva et al. (2010), Low and Pistaferri (2015), and Kitao (2014) study the impact of Disability Insurance on employment decisions. Moffitt and Wolfe (1992) and Pashchenko and Porapakkarm (2017) study work disincentives created by the means-tested Medicaid public health insurance program. We contribute to this literature by studying how means-tested social insurance reduces human capital accumulation and increases earnings inequality in an environment with both wage and health risk.

There is a large literature that studies the impact of education on health, but it faces difficult problems in assessing the direction of causality. Important recent work by Conti et al. (2010a,b), Heckman et al. (2018) and Hai and Heckman (2019) estimates significant positive effects of education on health, controlling for selection into education based (in part) on latent initial skills and initial health, which they control for using proxy variables in dynamic factor models. For instance, Hai and Heckman (2019) find that "endowments" of skill and health at age 16 are positively correlated. The correlation grows with age because youth with high initial levels of skill and health invest more in both health and education, and because education complements health investments.[8, 9] To capture this complementarity

[8] In related work, García and Heckman (2020) use random assignment into early childhood education programs to document strong positive effects of education on health.

[9] See also Adams et al. 2003, Stowasser et al. 2011, Lochner 2011 and Oreopoulos and Salvanes 2011.

we let the law of motion for health differ flexibly across education groups. But we do not attempt to estimate the causal effect of education on health: Our model starts at age 25 and takes education as given. We focus exclusively on interactions between health and human capital accumulation *after* school completion and labor market entry.

Finally, there is a literature on how income, wealth and employment shocks affect health. As Smith (1999, 2004) discusses, this literature also faces difficult issues of assessing causality. He recommends analyzing effects of employment and earnings shocks on health status while controlling for lagged health and human capital. Alternatively, several papers examine effects of exogenous job separations on health (Eliason and Storrie 2009, Black et al. 2015, Schaller and Stevens 2015). They find job loss leads to worse health behaviors, worse self-reported health, and worse mental health. But they do not find short-run effects on chronic conditions or frequency of health shocks. Similarly, Adda et al. (2009) look at effects of permanent and transitory income shocks on health using cohort level data. They find no effects on health over a 3-year horizon, but they do find effects on mortality and health related behaviors.

We argue that to estimate the effects of income and employment on health, it is important to control for health shocks in the health production function. Health shocks reduce contemporaneous earnings and labor supply. Hence, unemployment may be associated with worse health transitions in part because unobserved persistent health shocks reduce current labor supply and also lead to worse health transitions. This may lead to an upward bias in the estimated effect of employment on health. We contribute to this literature by estimating the effect of employment (and income) on health transitions using a model that explicitly controls for the onset of persistent health shocks, eliminating this potential bias.

3 Model

In our life-cycle model agents face idiosyncratic risk to wages, employment, earnings, health and survival. They enter the economy at age 25 and face survival risk every period. The model period is one year, and the maximum lifespan is 100. Retirement is exogenous at age 65. From age 25 to 64, agents receive employment offers probabilistically each year, and decide on whether to accept or reject them. They also make a continuous consumption/savings decision, but borrowing is not allowed. Workers accumulate human capital through work experience. The model is solved in partial equilibrium, assuming a fixed interest rate and a fixed rental rate on skill.

Education is taken as given at age 25 when agents enter the model. We assume three education groups: high school (HS) or less, some college (1-3 years), and college graduates.[10] We allow most model parameters, including the health and human capital production functions, tastes for leisure and job offer probabilities, to differ by education group. Consistent with prior work, we find the heath production function differs in important ways by education, but a limitation of our analysis is that we do not attempt to explain why.[11]

[10]These three education groups make up 40%, 27% and 33%, respectively, of the working age population in the CPS from 2000-2010. The fraction of HS dropouts is relatively small (11%), so we combine them with the HS graduates (29%).

[11]This is consistent with work by Hai and Heckman (2019), who estimate that education is complementary with inputs into health production.

3.1 The Timing of Decisions and Shocks

Agents begin each period (t) with stocks of assets A_t, human capital HC_t, functional health H_t, and asymptomatic risk factors R_t. Working age individuals in poor functional health also know their disability insurance (DI) status I_t^{DI}, which affects the level of government transfers received. Immediately after the start of the period, working age individuals receive an employment offer, which can be full or part-time, and with or without employer sponsored health insurance. Wage offers are determined by health and human capital and are subject to temporary and persistent shocks. Agents decide whether to accept or reject the tied wage/hours/insurance offer. Then health shocks are realized. These, together with functional health, determine mortality, medical expenditures and sick days. Sick days reduce work hours and reduce the accumulation of human capital. Next, agents make a continuous consumption/saving decision. Finally, next period state variables become known, and the next period begins. We let t denote both the time period and the age of the individual.

3.2 Health and Health Shocks

An important feature of our model is a detailed specification of the processes for health and health shocks over the life-cycle. There are two stocks of health: functional health (H_t) and underlying asymptomatic health risk (R_t). And in each period agents can experience three types of health shocks: predictable and persistent (d_t^p), unpredictable and persistent (d_t^u), and unpredictable and transitory (s_t). Section 4 explains how we classify dimensions of health and types of health shocks using the MEPS data. Here, we take the classification as given and explain how health and health shocks operate in the model:

Functional health status H_t measures the ability to perform daily activities and function in a work environment. Thus, it impacts on productivity. It is discrete and can take three values: poor, fair or good ($H_t \in \{P, F, G\}$). In contrast, the stock of underlying health risk R_t has no impact on current productivity. R_t captures asymptomatic risk factors whose only effect is to increase the probability of predictable health shocks (d_t^p) in the future. Examples are obesity and high cholesterol, which increase the probability of heart disease. R_t is also discrete with three values: low, medium or high ($R_t \in \{L, M, H\}$). H_t and R_t evolve from year-to-year with transition probabilities that we describe below.

Let $\Upsilon_t = (d_t^p, d_t^u, s_t)$ be a vector of indicator functions for occurrence of health shocks. All three types of health shock affect ability to function in the *current* period. The persistence of shocks is categorized as short or long-term. For example, a broken limb is a short-term shock that affects the individual *only* in the current period. Long-term shocks, such as damage to the spinal column, have effects that last for multiple periods. Our model captures this by letting the transition probabilities for H_t and R_t depend on persistent shocks (d_t^p, d_t^u).

Persistent shocks are classified as predictable (d_t^p), or unpredictable (d_t^u). We assume all transitory shocks (s_t) are unpredictable.[12] The "predictable" shocks (d_t^p) have a probability of occurrence that depends on H_t and R_t, along with age and education. Examples are stroke and lung cancer. Probabilities of "unpredictable" shocks d_t^u and s_t depend only on age.

The following table lists the state variables that enter the transition probabilities for H_t and R_t and the probabilities of health shocks d_t^p, d_t^u and s_t. For example, functional health H_t evolves according to a transition matrix that depends on the current level of H, age, long-term health shocks (d_t^p, d_t^u), employment and health insurance status (summarized by the categorical variable O), education, and income group (inc). We assume the probabilities of initial levels of H and R at age 25 depend only on education.

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

Finally, the survival probability (year-to-year) depends on functional health, age, and long-term health shocks, and is given by $\varphi(H_t, t, d_t^p, d_t^u)$. The risk factors R affect the survival probability indirectly, by altering the probability of adverse health shocks d_t^p.

3.3 Medical Expenditures

As in De Nardi et al. (2010) and French and Jones (2011), we treat medical expenditures as exogenous cost shocks. They are are given by the function $ME(H_t, \Upsilon_t, t, \varepsilon^{ME})$, which depends on health H_t, health shocks $\Upsilon_t = (d_t^p, d_t^u, s_t)$, age t, and a stochastic term ε^{ME}. The shock ε^{ME} determines whether the person must bear the "normal" treatment cost associated with their state ($\varepsilon^{ME} = 0$), or a higher "catastrophic" level of cost ($\varepsilon^{ME} = 1$). We assume the probability of a catastrophic shock $\delta = Pr(\varepsilon^{ME} = 1)$ is uniform across health states, but the catastrophic level of costs is allowed to vary by health state (H_t, Υ_t, t).

We assume that all individuals must bear the cost of treatment associated with their medical condition (as drawn from $ME(\cdot)$). In reality people may have choices about their course of treatment, and thus have some control over costs. But we abstract from this, in effect assuming people lack the medical knowledge to make such decisions. Thus, medical expenditures are non-discretionary, and they do not *directly* affect health in our model.

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

[12] In the data section, Section 4, we show there are very few medical conditions that are predictable but short lasting. So it did not seem worthwhile to complicate the model by including this additional type of shock.

3.4 Health Insurance

Health insurance is of three types: (1) employer provided, (2) Medicare, and (3) all other forms of public insurance captured by the consumption floor. Employer provided insurance is available to a fraction of workers, as described in the next section. Workers whose employers provide health insurance pay a (subsidized) out-of-pocket premium p^{EI}.[13] Employer insurance pays a fraction q^{EI} of workers total medical costs. Medicare is available to those 65 and older, and it covers a fraction q^{Med} of medical costs. The Medicare premium is p^{Med} is paid by those 65 and over, and a payroll tax τ^{Med} is paid by workers.

Given their resources, some individuals may be unable to afford the level of medical costs they draw from $ME(\cdot)$ while also maintaining a minimum level of consumption. In such cases, we assume the government provides a guaranteed consumption floor, described in Section 3.6. This is meant to capture programs like Medicaid that cover medical expenses of the poor, as well as other social programs like Foodstamps. It also captures the possibilities of simply not paying hospital bills or declaring medical bankruptcy.[14]

Finally, to capture disability insurance benefits in a simple way, we assume working age people in poor functional health are probabilistically eligible for a higher consumption floor (see Benítez-Silva et al. 1999, Low and Pistaferri 2015). This is meant to approximate benefits from the SSI and SSDI programs. See Section 3.6 for details.

3.5 Employment

3.5.1 Employment Offers

At the start of each period, and before health shocks are realized, individuals aged 25 to 64 receive employment offers probabilistically. If an offer is received, an individual decides whether to accept or reject it. Employment offers are characterized by a wage, number of hours, and the provision of employer health insurance. Letting * superscripts denote offers, we have: $\{W^*, h^*, ins^*\}$. Wage offers are continuous, and are described in detail in Section 3.5.4. The number of hours h^* takes one of three values, 0 (no offer), hrs^{PT} (part-time) or hrs^{FT} (full-time), $h^* \in \{0, hrs^{PT}, hrs^{FT}\}$. Insurance $ins^* \in \{0, 1\}$ is an indicator for whether the offer includes health insurance. We let the categorical variable O^* summarize employment offers based on the five possible combinations of hours and insurance.[15]

The probability of receiving each type of offer O^* depends on education and age, and is given by $\Pi(O^*, educ, t)$. To help capture the decline in hours at older ages observed in the data, we allow for a positive probability of receiving no offer at ages 54+. This may be interpreted as a simple way to capture various reasons that employers are reluctant to hire older workers. At younger ages, all non-employment is voluntary.

When employment offers are accepted or rejected, medical expenditures are not yet known, as health shocks occur after the decision is made. However, individuals know H_t and R_t, so they can calculate *expected* medical expenditures.

[13] Employers pay 81% of the health insurance premium for singles on average (Kaiser Family Foundation 2010). We only model the part paid by the employee, which does not vary based on personal characteristics.

[14] As we rule out borrowing, we cannot explicitly model bankruptcy decisions.

[15] Specifically, the five possibilities are: no offer ($h = 0$), part-time offer with and without insurance, and full-time offer with and without insurance.

After individuals accept/reject their employment offer(s), employment and health insurance status are summarized by the categorical variable $O = \{W, h, ins\}$.

3.5.2 Hours Worked and Sick Days

When an individual accepts an employment offer, he commits to working h^* hours at wage W^*. This commitment is fulfilled unless the worker experiences sick days. Sick days $sd(educ, H_t, \Upsilon_t)$ are a function of education, health and health shocks. The actual number of hours worked by employed workers is given by $h_t = h^* - sd(educ, H_t, \Upsilon_t)$.

We assume health shocks do not affect wages within a period. Employers cannot lower wages immediately if an employee receives a negative health shock. However, health shocks may force workers to reduce work hours so as to attend doctor appointments, undergo treatment, or simply rest. Thus, the model captures the fact that a worker may have high human capital and high wages, yet, have little earning capacity for health reasons. We allow sick days to vary by education level to capture the fact that ability to work after health shocks differs by occupation. We assume all sick days are unpaid.[16]

3.5.3 Human Capital Accumulation via Work Experience

Let HC denote the time-varying component of human capital that depends on work experience. It evolves probabilistically according to the law of motion:

$$HC_{t+1} = (HC_t + h_t)\varepsilon^{HC}_{t+1} \tag{3.1}$$

where ε^{HC} is a shock governed by:

$$\varepsilon^{HC}_{t+1} = \begin{cases} 1+\nu & \text{with probability } p^1(educ, I_w) \\ 1 & \text{with probability } 1 - p^1(educ, I_w) - p^2(educ, I_w) \\ 1-\nu & \text{with probability } p^2(educ, I_w) \end{cases} \tag{3.2}$$

Probabilities of human capital "shocks" (i.e., increments) depend on education and an indicator I_w equal to 1 if an agent is employed and 0 otherwise. We expect more educated employed workers are more likely to receive positive shocks, given the evidence they have faster wage growth with experience (Imai and Keane (2004)). We expect unemployed workers are more likely to receive negative shocks, due to skill depreciation during unemployment.

3.5.4 The Wage Offer Function

The wage offer function is given by (suppressing time subscripts):

$$lnW^* = w(educ, HC, H, h^*) + \kappa_j(educ) + \varepsilon^W \tag{3.3}$$

$$w(educ, HC, H, h^*) = \beta_0 + \beta_1 HC + \beta_2 HC^2 + \beta_3 HC^3 + \beta_4 I_{H\in\{F,G\}} + \beta_5 I_{H=G} + \beta_6 I_{h^*=hrs^{PT}} \tag{3.4}$$

where the parameters $\beta_0 - \beta_6$ of 3.4 are all allowed to be education-level specific.

[16] In reality, workers have on average 7 paid sick days per year (BLS Statistics).

Thus, the function $w(educ, HC, H, h^*)$ combines human capital (determined by education $educ$ and work experience HC) with functional health H to determine the mean of the (log) wage offer distribution. Health enters through the health status indicator functions $I_{H\in\{F,G\}}$ and $I_{H=G}$, which indicate fair or good health, and good health, respectively. Effects of both health and experience are allowed to differ by education. We also let the mean of the wage offer distribution depend on $I_{h^*=PT}$, and indicator equal to one for part-time offers, to capture the observation that part time-wages tend to be lower than full-time wages - see Moffitt (1984), Lundberg (1985), and Aaronson and French (2004).

As we see in equation 3.3, wage offers W^* depend on (1) the function $w(educ, HC_t, H, h^*)$ that determines the mean of the offer wage distribution, (2) the agent's latent productivity type κ_j, and (3) transitory shocks ε_t^W. The latent type κ is age invariant and discrete, with j indexing types. It is mean zero, but with dispersion that differs by education level (see Section 5.2.4 for details). Transitory wage shocks are distributed as $\varepsilon^W \sim N(0, \sigma^2_{\varepsilon^W}(educ))$.

To summarize, human capital consists of a fixed part determined by $educ$ and κ and a time varying part HC governed by work experience and persistent shocks. Human capital and health combine to determine wage offers. Persistent shocks to wages arise from three sources: 1) the persistent shocks ε^{HC}_{t+1} to the human capital process in 3.1, 2) persistent health shocks that affect wages through persistent effects on H, and 3) long-term effects that arise endogenously through workers' responses to all current period shocks, as these responses are embedded in the next period's human capital and assets. For instance, a shock that reduces labor supply today will reduce next period's HC via the law of motion in equation 3.1.

3.6 Taxes, Social Security and Social Insurance

At age 65 we assume all workers retire and start to receive Social Security payments. Social Security rules are complex, and our focus is on sources of earnings uncertainty for working age men, so we abstract from the details of the rules. We simply assume the Social Security benefit is a constant $SS(educ)$ that depends only on education.[17]

For individuals aged 25 to 64, taxable income y_t equals the sum of labor and capital income, minus the employee health insurance premium p^{EI} for those with insurance, and minus the tax deductible part of out-of-pocket medical expenditures (i.e., expenses in excess of 7.5% of income). The taxable income for retirees is similar, except Social Security income replaces labor income. Letting I_w be an indicator for employment, we have:

$$\begin{aligned} y_{t<65} &= max[0, rA + I_w(W^*h - p^{EI}ins^*) - max(0, ME(1 - q^{EI}I_w ins^*) - 0.075(rA + I_w W^*h))] \\ y_{t\geq 65} &= max[0, rA + SS - max(0, ME(1 - q^{Med}) - 0.075(rA + SS))] \end{aligned} \quad (3.5)$$

We follow Jeske and Kitao (2009) and Pashchenko and Porapakkarm (2017) in modeling income taxes. All individuals pay an income tax $T(y_t)$ that consists of a progressive and a proportional tax. The function $T(y)$ includes non-linear and linear components:

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

[17]This is a common assumption in the macro-health literature that focuses on working age individuals. See for example Jung and Tran (2016), Pashchenko and Porapakkarm (2017) and De Nardi et al. (2017) who also assume that Social Security payments depend only on fixed types.

The non-linear component approximates the progressive US federal tax schedule, following Gouveia and Strauss (1994). The linear component captures other taxes, such as State taxes.

Workers also face payroll taxes. They pay a Medicare tax τ^{Med} (on earnings minus the premium p^{EI}) and a Social Security tax τ^{SS} (on earnings minus the premium p^{EI}, up to the 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, which captures sales taxes.

We assume there exists a public social welfare program that guarantees a minimum level of consumption $\bar{c}(educ, I^{DI})$ to every individual. This consumption floor approximates a range of benefits we do not explicitly model, such as Medicaid, Food stamps, unemployment benefits, workers' compensation, Social Security Disability Insurance (SSDI), and Supplemental Security Income (SSI). I^{DI} is a 1/0 indicator for disability insurance (DI) eligibility.

As we noted in Section 3.4, our model incorporates a simple form of disability insurance. Individuals are eligible for disability with a probability $\eta(educ, H, t)$ that depends on education, functional health, and age. Only working age individuals in poor health have positive probability of DI eligibility. Those eligible for DI have a higher level of the consumption floor $\bar{c}(educ, I^{DI})$. We calibrate $\bar{c}(educ, I^{DI})$ to match benefits observed in the data.

When disposable income (net of medical costs) falls below $\bar{c}$, the person receives a transfer tr that compensates for the difference. Thus the transfer is given by:

$$\begin{aligned} tr_{t<65} &= max\{0, (1+\tau^c)\bar{c} + ME(1 - q^{EI} I_w ins^*) - (1+r)A - I_w(W^*h - p^{EI}ins^*) + Tax\} \\ tr_{t\geq 65} &= max\{0, (1+\tau^c)\bar{c} + ME(1 - q^{Med}) + p^{Med} - (1+r)A - SS + Tax\} \end{aligned} \tag{3.8}$$

3.7 Preferences

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

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

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

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

The time cost of work depends on education, health and hours of work (part-time or full-time). Workers in poor health must expend more effort to work any agreed number of hours h^*, so they have greater dis-utility of work (expressed in leisure units). Also, the dis-utility of work ϕ depends on h^*, not on the actual number of hours worked after sick days are realized h. This embeds an assumption that sick days provide no additional leisure to workers. For retirees, leisure is equal to 1, so utility is only a function of consumption.

The utility function in 3.9 creates an incentive for individuals to smooth the consumption/leisure aggregate $c^{\alpha} l^{(1-\alpha)}$ over time. This causes consumption to drop at retirement.

Also, given that poor health reduces effective leisure time of workers in 3.10, consumption will tend to increase if workers are in poor health (*ceteris paribus*).

We assume a utility cost of death ζ that is incurred only in the period when the individual dies, in which case the indicator $I_{death} = 1$. We introduce this feature because the first term of 3.9 can be negative. This is not a problem in life-cycle models without health, but here it could have the perverse effect of causing individuals to value behaviors that lower H so as to reduce the survival probability. Introducing a dis-utility of death avoids this problem.

3.8 Individual's Problem

3.8.1 Working Age Individuals

At the start of each period, an agent's state includes his age, education, fixed productivity type, human capital derived from work experience, functional health, health risk, assets, DI eligibility, and the employment offer. Letting χ denote the state vector we have:

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

Given χ, an agent decides whether to accept or reject the employment offer, so as to maximize the expected present value of lifetime utility. This decision is summarized by the indicator function I_w. After the labor supply decision is made, health shocks are realized. Then the agent draws medical expenses, including the shock ε^{ME} that determines if expenses are "catastrophic." The agent experiences sick days given by the function $sd(educ, H_t, \Upsilon_t)$. At this stage, the state of the agent is summarized by χ, I_w, the vector of health shocks $\Upsilon = (d^p, d^u, s)$, and ε^{ME}. Finally, he makes the consumption/savings decision.

The agent solves the problem in two stages. First, he solves for the policy function for consumption conditional on χ and all possible realizations of Υ, and ε^{ME}, for both $I_w = 0$ and $I_w = 1$. This policy function $c(\chi, I_w, \Upsilon, \varepsilon^{ME})$ is the solution to the problem:

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

where the expected value of the next period's state is calculated over the probabilities of all possible realizations of $\Psi \equiv (O^{*'}, H', R', I^{DI'}, \varepsilon^{HC'}, \varepsilon^{W'})$, which uniquely determine $W^{*'}$, and where the maximization is subject to equations 3.5 to 3.10 and:

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

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

Equation 3.14 is the no-borrowing constraint. After solving for the policy functions, the agent chooses whether to accept or reject the employment offer by solving:

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

Here the expectation is taken over the probabilities of all possible Υ and ε^{ME}. The survival probability $\varphi = \varphi(H_t, t, d_t^p, d_t^u)$ was defined in Section 3.2.

3.8.2 Retired Individuals

After age 65, when retirement occurs exogenously, consumption is the only choice variable. At the time consumption decisions are made, the state of an agent is given by age, education, health, health risk factors, assets, health shocks and medical expense shocks.[18] The agent maximizes the expected present value of lifetime utility by solving the problem:

$$V(t, educ, H, R, A, \Upsilon, \varepsilon^{ME}) = \max_{c} \left\{ u(c) + \beta E \varphi V \left(t+1, educ, H', R', A', \Upsilon', \varepsilon^{ME\prime} \right) \right\} \quad (3.16)$$

subject to equations 3.5 to 3.10 and:

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

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

The solution algorithm is described in Appendix A.

4 Data and Variable Construction

Our main data set is the Medical Expenditure Panel Survey (MEPS), a rotating panel in which each household is interviewed 5 times over two and a half years. A new panel is sampled every year. We use panels 5 to 16 covering years 2000 to 2012. Panels 1-4 are not used because some key variables are not available before 2000. Our sample consists of males 25 years of age and older as of the beginning of the survey. We also use the CPS, HRS, PSID and CEX to construct other statistics used in the analysis.

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

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 into three digit ICD-9 codes.[19] The high level of detail in the classification of conditions allows us to distinguish the different types of health shocks in our model.

We categorize each of the 989 3-digit ICD-9 medical conditions based on four criteria: 1) effect on productivity, 2) persistence, 3) predictive power, and 4) predictability.[20] Productivity loss includes both productivity at work and limitations in daily functioning. We define a medical condition as causing a *long-term productivity loss* if it has an impact on productivity for at least 2 weeks per year for more than two years. We define a condition as

[18] Regarding the three components of human capital that affect offer wages – education, productivity type κ, and human capital derived from work experience HC – it is worth noting that κ and HC no longer enter the state because the agent no longer works. But education still matters because it affects health transitions and the distribution of predictable health shocks.

[19] 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.

[20] We are grateful to Dr. Phil Haywood, a clinician and research fellow at the Centre of Health Economic Research and Evaluation at University of Technology Sydney, who classified ICD codes based on our criteria.

causing a *short-term productivity loss* if it has an impact for at least 2 weeks per year but for less than two years. If a condition causes a productivity loss for less than two weeks, we ignore it. The two week minimum is meant to rule out short-run minor illnesses like the common cold. A medical condition is classified as a *predictor* if it increases the probability of other medical conditions arising 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. We give more details in Appendix B.

Table 2 shows how we map ICD-9 conditions that satisfy different combinations of these four criteria into the d^p, d^u, and s shocks. Conditions with no effect on current productivity are not classified as health shocks, but they may be risk factors (see below). Conditions with both current and long-term effects are classified as d^p shocks if predictable, and d^u shocks if not. Conditions with only short-term effects are labeled s shocks. We define d_t^p, d_t^u, and s_t as 1/0 indicators of whether a respondent has one or more conditions of each type. They are constructed at the annual level, based on the the two years of interviews in each panel.

Table 2 also reports the number of ICD-9 codes in each category. A total of 65 conditions are classified d^p, while 290 are d^u and 315 are s. Note that only 9 short-term conditions are classified as predictable, and in our sample their combined prevalence is only 0.5%. Rather than have a separate category for such rare shocks, we include them as part of s. We also include the "unknown" conditions as part of s, because, as we show in Appendix B, they have characteristics similar to the short-term unpredictable health shocks.

4.2 Constructing Health (H)

Our functional health measure (H) combines self-reports and objective measures. Specifically, it is constructed from the following MEPS variables: 1) self-reported health, 2) self-reported mental health, 3) activities of daily living (ADL) limitations, 4) instrumental activities of daily living (IADL) limitations, and 5) a set of eight physical functioning limitations.[21]

Self-reported health and mental health take values from 1 to 5 indicating poor, fair, good, very good and excellent. The ADL and IADL variables are binary indicators for the presence of any limitations. We construct a score for physical functioning limitations from the eight categorical variables. All five variables are standardized using data on all men 25 and over.

We conduct factor analysis on these five standardized variables. The results are reported in Appendix B. All five variables load highly on the first factor, which we interpret as functional health. We use the factor scores to construct functional health for all individuals in interviews 1, 3, and 5. These correspond to initial health, as well as 1 and 2 years later.

Finally, as this health measure is continuous, we discretize it into three categories corresponding to poor, fair and good functional health (as in the model).[22] Figure 1 presents the distribution of H by age. Of course, the fraction of people in good health declines with age. The figure also reveals a strong positive correlation between education and good health even at young ages. At age 25 over 80% of college types are in good health, compared to about 60% of high school types. By age 65 the divergence swells to about 60% vs. 35%.

[21] These measure 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.

[22] Our discretization is based on the distribution of the continuous health factor among all males aged 25 and over. Good health corresponds to values of the health factor above the median. Poor health corresponds to values at least one standard deviation below the mean. Fair health corresponds to the interval in between.

4.3 Constructing Asymptomatic Health Risk (R)

Table 2 also lists the criteria a medical condition must satisfy to be categorized as an asymptomatic risk factor. These conditions do not affect current productivity but they predict future health conditions and/or long-term productivity. There are 41 ICD-9 conditions that meet our criteria. Of these, only 28 are present in our sample. In addition, we use 8 items in the ICD-9 classification that measure family history of disease. The 36 ICD-9 codes used in the construction of R are listed in Appendix B.

We first construct three variables that summarize these 36 conditions: 1) an indicator for essential hypertension, which has no identifiable cause, 2) an indicator for disorders of lipoid metabolism, e.g., high cholesterol, and 3) the count of all other ICD-9 conditions used to construct R. Hypertension and high cholesterol are by far the most common risk factors, which is why we group all others together. We construct a measures of excessive BMI and a measure of low BMI. All five variables are standardized using data on all men 25 and over.

We take a weighted sum of these five variables to form a scalar measure. The weights are based on the relative importance of each variable for predicting the health shocks d_t^p (see Appendix B for details).[23] We do this to construct measures of R for all individuals in interviews 1, 3, and 5. These correspond to initial R, as well as 1 and 2 years later.

Finally, we discretize the health risk variable into three categories corresponding to low, medium, and high risk, as in the model.[24] This is done separately by education, so a fixed fraction of individuals falls into each risk class *within* each education group.[25] Figure 1 shows the distribution of the final health risk variable by age. The fraction of high risk individuals is almost zero at age 25, but grows to approximately 30% at age 65.

4.4 Reduced Form Regressions

Table 1 presents regressions of labor market outcomes on health shocks, along with controls for lagged health and human capital, using data from the MEPS. These specifications are consistent with Smith (1999)'s approach to estimating effects of health shocks. We find no significant effects of health shocks on *current* wages, consistent with our assumption that wages do not respond immediately. But we see significant declines in work hours and annual earnings following all three types of shocks (d^p, d^u, s). The finding that health has greater short-run effects on hours than wages is consistent with our modeling assumptions. Notice also that the estimated effects of the persistent shocks (d^p and d^u) on hours and earnings are several times larger than the estimated effects of transitory shocks.

5 Calibration

Our benchmark model is calibrated to features of the US economy for the period 2000 to 2010, for civilian, non-institutionalized 25+ year old males who are not in school. We

[23] The astute reader may notice an asymmetry: We form H by combining conditions using factor scores, while we form R by taking a weighted sum based on predictive ability. We think this makes sense, given that H is meant to be a scalar measure of overall health, which is the type of measure factor analysis is designed to construct, while R plays a very different role as a best predictor of future medical conditions.

[24] We discretize continuous R analogously to how we discretized H. That is, R is "Low" if its value is below the median, "High" if it is above the mean plus one standard deviation, and "Medium" if it falls in between.

[25] We do this because the role of R in the model is to predict d^p shocks, and education is also a predictor.

estimate some parameters directly from the MEPS data, while calibrating others (i) to match moments of the data, or (ii) based on prior work. Most parameters are calibrated separately for the three education groups (high school, some college, college).

5.1 Parameters Estimated from the MEPS Data

5.1.1 Transition Probabilities: Functional Health and Health Risk

As H and R are discretized into 3 levels, we specify their laws of motion as multinomial logits. Recall we have $\Lambda_H(H', H, t, d^p, d^u, O, educ, inc)$ and $\Lambda_R(R', R, t, d^p, d^u, H, O, educ, inc)$. We estimate separate models for the 25-64 and 65+ populations. This is because O and inc are irrelevant for the latter, as we assume everyone retires at 65 and is covered by Medicare. The estimates are reported in Appendix B.[26]

Our logit specification for health transitions implies the existence of "idiosyncratic" health shocks that cause H and R to change from t to $t+1$ for reasons not captured by the observed health shocks or other state variables that enter $\Lambda_H(.)$ and $\Lambda_R(.)$. This "idiosyncratic" health risk is accounted for by agents when they solve the problem in Section 3.8. However, as these logit errors are not revealed until time $t+1$, they cannot directly affect time t decisions.

It is internally consistent to estimate the law of motion for health separately from our structural labor supply model if the errors in the H equation are independent of other sources of error in the structural model. That is true, given our assumption that the errors in the logit model $\Lambda_H(.)$ capture purely "idiosyncratic" health shocks, revealed after time t decisions are made. Then, the covariates in the H equation are exogenous. We argue this assumption is plausible given our rich controls for current health shocks and lagged health. In contrast, a failure to adequately control for time t health shocks may render O and inc endogenous in the H equation, as the omitted current health shocks could affect time t labor supply as well as H transitions. This illustrates why it is important to use the MEPS data to construct rich measures of health and health shocks. (A similar argument applies to the R equation, but we exclude O and inc from that equation as they were not significant).

Figure 1 shows distributions of predicted vs. actual H and R by age. Our models capture well the pattern that the prevalence of fair/poor health H both starts higher (at age 25) and increases much more quickly with age for less educated workers. In contrast, the rate of increase in risk factors R with age is similar for all education groups.

The left panel of Figure 2 shows how transition rates from fair-to-poor health vary by age and employment status for high school types with a d^u shock. The right panel shows the transition rate is small but positive even with no observed health shocks. This reflects the purely "idiosyncratic" health risk captured by the logit errors, as well as natural effects of aging. As expected, we see that the fair-to-poor transition rate increases substantially if a d^u shock occurs. Clearly, our measures of persistent health shocks are strong predictors of health transitions. Both panels show the transition rate increases if a person is not employed. In contrast, we find that R transitions are strongly predicted by lagged R, d^u and d^p shocks, but not by employment status or income.

[26] We find that income and employment do not significantly affect the transitions for R, so in practice the R transitions entered in the model are independent of income and employment.

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

The stochastic processes for the three types of health shock $\Gamma^{dp}(R, H, t, educ)$, $\Gamma^{du}(t)$, and $\Gamma^{s}(t)$ are specified as logits. The estimation results are reported in Appendix B.

Figure 3 shows that the frequency of unpredictable health shocks (d^u, s) increases rapidly with age, but it does not differ by education level (see Appendix B). In contrast, predictable health shocks (d^p) are more likely for men with less education, particularly at older ages.

5.1.3 Survival Probabilities

We specify the annual survival probability $\varphi(H_t, t, d_t^p, d_t^u)$ as a logit (see Appendix B). Consistent with Pijoan-Mas and Ríos-Rull (2014), we find mortality does not depend on income or education once we condition on health. Nor is it significantly affected by temporary shocks s or health risk R. Of course, R affects mortality through its affect on H and d^p.

5.1.4 Medical Expenditures

We use MEPS data on total annual medical expenditures to construct the expenditure function $ME(H_t, \Upsilon_t, t, \varepsilon^{ME})$, where $\Upsilon = (d^p, d^u, s)$.[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 mean medical expenditures for men 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 (see Appendix B) and use the fitted values to construct $ME(.)$. Consistent with this, we set the probability of catastrophic expenditures in each (H_t, Υ_t, t) state, δ, to 5.0%.

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

5.1.5 Hours Worked and Sick Days

We set hours in full and part-time employment offers, hrs^{FT} and hrs^{PT}, to 40 and 20 per week, respectively. These values are equal to median full and part-time hours of workers in good health with no health shocks in the MEPS.[28]

Next, we estimate sick days as the difference in annual hours worked between workers with no health shocks and those with various combinations of health shocks. Specifically, to estimate the function for sick days $sd(educ, H_t, \Upsilon_t)$ we run regressions of *weekly* hours worked on age, age^2, and all possible combinations of health shocks $\Upsilon = (d^p, d^u, s)$, separately by health H and education group. We report the results in Table 3.

Table 3 reveals that the long-term shocks d^p and d^u generate substantial losses of work hours. For example, for workers in fair health, and with college or some college education, a d^p shock reduces work hours by about 2.6 hours per week (or about 135 annually). Hours

[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.

[28] According to our definitions, "not employed" means annual hours worked less than 520, "part-time" means annual hours between 520 and 1,500, and "full-time" means annual hours of 1,500+.

lost are much greater if multiple shocks occur together. For example, for workers in fair health, and with college or some college education, the joint occurrence of d^p and d^u shocks reduces work hours by about 7.3 hours per week (or about 380 annually).

5.2 Calibration of Remaining Parameters

We take several parameters from prior literature. These include utility function parameters, and parameters related to taxes, social security and health insurance. The values are listed in Table 4. The coefficient of relative risk aversion σ is set to 2.0, a widely used value. We take the progressive tax function parameters a_0 and a_1 from Gouveia and Strauss (1994). We take mean SS benefit levels (by education) from the HRS. The ESHI and Medicare coverage rates are set to 70% and 50% of medical expenditures, respectively, consistent with Attanasio et al. (2010) and Pashchenko and Porapakkarm (2017).

Table 5 lists all calibrated parameters and key moments we target for each. Of course, all calibrated model parameters affect all moments, but some parameters are relatively more important for particular moments. We now discuss identification of each parameter:

5.2.1 Time Discounting

We calibrate the discount factor $\beta(educ)$ to match the average asset to income ratio observed in the PSID data for working age individuals aged 30 to 55, by education. As we see in the first row of Table 5, the college types are more patient.

5.2.2 Dis-utility of Work

The leisure cost of work $\phi(educ, H, h^*)$ is calibrated by targeting the shares of 30-50 year old men working full and part-time in the MEPS, by age, education, and health (H). To eliminate the effect of sick days on hours we look at these statistics only for those without health shocks. The calibrated taste for work parameters are near the top of Table 5. Interestingly, they differ modestly by education/health, implying that differences in employment by education/health are mostly explained by differences in productivity and offer probabilities.

5.2.3 Employment Offer Probabilities

We calibrate job offer probabilities $\mathit{\Pi}(O^*, educ, t)$ to target the shares of men employed full and part-time in the CPS, with and without insurance, conditional on education. The calibrated job offer probabilities are presented in Table 6. Clearly, the probability of receiving a full-time offer with health insurance is strongly increasing in education.

We assume men aged 25-53 always get a job offer, so all unemployment is voluntary.[29] At ages 54+, we allow for the possibility of receiving no offer, to better match the decline in labor force participation at later ages. We let the no-offer probability follow a linear trend in age, with a notch at 60, and parameters that differ by education.[30] In Table 5 we see the probability of receiving no offer increases more rapidly with age for the less educated.

[29] Of course, some transitions from employment to non-employment before age 54 are due to involuntary separations. Our model captures this implicitly through the possibility of poor wage draws.

[30] Specifically, $\mathit{\Pi}(O^*, educ, t) = \delta^O(educ, t)(t - 29)$ for $t > 29$ and $O^* = 1$ (no offer). Note that $t = 30$ corresponds to age 54. We let $\delta^O(educ, t)$ increase at $t = 35$, which is age 60.

5.2.4 Identification of the Offer Wage Function

In the data, we only observe wages of agents who *choose* to work. So estimates of the wage offer function would be subject to selection bias if estimated directly from observed wage data in a first stage.[31] Instead, we implement a selection correction by simulating data from the model, calculating the distribution of accepted wages among men who choose to work, and iterating on the model parameters until the mean of simulated accepted wages matches as closely as possible the mean of accepted wages in the data (conditional on age, health status, full and part-time status, and education).

If we interpret our structure as a complex selection model (Heckman (1974)), then identification (aside from functional form) relies on exclusions that R_t, A_t, I_t^{DI}, and ins_t^* enter the decision rule for work, but do not affect offer wages. Conversely, identification of preference parameters relies on the exclusion that HC affects wage offers but not preferences.

We also calibrate parameters that determine higher moments of wages. These are: (1) the mass points of the latent productivity types $\kappa_j(educ)$ within each education type, (2) the variance of the transitory wage shocks $\sigma^2_{\varepsilon^W}(educ)$, (3) the variance of measurement error in log wages, $\sigma^2_N(educ)$,[32] and (4) the parameters that characterize the human capital shocks (ν, $p^1(educ, I_{h_t>0})$, and $p^2(educ, I_{h_t>0})$) in equation 3.2.

To identify these parameters, we target: (i) the variance of log wages by education, (ii) the serial correlation of wage residuals, and (iii) annual transition rates from employment to non-employment for individuals in good health.[33] Measurement error affects targets (i)-(ii) but does not affect transition rates (iii), distinguishing it from true wage shocks. This lets us separately identify the true wage variance from the measurement error variance.

To construct residual wages, we regress wages on a cubic in age, separately by education. Then, as in indirect inference, we use residual wages from both simulated and real data to estimate a random effects plus AR(1) process, which we view as a descriptive model of the wage process. We adjust parameters of our structural model to fit three aspects of the descriptive model: the random effect and innovation variances, and the AR(1) parameter.

To calibrate the parameters of the human capital shock process in 3.2, we fix the increment ν to 0.3 and calibrate the probabilities of positive and negative shocks. For employed workers, we assume these probabilities are equal ($p = p^1 = p^2$). Higher values of p generate more dispersion in wages and higher transition rates between employment states. For the unemployed, we assume that only negative human capital shocks are possible ($p^1 = 0$), so we only calibrate p^2. A higher p^2 during non-employment periods implies more wage depreciation and a lower transition rate from non-employment to employment.

Finally, we allow for two productivity types (κ) in the "college" and "some college" groups, and three in the "high school" group (which is more diverse as it includes dropouts). Within education groups, all productivity types are equal in size. They cover a range of roughly $\pm$0.30 sd. All calibrated wage process parameters are shown in the second panel of Table 5.

[31] It is useful to compare the logic here, as to why the wage equation must be estimated simultaneously with the full structural model, with our previous argument in Section 5.1.1 that it *is* consistent with the internal logic of our model to estimate the health transition process separately in a first stage.

[32] It is well-known that wage data contain measurement error. We assume *observed* log wages include additive measurement error $\varepsilon^N \sim N(0, \sigma^2_N(educ))$, which we include when we simulate observed wages.

[33] Transitions are also induced by health shocks, so to identify effects of wage shocks we target only transition rates for workers in good health in consecutive periods.

5.2.5 Consumption Floor, Disability Benefits, Dis-utility of Death, Taxes

We calibrate the consumption floor to match the percent of working age men who receive non-DI government transfers (conditional on education). We calibrate disability benefits (i.e, the higher consumption floor for DI recipients) to match average DI benefits in the CPS. We estimate DI benefits to be \$10,400, \$14,040 and \$17,160 for the HS, some college and College types, respectively. The DI benefit levels are roughly double the basic (non-DI) floors.

Working age men in poor health are eligible for DI benefits with a positive probability $\eta(educ, H, t)$. Because we model DI as a higher consumption floor, only those who qualify for the floor $\bar{c}(educ, I^{DI})$ in the first place have the possibility of getting DI benefits. We calibrate η so the model matches the fraction of working age men who are DI recipients in the CPS.[34] We define DI benefits as including SSDI, SSI, and workers' compensation.

We set the utility cost of death ζ to equal the present value at age 25 of discounted future utility evaluated at the minimum consumption floor and a level of leisure associated with full-time employment in poor health, for those with high school or less. This ensures that all individuals prefer to live in all possible states. The final parameter value of $\zeta = -30$ is set after calibrating the minimum consumption floor and dis-utility of work.

Finally, we calibrate the tax parameters a_2 and τ_y in equation 3.6 to match effective tax rates by income level. Table 4 and the bottom panel of Table 5 lists calibrated values of the tax/transfer rule parameters discussed in this section.

6 Model Fit

A key feature of our model is that workers receive tied wage/hours/insurance offers. Table 6 reports on the model fit to the proportions of workers employed full and part-time with and without employer sponsored health insurance. The model captures well the pattern that more educated workers are more likely to receive full-time offers that include health insurance. For example, at ages 35-44, the model predicts that 82.4% of college types have full-time jobs with insurance, compared to only 56.8% of high school types, and these fractions align well with the data frequencies (82.3% and 59.7%).

Table 6 also shows that the model captures well the rapid declines in employment as workers approach age 65.[35] Less educated workers tend to stop working sooner, both in the model and the data. An important consequence is that only one-third of high school types have full-time jobs with insurance at ages 55-64.

Our model fits patterns of full and part-time employment by age and education very well, as we see in Figure 4. An exception is that part-time employment rises a bit as workers approach age 65, but the model does not generate this.

Figure 5 shows life-cycle paths of full-time employment, conditional on education and health. Clearly, both higher education and better health generate more full-time employment, and our model captures these features of the data well. The low full-time employment

[34] Assuming all DI recipients are in poor functional health, we can back out the percent of working age men who receive DI conditional on poor H.

[35] Recall that, starting at age 54, we assume a positive probability of receiving no job offer. This captures a number of reasons firms may be reluctant to hire older workers. For example, a match with an older worker is less valuable as it is likely to last for a shorter period of time. There may also be age discrimination.

rate of workers in poor health is striking. It hovers around 40% regardless of age/education. As we saw in Table 5, tastes for work only differ modestly by health in our calibration, and offer probabilities do not depend on health. So our model implies the low employment rate of workers in poor health is mostly due to low wage offers. This interacts in an important way with the consumption floor and disability insurance, as we will show in Section 7.[36]

Next, in Table 8, we show the model's fit to many of the key data moments that we listed in Table 5. The model gives a very good fit to asset/income ratios, which are higher for the college types. The second panel of Table 8 shows how the model fits full and part-time employment rates, conditional on education and health. The fit is generally very good. We are less accurate in the case of men in poor health with no health shocks, but the data moments are very noisy in those cells.

The third panel of Table 8 shows our fit to targeted moments of involving mean full-time wages, conditional on education, health and age. Again the fit is quite good. Figure 6 reports on how we fit the age profiles of wages more generally. It is evident that poor health shifts wage profiles downward, and the model captures this well. The model also captures the fact that wages start higher and grow faster over the life-cycle for more educated workers. The one area where the model fails is that it systematically overestimates wages at ages 55-64.

The fourth panel of Table 8 focuses on moments involving wage variability. The model matches moments of the stochastic process for residual wages fairly well, except that, for high school types, it understates the variance of the permanent error component and exaggerates that of the transitory component. Table 9 reports on how we fit quantiles of the distribution of wages, conditional on age and education. The model's fit to the quantiles of the wage distribution is very impressive, except at the 99th percentile for college types.

Regarding transition rates between employment states, the model slightly understates the transition rate from employment to unemployment, while slightly exaggerating the transition rate from unemployment to employment (for non-college types). In reality, unemployed workers without a college degree may not always have job offers, a possibility our model does not capture at ages younger than 54.

The bottom panel of Table 8 shows our fit to moments that involve the consumption floor and disability benefits. We slightly under-predict the (very high) fraction of men in poor health who receive disability benefits. For instance, for high school types, this fraction is 80% in the data vs. 74% in the model. We capture fairly accurately the (much smaller) fraction of working age men who receive non-DI transfers, which is about 4% to 9% depending on education. In our model this means these men are at the consumption floor.

Figure 9 describes the distribution of medical spending in our model vs. the MEPS data. The model does a reasonably good job matching the extreme skewness of the expenditure distribution (i.e., the top 1% of spenders account for 25% of total costs).

Finally, Figure 8 shows how our model fits the Gini coefficient for income by age, where income is defined as labor earnings plus asset income. This is an untargeted moment in estimation, yet we fit it quite well. This is critically important, as much of the next section focuses on how health shocks (and other factors) contribute to income inequality.

In summary, the fit of the model to key aspects of the data is generally good, giving it some credibility as a vehicle to quantify impacts of health shocks on earnings.

[36] As we see in Table 5, our calibration implies full-time work reduces leisure by about 52 to 55% for those in good or fair health. This only increases substantially with poor health for the some college type.

7 Results

7.1 Effects of Major Health Shocks on Earnings

First we use our model to simulate the impact of a major health shock on earnings. We focus on unpredictable persistent shocks d^u that are serious enough to cause deterioration in health H. For men aged 50-60 the annual frequency of d^u shocks is 29.0%, of which 22.0% are severe by our definition, giving a 6.3% annual frequency of severe d^u shocks.[37] We find on average a cumulative (non-discounted) earnings loss of \$40k over the ten years following such a major health shock for men at age 50. We can compare our results with Smith (2004) who estimates a cumulative income loss of \$37k over ten years (1994-2003) following major health shocks for men in the HRS. Although his definition of a major shock is narrower than ours, it is encouraging that our estimates are in the same ballpark.[38]

Next we use our structural model to simulate the effect of a health shock on the present value of remaining lifetime earnings, discounted to the age of the shock. A major health shock *directly* affects earnings by generating sick days, and, more importantly because worse health directly reduces wage offers and tastes for work (see equations 3.4 and 3.10). Hence, a health shock reduces wage offers and labor supply.

Human capital accumulation *amplifies* the effect of a health shock, as the decline in labor supply slows the accumulation of human capital, which further reduces wage offers, generating a feedback loop. Using our structural model, we can assess the importance of this human capital mechanism in generating the total effect of a health shock, by comparing simulations with and without the feedback loop. To shut down the human capital feedback loop, we run simulations where we hold the levels of the time-varying experienced-based component of human capital (HC) entering the offer wage function 3.4 fixed at the levels that prevailed in a baseline simulation where no major health shock occurred.

Figure 7 decomposes the effects of a health shock on wage offers: A major health shock leads to a sharp decline in wage offers in the first year after the shock (about 15%). Over time the effect diminishes. If we shut down the human capital feedback channel then wages return to their baseline level after about 5 to 6 years. But if we include the human capital feedback channel, offer wages never fully recover to their baseline levels.

Table 10 shows how major health shocks affect the present value of earnings. For example, for a college type at age 40, a major health shock reduces the PV of remaining lifetime earnings by \$44.7k or 4.5%.[39] We estimate the human capital feedback channel accounts for 40% of this effect. Notice that lifetime years of work decline by 0.93 years, but if we shut down the human capital channel the decline is only 0.39 years.

For individuals with high school or less education at age 40, a major health shock reduces the PV of earnings by \$33.4k or 7.9%. Of this, 25% is due to the human capital channel.

[37] We obtain very similar results for predictable persistent shocks d^p. We focus on d^u shocks as they are more common. For men aged 50-60 the annual frequency of severe d^p shocks is 3.2%, about half the frequency of severe d^u shocks. The frequency of a severe shock of either type is 8.2%.

[38] Smith (2004) looks at men in the HRS who were in roughly the 51 to 61 age range when they experienced what he terms a major shock, which he defines as cancer, heart disease and lung disease. He reports 21.4% of 51-61 year old men had a major health shock of this type over the first 8 years of the NHS survey.

[39] For men aged 40 the annual frequency of d^u shocks is 16.9%, of which 23.5% are severe by our definition, giving a 4.0% annual frequency of severe d^u shocks. The annual frequency of severe d^p shocks is only 0.9%.

Less educated workers have less wage growth over the life-cycle, so it is unsurprising that the human capital channel is *relatively* less important for them. However, their total percentage loss is much greater, and the loss through the human capital channel still represents 2.0% of the PV of earnings, compared to 1.8% for college workers. The *direct* health effect on the PV of earnings is much greater for high school types (5.9%) than for college types (2.7%).

As we would expect, if a health shock occurs later in life the human capital channel is less important. At age 60, the human capital channel accounts for only 4.7% of the effect on earnings for college workers, and even less for high school types. Table 10 also reveals that drops in earnings are much greater for college workers than less educated workers at age 60. This is because college types are more likely to be employed after age 60.

7.2 Effects of Health Shocks on Key Outcomes

Here we examine the impact of health shocks (s, d^u, d^p) on some key outcomes in our baseline model. To this end, we compare simulated life-cycle histories from the baseline model with alternative simulations in which agents are "lucky" and do not experience health shocks. We hold the perceived risk of health shocks (i.e., the "environment") unchanged.

In these experiments, agents' decision rules are unchanged, and they still behave *as if* they expect to draw health shocks from the distributions $\Gamma^{dp}(R, H, t, educ)$, $\Gamma^{du}(t)$, and/or $\Gamma^{s}(t)$. This allows us to examine what we call "direct" effects of health shocks. Later, in Section 7.4, we run counterfactuals where we shut down health risk, and let agents' decision rules adapt. That will allow us to also study "behavioral" responses to health risk.

To proceed, we run several experiments in which agents never receive s, d^u or d^p shocks.[40] Table 11 presents results for working age individuals (age 25-64), emphasizing effects on medical costs, health, labor supply, wages and transfers. First consider the effect of eliminating all three types of observed health shocks (s, d^u, d^p). Our model predicts this would reduce average annual medical expenditures from \$4465 to \$1041. Note that even people with no health shocks have some medical expenses, due to minor illnesses that we do not classify as shocks, chronic conditions, etc. According to our model, elimination of all health shocks at ages 25-64 would raise the probability of survival to age 65 from 85% to 92%, increase lifetime labor supply from 29.8 years to 32.1 years, increase the mean hourly wage offer from \$22.88 to \$23.25, and reduce the fraction of men who receive government transfers (including disability) from 12.9% to 8.9%. (Appendix A presents these results by education.)

It is also interesting to compare the impact of different types of health shocks. Our model implies that among working age men, unpredictable shocks (s, d^u) have larger effects than predictable shocks (d^p). Together, eliminating s and d^u shocks reduces medical expenditures by 65% and sick days by 86%. Eliminating the predictable shocks (d^p) reduces them by only 14% and 25%, respectively. This is not because unpredictable shocks are more severe, but because they are much more prevalent.[41] As we see in Table 11, life expectancy, labor supply and wage offers all increase more in the absence of unpredictable shocks.

[40] As we discussed in Section 5.1.1, our logit model for health transitions implies the existence of "idiosyncratic" health shocks that cause H and R to change from one year to the next for reasons not attributable to the observed health shocks (s, d^u, d^p) or other state variables. Here we focus entirely on the effects of the observed health shocks (s, d^u, d^p) that we can identify and categorize.

[41] The most prevalent shocks are transitory s shocks (39% of working age individuals experience these each year), followed by d^u (21%) and lastly by d^p (13% for HS, 12% for Some College, and 8% for College).

We also assess the importance of asymptomatic health risk R. Specifically, we run an experiment where we give all agents a low risk level initially (at age 25), and shut down transitions to higher levels of R. Agents' decision rules are again held fixed. Thus, all changes in outcomes arise solely due to "luck" rather than changes in decision rules.

We find that giving all individuals low health risk has fairly small effects. The probability of having a d^p shock falls by 41%. However, as only about 11% of working age men experience d^p shocks, the overall benefit of reducing R is modest. In the bottom row of Table 11, we see that average medical expenditures decrease by only 5.6% and the fraction of those relying on social insurance decreases by only 5.8%. The fraction of men in good functional health would increase by only 1.2 percentage points. In general, most health shocks that occur at working ages are unrelated to R, so reducing health risk has fairly small effects.

These findings suggest a limited potential impact of policies aimed at reducing risk factors like high blood pressure, cholesterol and obesity, as they are not likely to have large effects on health or labor market outcomes for the working age population. Of course, the potential benefits of reducing health risk are greater at ages over 65, when predictable shocks such as heart attack become more prevalent.

7.3 Decomposing Sources of Earnings Inequality

Next we use our model to estimate the fraction of variance (across people) in the present value of lifetime earnings (PVE) that is explained by initial conditions and health shocks. We generate simulated life-cycle histories from the benchmark model, and calculate the PVE discounted to age 25 for each simulated agent. Then, similar to Keane and Wolpin (1997), we run regressions of the PVEs on initial conditions (i.e., education, skill type, initial health). But we also include measures of health shocks that occur at ages 25-64.

Table 12 presents the R^2 values from alternative specifications of these regressions, both run separately by education and for all groups combined. First we focus on the combined results. Similar to results in Keane and Wolpin (1997), we find that a substantial 86.8% of the variance in the PVE across agents can be explained by initial conditions at age 25, primarily education and a fixed productivity type. There is only a small contribution of initial health H and the initial risk level R, which vary little across people.

Next, we add a set of variables designed to capture flexibly the impact of health shocks throughout working life. We include the number of times the agent experienced each of the eight possible combinations of the three health shocks (s, d^u, d^p). We enter these as separate variables to allow the health shocks to have different effects when they occur in combination. We also enter as separate variables the counts of health shocks that occurred when the agent was in poor, fair, or good health. This captures the fact that health shocks may have a larger effect if the person was in worse health to begin with. We also include the number of years the person spent in good, fair or poor health, primarily to pick up the effects of the "idiosyncratic" health shocks (i.e., the logit errors in the health transitions). Finally, to control for mortality shocks, we include the number of years prior to age 65 when the individual died, if positive. We were not able to find additional health variables that significantly improved the fit of our PVE regression.

When we include this array of health shock measures, the R^2 of our PVE regression increases to 92.4%. Thus, initial conditions (at age 25) and health shocks together can "explain" (or predict) 92.4% of the variance of lifetime earnings. The independent contribution of health shocks to explaining the variance of the PVE, beyond what can be predicted based solely on initial conditions, is 5.6%.[42, 43]

Finally, Table 12 row three presents regressions that only control for initial health and the array of health shock variables, while omitting education and the skill endowment. Here, we find that initial health and health shocks explain 40.0% of the variance in the PVE across all agents. Almost all of this is due to the health shock variables because, as we noted earlier, initial health at age 25 does not vary much across people.

Combining these results, we see that initial conditions independently explain 52.5% of the variance of the PVE, while health shocks independently explain 5.6%. A substantial 34.4% of the variance is "explained" by the covariance between initial conditions and health shocks. The covariance term is so large because of the strong negative correlation between education/productivity and the incidence of health shocks.[44]

There are three basic explanations for this correlation: First, causality may run from education to health, if more educated people are better are utilizing health improving technologies/treatments, have a better understanding of health risks, have better nutrition, etc.. Second, there may be an omitted factor that causes people to get more education and take better care of their health - perhaps a personality trait like "good judgment" or "self control." Third, it is possible that knowledge of one's health transition function impacts one's human capital investment decisions. Thus, we cannot rule out causality running from health outcomes to education, even if education decisions are temporally prior to those outcomes.

This discussion highlights the limitation of using a regression decomposition of variance to assess the importance of health shocks for earnings inequality. What we can say is that, for all workers, health shocks "explain" roughly 40.0% of the variance of the PVE, but 34.4% of that variation is predictable based on one's initial education and skill type. Thus, it is not clear how much of that 34.4% is actually caused by health shocks, and, indeed, our prior is that most of it reflects causality running from education to health, or from some omitted third factor to both education and health. What is clear, however, is that 5.6% of the variance of lifetime earnings is directly attributable to "luck" whereby agents with the *same initial conditions* experience different incidence of health shocks.

7.4 The Role of Health Shocks in Generating Earnings Inequality

Next, we use our model to conduct counterfactual experiments that clarify how health shocks contribute to earnings inequality. Specifically, we eliminate health shocks from the baseline model and simulate life-cycle histories for agents in the new environment. Shutting

[42] We run similar regressions for the present values of utility and consumption. We find that initial conditions explain 82% of the variance of the present value utility and 87% of the variance of the present value of consumption. Both these figures increase to 93% when health shocks are included.

[43] If we look within education types, the results are very similar, except that health shocks are somewhat more important, particularly for the less educated. Within education types, the initial conditions (primarily the latent skill endowment) explain 79% to 86% of the variance of the PVE. The incremental contribution of health shocks ranges from 7.0% for the some college type to 10.1% for the high school type.

[44] The source of the positive correlation between education and health, often called the "SES gradient," is of course one of the great open questions in the social sciences. See Smith (2004) for a discussion and Heckman et al. (2018) and Hai and Heckman (2019) for recent advances in this area.

down health shocks affects earnings inequality for three reasons: (1) it eliminates the "luck of the draw" whereby agents with the same initial conditions (education/productivity/initial health) experience different health shock realizations, (2) it eliminates the advantage of better-educated workers that arises because they face more favorable probability distributions of predictable health shocks, and (3) it induces a behavioral response as agents update their decision rules in response to the new health risk environment.[45] We call effects that arise given fixed decision rules the "direct" effects of eliminating health shocks, and effects that arise from changing decision rules the "behavioral" response to reduced health risk.

An advantage of the counterfactual simulation approach is that we can run simulations where we hold decision rules fixed (i.e., the same as the baseline model), just as we did in Section 7.2. Comparing the results of such simulations with ones that also allow decision rules to adapt enables us to isolate both the direct effect of health shocks and the behavioral response to reducing health risk.

To proceed, Table 13 reports both means and measures of dispersion for the present value of lifetime earnings (PVE), both in the baseline model and in counterfactuals where we eliminate health shocks for working-age men.[46] In the baseline, the mean PVE is \$762k, with a standard deviation of \$422k, implying a coefficient of variation of 0.555. The great heterogeneity of the PVE across education/productivity types, already apparent from the regressions of Section 7.3, is clearly evident. The mean PVE ranges from only \$294k for low-skill high school types to \$1,522k for high-skill college types.

The middle columns of Table 13 show how the distribution of the PVE is altered when we eliminate health shocks for working-age men, while holding their decision rules fixed. The mean PVE increases by 5.6% to \$805k. The coefficient of variation (CV) of the PVE decreases 4.9% from 0.555 in the baseline to 0.528 in the experiment. And the Gini inequality measure also decreases 4.9% from 0.304 to 0.289.

The right columns of Table 13 show how the distribution of the PVE is altered when we also allow agents' decision rules to adapt to the lower health risk environment. Compared to the baseline, the mean PVE increases by 9.3% to \$833k. The coefficient of variation (CV) of the PVE decreases by 13.7% from 0.555 in the baseline to 0.479 in the experiment, and the Gini inequality measure decreases by 15.1% from 0.304 to 0.258.

Thus, health shocks generate about 15% of inequality in present value of lifetime earnings for men. Notably, direct effects of health shocks on health/productivity account for only about 1/3 of their impact on inequality, while behavioral responses account for 2/3.

The reason behavioral responses to health risk contribute substantially to inequality becomes apparent if we examine how mean PVE changes for different education and productivity types when health shocks are eliminated. We report this in the bottom panel of Table 13. For the low-skill high school type the direct effect of eliminating health shocks is to increase mean PVE by 12.9% (from \$294k to \$331k). But when we factor in their behavioral response, mean PVE increases by 37.5% (to \$404k).

[45] These counterfactuals differ in important ways from the regression decompositions of variance reported in Section 7.3. The regressions do not capture channel (3), the behavioral response to reduced risk. They only capture the impact of different incidence of health shocks (due to "luck") in a fixed risk environment.

[46] Eliminated health shocks for men aged 65+ leads to an increase in average lifespans of 10 years, drastically changing the savings needs for retirement, and affecting savings and labor supply decisions. On the other hand, eliminating shocks only at working ages leads to an increase in average lifespans of only 1.5 years.

The large behavioral effect of health risk on earnings arises because, in the baseline model, low-skill high school types have a strong incentive to hold down their labor supply and human capital accumulation so as to maintain eligibility for social insurance that cushions against high medical costs. In fact, as we see in Table 16, eliminating health shocks increases the employment rate for low-skill high school types from 57.1% to 84.3%, and reduces the fraction who receive social transfers from 42% to 9%. As we report in Appendix Table A4, only ten points of that decline is due to health shocks *per se*, while 24 points is due to the behavioral response. Thus, in an environment with costly health shocks, social insurance creates a type of "moral hazard" that reduces labor supply and human capital investment (analogous to how health insurance generates moral hazard by reducing the incentive to invest in health).

Next, consider the effects of health shocks on the medium and high productivity types within the high school group. For them, the direct effects of eliminating health shocks are to increase mean PVE by 7.1% and 5.5% respectively, but the additional behavioral effects are trivial. Thus, among the medium and high skill types, social insurance has no significant moral hazard effect on labor supply and human capital investment.

The same pattern holds within the some college and college groups: For low skill types there is a large behavioral effect of health shocks on mean PVE, while for high skill types the behavioral effects are very small. In fact, within all three education groups, the behavioral effect of eliminating health shocks is to slightly *reduce* PVE for the high skill type. These agents are unlikely to use transfers to help pay medical costs, and they instead self-insure. Removing health shock risk reduces the need for precautionary savings, slightly reducing the incentive to supply labor. For instance, in Table 16 we see the employment rate of high skill college types declines slightly from 93.7% to 92.6% when health shocks are eliminated.

To compare how different types of health shocks affect earnings and earnings inequality, we run simulations where we eliminate one type of shock at a time, either s, d^u or d^p, allowing decision rules to adjust. In Table 14 we see unpredictable persistent shocks (d^u) have the greatest influence: Their elimination increases the present value of lifetime earnings by 6.6%, and reduces the Gini inequality measure from .304 to .269. Transitory shocks have a smaller effect, despite being much more common, precisely because they are transitory. Predictable persistent shocks (d^p) have the smallest impact. This is primarily because, as we see in Figure 3, the d^p shocks are less common than d^u shocks, especially for college types.

Table 14 also reveals that the relative impact of predictable persistent shocks (d^p) on the PVE for high school workers (+2.9%) is greater than for college workers (+3.4%). This may seem surprising, as high school workers have more d^p shocks than college workers (see Figure 3). The explanation is that predictable persistent shocks (d^p) tend to happen later in life, and college workers are more likely to be working later on life.

7.4.1 The Role of Medical Cost Shocks

Next, we consider simulations where, instead of eliminating health shocks, we eliminate only the medical expenses created by those shocks.[47] This allows us to disentangle effects of health shocks operating through their impact on health and productivity vs. effects operating through their impact on the lifetime budget constraint.

[47]This is a partial equilibrium experiment where we insure all health care costs, but we do not finance the program by raising taxes. It is only meant to clarify how health care costs affect behavior. Later, in Section 7.7 we consider experiments where we introduce health insurance financed by premiums and/or taxes.

Table 15 reports our results. The middle columns show how the distribution of the PVE is altered when we eliminate the medical costs of health shocks for working-age men, while holding their decision rules fixed. Notice that the effects on both mean PVE and measures of inequality are trivial, and this is true for all education/productivity types.

The right columns of Table 15 show how the distribution of the PVE is altered when we also allow agents' decision rules to adapt to the lower medical cost risk environment. Compared to the baseline, across all agents, the mean PVE increases by 2.5% to \$781k, and the Gini measure of inequality drops by 8.6% to 0.278. This masks substantially heterogeneity across types: The mean PVEs of low-skill types within the high school, some college and college types increase by 16.3%, 8.9% and 9.2% respectively. And inequality measures drop by about 1/4 to 1/3 within the low productivity types. In contrast, the behavioral responses among high-productivity types are trivial within all education groups.

These results highlight the strong impact of health care costs on the behavior of the low productivity types. According to our model, they have strong incentives to reduce labor supply and invest less in human capital so as to maintain eligibility for social insurance that protects them from high medical costs. In fact, as we see in Table 16, the employment rate of the low-skill high school type increases from 57.1% to 71.7% when the cost of health shocks is eliminated. The increases in employment for the low productivity types within the college and some college groups are substantial as well. Reliance on social insurance declines dramatically for almost all groups, but the largest absolute decline is observed for the low productivity high school type, for whom receipt of transfers drop from 42% to 22%.

7.4.2 Effects of Health Shocks on Income Inequality over the Life Cycle

Next we examine how income inequality varies over the life-cycle. Figure 10 plots the Gini coefficient for cross sections of agents at each age from 25 to 64. Recall from Figure 8 that our model fits the life cycle pattern of income inequality very well. In both the model and the data, cross-sectional income inequality increases as people age. The increase is very gradual in the 40s, but accelerates for agents in their 50s and 60s. Much of the increase at later ages is driven by retirement behavior, but much is also due to health shocks.[48]

Consider the experiment where we eliminate health shocks, and allow agents to update decision rules. As we see in Figure 10, this causes income inequality to drop at all ages, but the drop is much greater for workers in their 50s and 60s. For example, at age 55 the Gini drops substantially by .11 points (from .46 to .35), while at age 40 it only drops by .03 (from .34 to .31). Half the drop (even more at younger ages) arises from the behavioral effect.

It is interesting to contrast the .11 point drop in the Gini at age 55 with the .046 point drop (from .304 to .258) that we saw in Table 13 for the present value of lifetime earnings evaluated at age 25. The drop in the Gini of the present value at age 25 is relatively modest because later ages, where health shocks are more influential, are discounted in the present value calculation. There is no inconsistency in finding that health shocks can explain about a quarter of income inequality for people in their 50s and 60s and our earlier finding that health shocks only explain about 15% of PVE inequality at age 25.

[48]The model generates a jump in income inequality at age 60 because the probability of receiving no job offer jumps at 60. Figure 4 shows how the model also generates a drop in full-time employment at 60.

7.5 Direct and Behavioral Effects of Health Shocks

In the previous section we explored how health shocks contribute to earnings inequality. In this section we explore how health shocks affect a range of behaviors and outcomes including health itself, work experience, wage offers, and reliance on social transfers and disability benefits. This clarifies the channels through which health shocks affect earnings.

To disentangle direct and behavioral effects of health shocks, we compare results from three experiments: (1) eliminate health shocks but hold labor supply and savings fixed, (2) eliminate health shocks but hold decision rules fixed (allowing labor supply and savings to change according to the optimal policy functions of the benchmark environment), and (3) eliminate health shocks and allow agents to update their optimal decision rules. As we explained in Section 7.4, the first two simulations capture the direct effects of health shocks, while the latter experiment incorporates the behavioral response to reduced health risk.[49]

7.5.1 Effects of Health Shocks on Health

Figure 11 shows how the evolution of health itself (H) is altered in counterfactuals where we shut down health shocks for working age men. The figure reports the fraction of men in fair and poor health in the baseline model and in the three counterfactual simulations described above. We label these "No Shocks 1," "No Shocks 2," and "No Shocks 3."

Not surprisingly, the direct effect of eliminating health shocks (without any decisions changing) is to improve health substantially (as health shocks are key drivers of H and R transitions). For example, the fraction of men in poor or fair health at age 64 drops from .56 in the baseline to only .42 in the absence of health shocks. This improvement in health leads to higher wage offers, higher employment and higher incomes. These in turn have an additional positive reinforcement effect on H as seen in experiments (2) and (3).

However, Figure 11 reveals these reinforcement effects are modest: the fraction of men in poor or fair health at age 64 drops by only an additional .01 under "No Shocks 2" and an additional .01 when decision rules are allowed to adapt ("No Shocks 3"). Thus, the bulk of the inequality in H generated by health shocks is accounted for by the immediate effect of health shocks on H, not reinforcement effects operating through employment and income.

7.5.2 Effects on Employment, Human Capital and Wage Offers

Figure 12 plots the mean and coefficient of variation of experience, human capital, and wage offers from the same set of three experiments. In the first experiment experience and human capital remain unchanged from the benchmark, because we hold labor supply fixed. But offer wages can change, because they depend on H. Thus, the first experiment shows only the direct effect of health shocks on wages through their direct impact on H.

As we see in the third panel of Figure 12, the direct effect of health shocks on wages (operating through H itself) is very modest. Only when workers reach their 50s and 60s does it start to become a non-negligible factor. For example, the mean offer wage of 50 year old workers only increases from \$25.0 to \$25.2 per hour if health shocks are eliminated, but that of 60 year old workers increases from \$25.5 to \$25.9.

[49] Experiments (1) and (2) can be interpreted as a situation where all agents are "lucky" and experience no health shocks, but where the perceived probabilities of health shocks are unchanged (at baseline levels).

In the second experiment we let elimination of health shocks alter labor supply decisions and employment. We still call this a "direct" effect because decision rules are held fixed, but it includes the reinforcement effect that arises because increased employment and income further improve health and increase human capital.[50] In this experiment work hours increase both because sick days are eliminated and because improved health leads to higher wage offers, which increases labor supply. As we saw earlier in Table 11, the elimination of health shocks causes lifetime work experience to increase by 2.3 full-time equivalent years. However, as we now see in the top two panels of Figure 12, impacts on accumulated work experience and human capital are very modest until workers are in their 50s and 60s.

When we account for how eliminating health shocks alters the accumulation of work experience and human capital, the implied effect on offer wages roughly doubles. Now, as we see in the third panel of Figure 12, the mean offer wage of 50 year old workers increases from \$25.0 to \$25.4 per hour, while that of 60 year olds increases from \$25.5 to \$26.3.

Finally, in the third experiment we let agents' decision rules for labor supply and saving adapt to the reduced risk environment. As we see in Table 17, elimination of health shocks causes lifetime full-time equivalent work to increase by 4.5 years (or 15%). This is almost double the increase of 2.3 years that we found from the direct effects of health shocks (holding decision rules fixed). Once all three channels of effects are factored in, the mean offer wage of 50 year old workers increases from \$25.0 to \$25.9 per hour when health shocks are eliminated, while that of 60 year olds increases from \$25.5 to \$26.8.

It is worth emphasizing that the reduced form studies reviewed in Section 2 do not attempt to capture behavioral effects of health risk on employment and wages. They estimate only what we call the "direct" effects of differential incidence of health shocks (i.e., "luck") within a given risk environment (with fixed decision rules). But we find that the behavioral effects on employment and wages are as large as the direct effects.

Inequality in work experience drops very sharply when we allow decision rules to adapt to the lower risk environment (see the top right panel of Figure 12). This is primarily because labor supply of low-skill workers increases sharply when health shocks are eliminated, as they no longer have an incentive to constrain their labor supply and human capital accumulation to maintain eligibility for social insurance that protects them from high medical costs. For example, in Table 17, note that lifetime full-time equivalent work increases from 19.9 to 31.1 years for low-skill high school types. As we see in the bottom panel of Figure 12, the drop in inequality in work experience translates into a sharp drop in inequality in wage offers.

Eliminating health shocks only has large *direct* effects on hours at older ages, but it has a substantial positive *behavioral* effect on hours of low-skill workers even at young ages. As a result, the behavioral response generates noticeable increases in mean offer wages, and declines in wage inequality, at much younger ages than implied by direct effects alone.

As a summary of how health shocks affect wage inequality through the three channels, note that the coefficient of variation of wage offers at ages 50 (60) declines by 0.9% (1.7%) in the first experiment due to changes in H, by an additional 1.6% (2.0%) in the second experiment due to less dispersion in human capital, and by an additional 3.8% (4.3%) in the third experiment due to the behavioral response to reduced health risk. Thus, the behavioral

[50] In contrast to our model De Nardi et al. (2017) introduce heterogeneity by having different health types within each education group. Then, the poor health types tend to spend longer periods in poor health states and non-employment, but there is no feedback effect of employment or income on health.

response to health risk accounts for the bulk of the effect of health shocks on wage inequality.

Next, we examine how health shocks affect wage offers for different education groups. Figure 13 plots age profiles of the mean and coefficient of variation of offer wages, separately by education. The mean offer wage at age 25 is normalized to 1.0, so one can read wage growth off the graphs. In the benchmark, wage growth from age 25 to 55 is 27% for the high school and some college types, and 74% for the college type. When we shut down health shocks, and allow decision rules to adapt, wage growth increases to 35% for the high school type, 34% for some college types, and 81% for college types.

In the baseline model, the coefficient of variation (CV) of offer wages grows substantially from age 25 to 55, from .37 to .45 for the high school type, .40 to .48 for the some college type, and .42 to .58 for the college type. Thus, for the more educated, the CV starts higher and grows more with age. When we shut down health shocks and allow decision rules to adapt, the growth of the CV declines by 2/3 within the high school and some college types. But for the college type the figure is only 23%. Thus, health shocks account for only a modest fraction of the growth in offer wage inequality over the life-cycle for college workers, but for a very large share within the high school and some college groups. And, as we see in Figure 13, most of that large share is due to the behavioral response to health risk.

Table 17 reports how eliminating health shocks at ages 25-64 affects mean offer wages across all ages. Averaged over all types, the mean offer wage increases from $22.88 in the baseline to $23.56 in the counterfactual, which is only 3%. However, Table 17 also reveals that the growth in mean offer wages is very concentrated among the low-skill types. Within the high school, some college and college types the mean offer wage of the low-skill types grows by 11.1%, 7.5% and 7.1%, respectively. The growth for higher skill types is much smaller. This largely reflects the increased labor supply and human capital accumulation of low skill workers in the absence of health shocks.

Finally, the results in Table 17 show that eliminating health shocks at ages 25-64 causes mean lifetime work hours to increase by 15.1% while the mean offer wage increases by only 3%. Thus, health shocks reduce work hours far more than they reduce offer wages. We saw in Table 13 that elimination of health shocks increases PVE by 9.3%, which is much less than the roughly 18% increase in undiscounted earnings. This is because most of the increases in hours and wages are concentrated at older ages.

7.5.3 Health Shocks and Social Insurance

As we saw in Table 8, our baseline model accurately predicts the fraction of working age men who receive social transfers or disability benefits. In Table 16, our model predicts the elimination of health shocks would cause the fraction who receive social transfers to drop from 12.9% to 2.0%. This is a much larger than the drop to 8.9% that we saw in Table 11 in the exercise where we held decision rules fixed. Thus, roughly 2/3 of the drop in social transfer receipt is due to the behavioral response to reduced health risk.

The behavioral response is a substantial increase in labor supply, concentrated among low-skill workers. In Table 11 we saw the direct effect of eliminating health shocks is to increase lifetime work from 29.8 full-time equivalent years to 32.1 years, while in Table 17 we see that the behavioral effect leads to an additional increase to 34.3 years. Among low-skill high school types average work years increase from 19.9 to 31.1, the drop in all social transfer receipt is 41.6% to 8.6%, and the drop in disability receipt is 8.4% to 1.5%.

The behavioral response of reduced health risk generating increased labor supply arises because, once health risk is reduced, agents have less incentive to constrain labor supply so as to maintain eligibility for social insurance. Similarly, Pashchenko and Porapakkarm (2017) find that means-tested Medicaid discourages labor supply, as some agents would rather exit the labor force and receive Medicaid than work and pay medical costs out-of-pocket.[51]

New from prior literature, in our model health risk and social insurance also interact to reduce incentives for human capital investment. Agents anticipate that future health shocks and the possibility of qualifying for means-tested transfers will reduce future employment. As human capital generates zero returns in periods of non-employment, this reduces the incentive for human capital investment today, further reducing current labor supply.

7.6 The Effect of Health Risk on Earnings Inequality

Next we ask how heterogeneity in health *risk* contributes to earnings inequality. In our model, the probability distribution of predictable health shocks (d^p) and the laws of motion for health (H) and risk factors (R) differ by education. Less educated workers face a higher probability of predictable health shocks, and they face higher probabilities of transition to inferior health states (see Figures 1 to 3).[52] To what extent do these differences in health risk by education generate differences in labor supply, human capital investment and earnings?

To address this question, we conduct counterfactuals where we equalize heath risk across different types of agents. Specifically, we give all agents, regardless of education, the health transition functions and health shock distribution of the some college type.[53] The results are reported in Table 18. Our key finding is that the mean present value of earnings (PVE) of high school types only increases by 2.8% in this experiment. In contrast, in Table 13, when we eliminated health shocks entirely, the PVE of high school types increased by 11.8%. Furthermore, because the earnings of high school types increases so modestly, the overall Gini coefficient actually increases from .304 to .319 when we equalize health risk.[54]

Do these results imply that heterogeneity (by education) in the risk of health shocks is not an important source of earnings inequality? That would be an incorrect interpretation. Rather, what drives these results is that, even in the lower risk environment, high school

[51] Hubbard et al. (1995) quantify the degree to which social insurance, that cushions against idiosyncratic *income* shocks, discourages labor supply and saving for self-insurance purposes. Our results extend theirs by quantifying how means-tested health insurance programs (like Medicaid) discourage labor supply in an environment with health shocks that generate health care costs.

[52] It is well known that education is positively associated with health (e.g., Grossman and Kaestner (1997), Grossman (2000), Smith (2004, 2007), Cutler and Lleras-Muney (2008). We discuss possible reasons for the correlation in Section 7.3, but it is beyond the scope of our analysis to explain what ultimately drives the positive education/health association (see Hai and Heckman 2019 and Heckman et al. 2018 for recent work on this question). Instead, we focus on using our model to examine how differences in health risk by education level – taken as given – affect earnings inequality, labor supply and other behaviors.

[53] We do this because the level of health risk faced by the some college type is intermediate between that faced by the high school and college types. Alternatively, we can also re-estimate the H, R and d^p functions with education omitted, and simulate the behavior of all agents when they face these common equations describing health risk. That approach generates very similar results.

[54] What drives the increase in the Gini is that low-skill college types work quite a bit less when their health risk is increased to the level of the some college type. This enables them to stay eligible for transfers in the event of expensive health shocks. Thus, inequality increases substantially within the college type.

types still have a strong incentive to constrain their labor supply so as to maintain eligibility for transfers that protect them from high medical costs. Reducing the health risk they face to the some college level does little to change that fact. In contrast, the larger risk reduction generated by removing health shocks entirely does change their incentives fundamentally.

7.7 Providing Public Health Insurance to the Uninsured

Finally, we use our model to simulate the impact of providing government funded health insurance to uninsured workers. In the baseline environment 35% of working age men lack employer provided health insurance (ESHI), and 12.9% resort to social insurance (including disability benefits) to pay health care costs. As we saw in Table 7, rates of coverage by ESHI vary greatly by age, education and full or part-time employment status, and our model provides a good fit to these patterns.[55] The fractions of high school, some college and college types with ESHI are 54%, 67% and 77%, respectively.

In our counterfactual experiments we leave ESHI as in the benchmark, but assume that all uninsured individuals participate in a mandatory government funded health insurance program.[56] Participants in the public plan pay an annual premium equal to the employee's share of the ESHI premium in the benchmark ($652/year), and this is tax deductible. They face a co-insurance rate of 30%, which is comparable to the typical ESHI plan.

Tables 19 and 20 present the results. The mandatory public insurance program spends on average $4,031/year per privately uninsured individual. A large fraction of this is accounted for by expenditures on those who were previously covered by Medicaid/DI. The average Medicaid/DI expenditures per uninsured person decline from $2,886 in the baseline to $599. The average out-of-pocket medical expenses of the uninsured decline from $2,858 to $1,130.

The employment rate increases from 83.1% to 85.3% when the public plan is introduced. Not surprisingly, this is primarily driven by an increase in the fraction of job offers without ESHI that are accepted, from 84.8% in the baseline to 89.8%. The fraction of job offers with ESHI that are accepted also increases slightly from 89.1% to 90.6%. Lifetime labor supply increases from a mean of 29.8 years in the baseline to 30.6 years in the experiment (a 2.7% increase). Because labor supply increases, human capital accumulation, wage offers and lifetime earnings increase as well. The mean offer wage increases from $22.55 per hour to $22.68 per hour, and the present value of lifetime earnings increases from $762k to $772k, a 1.3% increase. Increases in labor supply and earnings are greater among the low-skill types.

In addition to increasing labor supply, introduction of public health insurance also reduces the fraction of working age men who rely on social insurance (i.e., the consumption floor, including Medicaid, disability, Foodstamps, etc.), from 12.9% in the benchmark to 8.8% in the experiment. As we see in Table 19 government expenditures on social insurance decline by $762 per capita (36%) from the benchmark, a substantial cost savings.

[55] A limitation of our model is we assume all unemployed workers lack ESHI. In reality, 10% (17%) of unemployed men aged 26-44 (45-64) were covered by their previous employer's plan in 2010 (Janicki (2013)). Accounting for this would significantly complicate the model, as we would need to add a state variable.

[56] If we were to introduce a universal health insurance plan that *replaced* employer provided health insurance we would need to account for how wage/job offer distributions and government revenues change when firms no longer receive tax benefits for providing ESHI. But this is beyond the capacity of our partial equilibrium model. For this reason, we only present results from experiments where ESHI remains unchanged.

Together, the declines in social insurance payments slightly outweigh the \$689 per capita cost of the new public health insurance plan. After taking into account all changes in expenditures on other programs, as well as the increase in government revenue stemming from the increase in labor supply, we find that the introduction of the public insurance plan actually saves the government \$64 per capita.[57]

There are two important caveats to this finding: First, we abstract from any moral hazard effects of enhanced insurance coverage on total medical expenditures. Second, if provision of public insurance increases demand for medical services, it could increase their price. Thus, our experiment is likely to understate the cost of providing public insurance.[58] Given these limitations, our aim is simply to quantify the extent to which provision of public health insurance would (i) increase labor supply and tax revenues, and (ii) reduce reliance on Medicaid and other social transfers, reducing government spending. These two channels are important enough to outweigh the direct cost of the program, so that any cost increase arises through the secondary effects of moral hazard and increased prices.

Finally, assuming it would be self-financing, we find that the consumption equivalent variation (CEV) of introducing the public insurance plan is 1.44% of baseline consumption.[59] In Table 20 we see that the low educated groups experience larger welfare gains: 2.0% in CEV for HS types, 1.1% for some college and 0.9% for college graduates.[60]

7.8 Labor Supply Elasticities

In early life-cycle labor supply models saving is the only source of dynamics, and wages are taken as exogenous (see MaCurdy 1981). As life-cycle models are extended to include additional sources of dynamics, such as human capital and persistent health shocks, it is important to assess the implications for labor supply elasticities. Table 21 reports elasticities with respect to permanent and transitory wage/tax changes implied by our model.

The elasticity of lifetime hours with respect to a permanent wage/tax change is 1.32. If we look at effects on labor supply at different ages, we see the elasticity increases with age,

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[57]In this calculation, we factor in all expenditures on social insurance, social security, and medical expenses covered by Medicare and the public insurance program, as well as all taxes and premiums collected.

[58]We may also understate the benefit of public insurance if it improves health. We do not know how H and R transitions would change for the uninsured who obtain public insurance, so we take a conservative approach and assume they have the same H and R transitions as the uninsured in the benchmark economy. If public insurance leads to better health transitions, our experiments will underestimate its value.

[59]The consumption equivalent variation (CEV) is given by: $CEV = \left[\frac{V(c^*,l^*)-D(c_0,l_0)}{V(c_0,l_0)-D(c_0,l_0)}\right]^{\frac{1}{\alpha(1-\sigma)}} - 1$, where ($c_0$, l_0) and (c^*, l^*) are the consumption-labor allocations in the benchmark and in the counterfactual, V is the expected discounted value at age 25, and $D(c_0, l_0)$ is the expected discounted sum of death costs at age 25 in the benchmark. D depends on (c, l) up to age 65 since these affect employment decisions and income, which in turn affect H and R transitions and thus the probability of death. The CEV takes into account changes in welfare arising from different life expectancies in the counterfactuals.

[60]Within education groups, gains are larger for those with high productivity. For example, for those with high school or less, the welfare gains are 1.0%, 2.4%, and 2.7% for the low, medium and high productivity groups. The higher productivity types benefit more because fewer of them are at the consumption floor, and hence fewer of them can rely on government transfers to cover medical costs. Note that the new public insurance plan covers 70% of medical expenditures, which are on average \$4,500/year. Given the premium is \$652/year, those not at the consumption floor get approximately \$2,500 in additional disposable income, which translates into a 2-3% increase in consumption.

from 0.92 at age 30 to 2.4 at age 60. Thus, a permanent wage increase leads to a relatively much greater increase in labor supply at older ages.

Table 21 also reports Frisch elasticities of labor supply with respect to transitory anticipated wage/tax changes. The Frisch elasticity follows a U-shape by age, going from 0.35 at age 30 down to 0.21 at age 40 and then up to 0.51 at age 60. This pattern is not surprising: Keane and Wasi (2016) explain why, in models with both human capital and a participation margin, the Frisch elasticity tends to follow a U-shape with age.

Looking at results by education, one finding is especially notable: The labor supply of young college workers is particularly sensitive to permanent wage/tax changes. This reflects the fact that returns to experience are substantial for young college workers, and a permanent tax increase has a large negative impact on that return.

8 Conclusion

In this paper, we study how health shocks affect earnings and contribute to life-cycle earnings inequality. We extend the basic life-cycle model of labor supply and savings by adding four key features: (1) a detailed health process that includes several dimensions of health: functional health, health risk factors, and health shocks that are predictable/unpredictable and temporary/persistent, (2) endogenous wage determination via human capital accumulation, (3) tied job offers that specify the wage, hours and employer sponsored health insurance coverage, and (4) a simple specification of means-tested social insurance. Previous work has included some of these features, but not all four simultaneously. Our model provides a good fit to many important aspects of the data, such as life-cycle paths of full-time employment, assets and wages (conditional on education/health), the evolution of the Gini coefficient for earnings by age, the fraction of men (by age/education) who receive social transfers and disability benefits, and the distribution of medical spending.

The extended features of our model enable us to quantify the channels through which health shocks affect earnings. For instance, we show how a substantial part of the impact of health shocks on earnings arises via their effect on human capital accumulation. In particular, we use our model to simulate a persistent health shock that is serious enough to cause a drop in functional health. The model implies such a "major" health shock reduces present value of remaining lifetime earnings for a male college graduate at age 40 by \$44.7k or 4.5%. We estimate that 60% of this loss is due to the *direct* impact of the health shock on offer wages and labor supply. But a substantial 40% of the loss arises because the health shock slows the rate of human capital accumulation. For those with a high school degree or less, a similar major health shock reduces the PV of earnings at age 40 by \$33.4k or 7.9%. Of this, 25% is due to the human capital channel. The human capital channel is *relatively* more important for college graduates because they have a higher rate of human capital accumulation.

We also quantify how different types of health shocks affect earnings and labor supply of working age men. We find health shocks that are predictable - based on health, education and risk factors like hypertension and high cholesterol - have much smaller impacts than unpredictable shocks. For example, our model implies unpredictable health shocks reduce lifetime labor supply by 1.7 years (or 5%) for a typical man (with most of this due to the *persistent* predictable shocks), while predictable shocks only cost 0.4 years. The predictable health shocks play a smaller role because they are much less common than unpredictable shocks prior to age 65. As a consequence, policies aimed at reducing risk factors like high blood pressure and cholesterol are not likely to have large effects on labor market outcomes for working age men. Of course, the potential benefit of reducing risk factors is greater at ages over 65, when predictable shocks become more prevalent.

Our model implies that health shocks explain roughly 15% of inequality in present value of lifetime earnings (PVE) across all workers. Within education groups, health shocks explain roughly 25% of inequality within high school workers, 21% within some college workers, and 17% within college workers. However, analogous with results in Keane and Wolpin (1997), we find that, even in a life-cycle model extended to include health and health shocks, worker's education and "skill endowment" (at labor market entry) still explain over 80% of the heterogeneity in the PVE. Importantly, health shocks mostly affect earnings of older workers, which are discounted when taking present values at age 25. For men in their 50s and 60s, we find that health shocks can explain about a quarter of income inequality.

We use our structural model to decompose effects of health shocks on earnings into "direct" effects that hold decision rules fixed, and "behavioral" effects that arise because health risk changes decision rules for labor supply and savings. We find direct effects of health shocks account for only 1/3 of their impact on earnings inequality, while behavioral responses account for 2/3. The extended features of our model are important in this decomposition:

The large behavioral effect of health risk on earnings inequality arises because low-skill workers - who often lack employer sponsored insurance - have a strong incentive to hold down their labor supply so as to maintain eligibility for means-tested social insurance that cushions against high potential medical costs. This reduces their rate of human capital accumulation, leading to slower wage growth over the life-cycle, and lower earnings. In contrast, among high skill workers, social insurance has no significant effect on labor supply. This asymmetry in responses generates the positive behavioral effect of health risk on earnings inequality.

Thus, in an environment with costly health shocks, means-tested social insurance creates a type of "moral hazard" that reduces labor supply and human capital investment of low skill workers (analogous to how health insurance may generate moral hazard by reducing the incentives to invest in health). Quantitatively, we find this moral hazard effect on labor supply is substantial. Providing public health insurance to those who lack employer sponsored insurance counteracts it, leading to both (i) substantial government cost saving on means-tested social insurance programs, and (ii) increased tax revenues due to increased labor supply. Hence, our model predicts that a program providing subsidized mandatory public health insurance to the uninsured would be self-financing and welfare improving.

Previous literature has considered the potential for public health insurance to generate an *ex-ante* moral hazard effect that reduces the incentive to invest in health (see Khwaja 2001). In contrast, we find public health insurance alleviates the moral hazard problem that arises because means-tested social insurance discourages labor supply and human capital investment in the presence of health risk. A limitation of our analysis is we ignore any effect of public insurance on (i) health care spending of the newly insured (via the *ex-post* moral hazard effect), or (ii) the price of medical care (via increased demand for services). So we likely understate the cost of the program. Nevertheless, our key point is that any cost evaluation of public health insurance should factor in the positive effect on labor supply and the savings on social transfers.

Tables

Table 1: Wages, Hours and Earnings Regression Results, MEPS

Dependent Var	Log Wage	Weekly Hours	Annual Earnings
Mean	3.056	35.098	82.888
SD	0.563	19.283	38.564
s	0.003	-0.397***	-0.717***
	(0.004)	(0.174)	(0.305)
d^p	0.003	-1.216***	-2.543***
	(0.006)	(0.284)	(0.522)
d^u	0.005	-1.375***	-2.123***
	(0.005)	(0.227)	(0.405)
Lagged Dep. Var.	0.878***	0.679***	0.734***
	(0.006)	(0.007)	(0.006)
Education			
Some College	0.031***	1.040***	2.588***
	(0.005)	(0.211)	(0.368)
College	0.085***	2.166***	7.005***
	(0.006)	(0.192)	(0.377)
Initial Health			
Fair	0.020	5.151***	8.916***
	(0.020)	(0.405)	(0.761)
Good	0.036*	6.543***	12.020***
	(0.020)	(0.429)	(0.796)
R^2	0.836	0.552	0.643
Observations	22,875	37,004	38,065

Standard errors in parentheses

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

Notes: s, d^p and d^u are health shock indicators defined in the text. All regressions include year dummies, and a cubic in age. The wage regression is estimated using only workers employed in both interviews 1 and 5. The Weekly Hours regression is estimated on all workers, including those with zero hours. For the 79.2% of the sample with positive hours, mean hours are 43.083 with a standard of 10.620. The earnings regression also includes non-employed workers, and incorporates a Box-Cox transform of annual earnings, with lambda = 0.326. If we drop controls for health and health shocks, the R-squared of the three regressions decline to 0.836, 0.543 and 0.635, respectively.

Table 2: Classifying Medical Conditions

Assignment	Short-Term Productivity	Long-Term Productivity	Predictor	Predictable	Number of ICD codes
dp	YES	YES	YES	YES	27
du	YES	YES	YES	NO	18
dp	YES	YES	NO	YES	38
du	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	Unknown condition or condition details missing				1
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 3: Work Hours Lost Due to Health Shocks (Sick Days)

	HS or Less			**Some College and College**		
Health Shocks	**H=Poor**	**H=Fair**	**H=Good**	**H=Poor**	**H=Fair**	**H=Good**
$du = 0,\ dp = 1,\ s = 0$	0.0	4.0	0.0	0.0	2.6	1.4
$du = 0,\ dp = 0,\ s = 1$	0.0	2.5	0.0	1.3	1.5	0.6
$du = 0,\ dp = 1,\ s = 1$	4.2	6.0	5.5	7.6	6.1	3.6
$du = 1,\ dp = 0,\ s = 0$	5.0	7.5	1.4	1.7	1.6	1.0
$du = 1,\ dp = 1,\ s = 0$	8.5	9.6	0.0	8.3	7.3	3.9
$du = 1,\ dp = 0,\ s = 1$	7.1	9.1	4.0	7.1	5.8	3.6
$du = 1,\ dp = 1,\ s = 1$	6.1	13.4	9.5	19.7	14.3	12.1

Note: We estimate weekly lost work hours using a regression of weekly hours worked on health risk, age, age^2 and all health shock combinations (no health shocks is the base group). Regressions are run separately by functional health and education. Coefficients that are not statistically significant at the 10% level are set to zero.

Table 4: Model Parameters

Parameter	**Value**
Preferences	
CRRA parameter α	0.4
Intertemporal substitution parameter σ	2.0
Cost of death ζ	-30.0
Interest rate	
r	0.04
Tax Parameters	
Consumption tax τ^c	5.70%
Social Security tax τ^{SS}	6.20%
Medicare tax τ^{Med}	1.45%
Income threshold $\overline{y}_{ss}$	$98,000
Tax function parameter a_0	0.258
Tax function parameter a_1	0.768
Social Security Income	
HS or Less	$13,655
Some College	$14,678
College	$15,883
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}	$854
Employer Insurance Premium (Employee's Share) p^{EI}	$652

Note: Average Social Security income is calculated from the HRS. The tax function parameters a_0 and a_1 are taken from Gouveia and Strauss (1994). The co-insurance rates q^{EI} and q^{Med} are taken from Attanasio et al. (2010). The Medicare premium p^{Med} is set to the average annual Medicare Part B premium over the sample period, adjusting for the CPI. The average employee's share of the ESHI premium p^{EI} for a single's plan is calculated using the MEPSnet/IC Trend Query tool available at `https://www.meps.ahrq.gov/mepsweb/data_stats/MEPSnetIC.jsp`.

Table 5: Parameters Calibrated by Matching Moments

Parameter	Parameter Description	Target	Parameter Values		
			≤HS	**<College**	**College**
β	Time discount factor	Asset to inc ratio, ages 30-55	0.962	0.968	0.984
$\phi(educ, H = P, h^* = h^{FT})$	Leisure cost of FT work - Poor H	% FT, no health shocks, 30-55 - Poor H	0.525	0.700	0.540
$\phi(educ, H = F, h^* = h^{FT})$	- Fair H	- Fair H	0.525	0.552	0.540
$\phi(educ, H = G, h^* = h^{FT})$	- Good H	- Good H	0.520	0.545	0.540
$\phi(:, :, h^{PT})/\phi(:, :, h^{FT})$	Leisure cost of PT work rel. to FT	% PT, by H, relative to FT, 30-55	0.500	0.500	0.500
$\mathit{\Pi}(O^*, educ, t)$	Employment offer probabilities	Emp shares by age, by PT/FT and ESHI		See Table 6	
$\delta^O(educ)$, ages 54-59	Age trend of prob of no emp offer	Emp shares, ages 54-59	0.030	0.014	0.015
$\delta^O(educ)$, ages 60-64	Age trend of prob of no emp offer	Emp shares, ages 60-64	0.053	0.035	0.038
$\beta_0(educ)$	Offer wage func - Intercept	Avg FT wages by age group if $H = G$	2.08	2.30	2.52
$\beta_1(educ)$	- HC coeff	Avg FT wages by age group if $H = G$	0.0425	0.0425	0.089
$\beta_2(educ)$	- HC^2 coeff	Avg FT wages by age group if $H = G$	-0.0014	-0.00145	-0.00365
$\beta_3(educ)$	- HC^3 coeff	Avg FT wages by age group if $H = G$	0.000016	0.000017	0.00005
$\beta_4(educ)$	- $I_{H\in\{F,G\}}$ coeff	Avg FT wages, 30-55, penalty if $H = P$	0.423	0.420	0.400
$\beta_5(educ)$	- $I_{H=G}$ coeff	Avg FT wages, 30-55, penalty if $H = F$	0.490	0.500	0.470
$\beta_6(educ)$	- $I_{h^*=hrs^{PT}}$ coeff	Average PT wages /FT wages, ages 30-55	0.920	0.930	0.880
$\kappa_1(educ)$ -$\kappa_3(educ)$	Fixed productivity types	Var fixed type, residual wage reg.	+/-0.283; 0	+/-0.311	+/-0.339
$\sigma^2_{\varepsilon^W}(educ)$	Variance transitory wage shocks	Var trans shock, residual wage reg.	0.125	0.097	0.100
$\sigma^2_N(educ)$	Variance wage noise	Var log wages, FT, ages 30-35	0.360	0.260	0.250
ν	Multiplicative shock to HC	Assumed		+/-0.3	
$p^1(educ, I_{h>0} = 1)$	Prob of +/-ve HC shock, working	AR(1) process param, residual wage reg.	0.330	0.330	0.400
$p^2(educ, I_{h>0} = 0)$	Prob of -ve HC shock, not working	% transition from Non-Emp to Emp, 30-55	0.950	0.950	0.850
$\eta(educ, H = P, t < 65)$	Prob of DI benefits if Poor H	% of Poor health receiving DI, 25-64	0.950	0.980	0.930
$\bar{c}(educ, I^{DI} = 0)$	Consumption floor, non-DI	% non-DI individuals getting TR, 30-55	4,696	5,408	8,840
$\bar{c}(educ, I^{DI} = 1)$	Consumption floor, DI recipients	Average DI benefits	10,400	14,040	17,160
a_2	Tax function parameter	Effective tax rate by inc group		0.08	
τ_y	Tax function parameter	Effective tax rate by inc group		0.0	

Notes: 1. The leisure cost of work is the fraction of total leisure time lost if working. 2. The probability of positive and negative human capital shocks are equal if employed ($p^2(educ, I_{h>0} = 1) = p^1(educ, I_{h>0} = 1)$. If not employed the probability of a good shock is set to zero $p^1(educ, I_{h>0} = 0)$. 3. The consumption floor is expressed in dollars per year. 4. Within the High School type we allow for 3 latent productivity types (i.e., three levels of κ), with type proportions 1/3 each. Within the Some College and College types we allow for two latent types, with proportions 1/2 each.

Table 6: Calibrated Employment Offer Probabilities, ages 25-53

	HS or Less	**Some College**	**College**
PT, no ESHI	0.050	0.031	0.013
PT, ESHI	0.050	0.030	0.032
FT, no ESHI	0.288	0.167	0.100
FT, ESHI	0.613	0.772	0.855

Notes: At ages 54-64, we allow for a positive probability of having no employment offer. The probabilities of PT and FT offers are scaled down appropriately.

Table 7: The Distribution of Employment, Model and Data

	<=HS		**Some College**		**College**	
	Model	**Data**	**Model**	**Data**	**Model**	**Data**
Ages 25-34						
NE	7.5	8.2	8.4	6.0	8.0	4.9
PT, no ESHI	4.6	5.7	2.9	4.2	1.1	2.4
PT, ESHI	4.5	2.8	2.7	3.4	2.6	4.1
FT, no ESHI	26.5	31.1	15.3	17.5	9.1	9.6
FT, ESHI	56.9	52.2	70.7	68.9	79.1	78.9
Ages 35-44						
NE	8.1	10.2	6.3	6.5	3.8	3.5
PT, no ESHI	4.6	4.4	2.9	2.6	1.3	1.3
PT, ESHI	4.5	2.7	2.8	2.9	3.0	2.7
FT, no ESHI	26.0	23.1	15.3	14.0	9.6	10.2
FT, ESHI	56.8	59.7	72.7	74.1	82.4	82.3
Ages 45-54						
NE	16.8	18.0	15.7	12.3	8.0	6.3
PT, no ESHI	4.0	3.8	2.6	2.6	1.2	1.4
PT, ESHI	4.0	3.2	2.4	3.6	2.9	3.1
FT, no ESHI	22.8	17.8	13.3	12.9	9.1	10.2
FT, ESHI	52.4	57.2	66.0	68.6	78.8	78.9
Ages 55-64						
NE	50.0	43.7	41.4	36.3	34.0	26.1
PT, no ESHI	2.5	4.1	1.9	3.1	1.0	2.3
PT, ESHI	2.3	4.9	1.6	6.3	2.1	6.8
FT, no ESHI	12.9	11.4	8.8	10.0	6.1	9.3
FT, ESHI	32.4	35.8	46.3	44.3	56.7	55.5

Table 8: Calibration Moments, Model and Data

	HS or Less		Some College		College	
	Model	**Data**	**Model**	**Data**	**Model**	**Data**
1. Identifying β						
Assets/income ratio, ages 30-55	1.22	1.21	1.27	1.32	1.85	1.88
2. Identifying the leisure cost of work						
% emp FT, no shocks, ages 30-50: $H = Poor$	26.11	31.01	17.53	11.11	34.68	57.14
$H = Fair$	78.43	78.00	80.64	82.22	86.54	88.26
$H = Good$	85.97	85.22	90.25	89.21	92.47	91.42
% emp PT, no shocks, ages 30-50: $H = Poor$	3.08	11.63	1.23	0.00	1.50	0.00
$H = Fair$	8.31	6.13	5.14	6.43	3.98	6.33
$H = Good$	9.30	5.13	5.84	4.30	4.22	3.82
3. Identifying Mean of the Offer Wage Function						
Wages, FT, $H = Good$: ages 25-34	16.57	15.30	20.66	19.47	27.60	29.94
ages 45-54	20.53	18.98	25.70	25.44	39.38	37.95
Wages, FT, ages 30-55: $H = Poor$	13.88	15.59	18.92	21.52	25.06	29.32
$H = Fair$	18.18	16.14	22.21	22.32	32.68	32.65
$H = Good$	19.01	17.68	23.71	23.77	35.37	35.81
Wages PT/ Wages FT, ages 30-55	0.93	0.93	0.94	0.94	0.90	0.90
4. Identifying Covariance Structure of Wages						
Variance of fixed effect	0.03	0.11	0.06	0.08	0.09	0.08
Variance of transitory shock	0.20	0.07	0.12	0.07	0.11	0.08
Permanent shock persistence	0.85	0.94	0.86	0.84	0.89	0.93
Variance of innovation	0.01	0.02	0.01	0.04	0.01	0.03
Variance of log wages, FT, ages 30-55	0.26	0.26	0.23	0.24	0.27	0.28
% Emp to Non-Emp trans. rate, ages 30-55, $H = Good$	2.61	3.02	2.29	2.86	1.51	2.29
% Non-Emp to Emp trans. rate, ages 30-55, $H = Good$	63.08	42.51	66.20	46.59	48.57	48.72
5. Identifying Consumption floor and DI (%)						
% non-DI individuals getting transfers, ages 30-55	8.46	9.26	7.22	7.53	5.02	3.68
Average DI benefits	10,268	9,920	14,175	11,941	17,653	16,839
% receiving DI if $H = Poor$	73.87	80.33	78.41	83.56	55.85	64.30

Table 9: Wage Distribution, Model and Data (CPS)

	HS or Less		Some College		College	
Distribution of Wages	**Model**	**Data**	**Model**	**Data**	**Model**	**Data**
Percentiles, Ages 30-35						
5	6.5	7.1	8.6	9.1	11.3	12.2
25	10.5	11.7	13.3	15.6	17.8	21.0
50	14.8	16.5	18.6	21.1	25.6	29.3
75	20.9	22.6	26.2	28.3	37.2	41.4
90	28.4	29.7	34.9	37.4	50.4	54.8
95	34.0	36.1	40.6	44.3	58.8	66.8
99	46.9	50.8	51.9	65.1	76.7	114.0
Percentiles, Ages 50-55						
5	8.0	7.7	10.9	9.7	14.7	12.0
25	12.8	13.5	16.6	17.1	23.9	23.4
50	18.0	19.3	23.1	24.4	34.9	34.3
75	25.4	26.4	32.3	33.1	50.7	48.9
90	34.6	35.3	42.5	43.5	69.7	68.1
95	41.5	41.7	49.5	52.0	83.3	89.2
99	57.4	59.2	63.9	76.2	120.5	168.1

Notes: Hourly wages expressed in constant 2010 CPI adjusted dollars. The data is from the CPS, screening out workers in the top 1% of the wage distribution, or with wages below $3.50/hour.

Table 10: Effects of Severe Health Shocks on Present Value of Earnings

Age of Shock	**Δ PV Earnings**					**Δ FT Yrs Work**	
	HC **fixed**		**Total Effect**		**Due to** *HC*	*HC* **fixed**	**Total**
		%		**%**	**% of total**		
≤High School							
30	-19,495	-3.7	-28,345	-5.4	31.2	-0.64	-0.99
40	-25,015	-5.9	-33,410	-7.9	25.1	-0.73	-1.05
50	-29,348	-11.1	-33,848	-12.8	13.3	-0.78	-0.92
60	-13,777	-21.6	-13,959	-21.9	1.3	-0.31	-0.31
Some College							
30	-21,335	-3.0	-33,226	-4.6	35.8	-0.55	-0.99
40	-27,028	-4.6	-40,555	-6.8	33.4	-0.66	-1.19
50	-31,225	-8.0	-37,710	-9.7	17.2	-0.70	-0.91
60	-18,013	-15.6	-18,377	-15.9	2.0	-0.30	-0.31
College							
30	-19,527	-1.7	-39,688	-3.5	50.8	-0.34	-1.02
40	-26,733	-2.7	-44,749	-4.5	40.3	-0.39	-0.93
50	-33,487	-4.9	-40,214	-5.9	16.7	-0.39	-0.55
60	-25,227	-13.6	-26,462	-14.2	4.7	-0.24	-0.26

Notes: We compare simulations where all individuals experience a d^u shock followed by a drop in H at the indicated age, with simulations where no individuals experience such an event. Thus we report average effects. In the "HC Fixed" scenario we hold human capital (HC) fixed at the levels that arise in the scenario where the health shock does not occur. Present values are calculated from the age of the shock to age 65.

Table 11: The Importance of Health Shocks in the Benchmark Model

	ME	**Sick days**	**Surv to 65 (%)**	**Emp (%)**	**Yrs Worked**	**SI (%)**	**Wage Offer**
Benchmark	4,465	8.26	85.18	83.13	29.82	12.86	22.88
No s shocks	2,894	4.35	85.74	83.87	30.60	11.42	22.98
No d^u shocks	3,050	3.85	90.09	84.66	31.24	10.48	23.13
No d^p shocks	3,858	6.23	89.64	83.55	30.47	12.08	22.95
No s and d^u	1,571	1.15	90.10	85.08	31.74	9.53	23.18
No s, d^u, d^p	1,041	0.00	92.38	85.41	32.14	8.92	23.25
Low R	4,211	7.47	87.22	83.73	30.25	12.11	22.92

Notes: Data are simulated from the Benchmark model, with the indicated health shocks shut down at ages 25-64, but with decision rules unchanged. ME is total annual medical expenditure in dollars. Sick days are expressed in number of lost full time work days per year. "Yrs Worked" is lifetime labor supply in full time equivalent years (max = 40 years). Statistics are for ages 25-64 only, and we combine all education groups.

Table 12: Explaining the Variance of the Present Value of Lifetime Earnings

	R^2 from PV Earnings Regressions			
Independent Variables Included	**<=HS**	**Some College**	**College**	**All**
1. Initial conditions*	0.797	0.855	0.787	0.868
2. Health, health shocks + Initial conditions	0.898	0.928	0.866	0.924
3. Health, health shocks only	0.358	0.337	0.230	0.400

Notes: The table reports R^2 from regressions of the present value of lifetime earnings on initial conditions and/or health measures, using simulated data from the benchmark model. Initial conditions are the latent skill type (κ) and H and R at age 25. In the "All" column that combines education groups, we also include education and its interactions with κ, H_{25} and R_{25}. In Rows 2 and 3, "health, health shocks" are H and R at ages 25 and 64, age of death if less than 65, ages that d^u and d^p shocks first occur, total years the agent was in Poor/Fair/Good health, and the total number of times each possible combination of health shocks occurred between the ages of 24 and 64, entered separately by health status at the time of occurrence.

Table 13: Health Shocks and Inequality in the Present Value of Lifetime Earnings

	Benchmark			**No Health Shocks**			**No Health Shocks**		
				Decision Rules Fixed			**Decision Rules Change**		
	Mean	**CV**	**Gini**	**Mean**	**CV**	**Gini**	**Mean**	**CV**	**Gini**
All	762,177	0.555	0.304	+5.56%	0.528	0.289	+9.26%	0.479	0.258
By Education									
≤High School	523,423	0.376	0.216	+7.41%	0.350	0.200	+11.83%	0.286	0.163
Some College	711,746	0.435	0.245	+5.72%	0.411	0.231	+9.94%	0.350	0.194
College	1,091,345	0.445	0.253	+4.42%	0.425	0.241	+7.41%	0.375	0.210
By Productivity									
≤High School									
Low Productivity	293,730	0.300	0.170	+12.85%	0.273	0.155	+37.49%	0.169	0.089
Med Productivity	539,185	0.150	0.077	+7.14%	0.130	0.063	+7.43%	0.125	0.060
High Productivity	734,667	0.134	0.065	+5.47%	0.122	0.059	+5.36%	0.124	0.059
Some College									
Low Productivity	425,701	0.256	0.144	+9.18%	0.233	0.130	+23.80%	0.140	0.072
High Productivity	997,662	0.127	0.059	+4.24%	0.114	0.053	+4.04%	0.114	0.053
College									
Low Productivity	661,093	0.312	0.172	+7.09%	0.279	0.149	+17.34%	0.166	0.086
High Productivity	1,521,622	0.158	0.080	+3.26%	0.152	0.077	+3.10%	0.150	0.076

Note: The mean (across simulated agents) of the present value of earnings (PVE) is expressed in 2010 dollars. CV denotes the coefficient of variation.

Table 14: Effects of Health Shocks on the Present Value of Lifetime Earnings

	Benchmark		**No s Shocks**		**No d^p Shocks**		**No d^u Shocks**	
	Mean	**Gini**	**Mean**	**Gini**	**Mean**	**Gini**	**Mean**	**Gini**
All	762,177	0.304	+4.20%	0.282	+3.37%	0.287	+6.57%	0.269
By Education								
≤High School	523,423	0.216	+4.12%	0.194	+2.91%	0.202	+7.85%	0.179
Some College	711,746	0.245	+4.45%	0.222	+3.96%	0.225	+6.96%	0.208
College	1,091,345	0.253	+4.12%	0.226	+3.35%	0.229	+5.62%	0.216

Note: The mean of the present value of earnings (PVE) is expressed in 2010 dollars. Decision rules are allowed to change when eliminating each type of shock.

Table 15: Inequality in the Present Value of Earnings, Evaluated at Age 25

	Benchmark			**No ME of Health Shocks**			**No ME of Health Shocks**		
				Decision Rules Fixed			**Decision Rules Change**		
	Mean	**CV**	**Gini**	**Mean**	**CV**	**Gini**	**Mean**	**CV**	**Gini**
All	762,177	0.555	0.304	+0.23%	0.551	0.302	+2.49%	0.511	0.278
By Education									
≤High School	523,423	0.376	0.216	+0.37%	0.372	0.213	+3.28%	0.329	0.188
Some College	711,746	0.435	0.245	+0.15%	0.434	0.245	+2.73%	0.395	0.221
College	1,091,345	0.445	0.253	+0.18%	0.440	0.250	+1.93%	0.395	0.223
By Productivity									
≤High School									
Low Productivity	293,730	0.300	0.170	+1.08%	0.302	0.172	+16.32%	0.232	0.129
Med Productivity	539,185	0.150	0.077	+0.63%	0.148	0.075	+1.04%	0.141	0.070
High Productivity	734,667	0.134	0.065	-0.12%	0.132	0.064	-0.01%	0.134	0.064
Some College									
Low Productivity	425,701	0.256	0.144	+0.20%	0.260	0.146	+8.87%	0.198	0.107
High Productivity	997,662	0.127	0.059	+0.14%	0.125	0.059	+0.11%	0.123	0.059
College									
Low Productivity	661,093	0.312	0.172	+0.90%	0.303	0.165	+9.21%	0.206	0.108
High Productivity	1,521,622	0.158	0.080	-0.13%	0.158	0.080	-1.24%	0.162	0.082

Notes: The mean (across simulated agents) of the present value of earnings (PVE) is expressed in 2010 dollars. CV denotes the coefficient of variation.

Table 16: Counterfactual Experiments: Employment and Social Insurance

	Employment (%)			**Social Insurance (%)**		
	Bench	**No HS**	**No ME-HS**	**Bench**	**No HS**	**No ME-HS**
All	83.1	91.2	87.6	12.9	2.0	5.6
≤High School	80.2	89.6	85.6	15.9	2.9	7.6
Some College	82.7	92.5	87.7	14.1	1.9	6.6
College	86.9	92.2	89.9	8.2	0.9	2.4
≤High School						
Low Productivity	57.1	84.3	71.7	41.6	8.6	22.1
Med Productivity	89.0	91.8	91.1	7.3	0.4	1.6
High Productivity	92.7	92.2	92.7	0.7	0.1	0.2
Some College						
Low Productivity	69.9	89.9	79.9	28.1	3.7	13.2
High Productivity	95.4	95.2	95.3	0.2	0.1	0.1
College						
Low Productivity	80.1	92.0	88.5	16.4	1.8	4.9
High Productivity	93.7	92.5	91.2	0.0	0.0	0.0

Notes: In the "No HS" counterfactual we eliminate health shocks at working ages. In "No ME-HS" we remove (only) the medical expenditures associated with health shocks at working ages. In each counterfactual, agents update their decision rules (for labor supply and saving) to reflect the new environment. The full-time employment rate and the rate of receiving government transfers are both calculated in the cross-section of working age men.

Table 17: Counterfactual Experiment: Effects of Eliminating Health Shocks

	FT Yrs Worked		**Mean Wage Offers**		**DI (%)**	
	Bench	**No HS**	**Bench**	**No HS**	**Bench**	**No HS**
All	29.83	34.33	22.88	23.56	2.46	0.38
≤High School	27.96	33.11	16.07	16.64	3.62	0.61
Some College	29.94	35.01	20.78	21.41	2.79	0.47
College	32.01	35.26	32.03	32.90	0.82	0.05
≤High School						
Low Productivity	19.93	31.13	10.76	11.95	8.40	1.53
Med Productivity	31.04	33.92	15.95	16.31	2.42	0.25
High Productivity	32.38	34.14	21.44	21.71	0.31	0.10
Some College						
Low Productivity	25.32	33.99	13.70	14.73	5.43	0.83
High Productivity	34.56	36.03	27.81	28.09	0.17	0.11
College						
Low Productivity	29.44	35.16	20.53	21.98	1.61	0.08
High Productivity	34.58	35.35	43.47	43.81	0.03	0.02

Notes: In the counterfactual we eliminate health shocks at ages 25-64, and let agents re-optimize their decision rules to the new environment. Full-time equivalent years worked over the life-cycle is an average over all simulated agents. All other statistics are calculated in the cross-section of working age men. Mean offer wages are calculated using only individuals with full-time employment offers.

Table 18: Inequality in the Present Value of Earnings, Evaluated at Age 25

	Benchmark			**Some College Λ_H, Λ_R and Γ^{dp}**		
	Mean	**CV**	**Gini**	**Mean**	**CV**	**Gini**
All	762,177	0.555	0.304	-3.14%	0.581	0.319
By Education						
High School or Less	523,423	0.376	0.216	+2.81%	0.353	0.203
Some College	711,746	0.435	0.245	+0.00%	0.435	0.245
College	1,091,345	0.445	0.253	-8.23%	0.560	0.319
By Productivity						
≤High School						
Low Productivity	293,730	0.300	0.170	+8.85%	0.275	0.156
Med Productivity	539,185	0.150	0.077	+2.08%	0.145	0.072
High Productivity	734,667	0.134	0.065	+1.00%	0.135	0.065
College						
Low Productivity	661,093	0.312	0.172	-24.34%	0.516	0.297
High Productivity	1,521,622	0.158	0.080	-1.22%	0.161	0.081

Notes: The counterfactual sets the distribution of health shocks, and (H, R) transition rates, for all education types, to the Some College levels. The mean (across simulated agents) of the present value of earnings (PVE) is expressed in 2010 dollars. CV denotes the coefficient of variation.

Table 19: Mandatory Public Health Insurance

	Benchmark	**Public HI**
Average Medical Expenses, ages 25-64		
- If covered by ESHI	3,775	3,770
- If no ESHI:		
-Out-of-pocket	2,858	1,130
-Public HI	-	4,032
-SI	2,886	599
-Total	5,743	5,761
Wage Offers	22.55	22.68
FT Years of Work	29.83	30.61
Mean Government Expenditures per capita		
-Public HI	-	689
-SI	2,098	1,336
Government Deficit per capita	2,694	2,630

Notes: Mean government expenditures per capita are calculated as the total expenditures across all ages, divided by the total number of agents in the economy.

Table 20: Mandatory Public Health Insurance Covering 70% of Medical Expenditures

	EMP (%)		**SI (%)**		**PV Earnings**		**CEV (%)**
	Bench	**Public**	**Bench**	**Public**	**Bench**	**Public**	**Public**
All	83.1	85.3	12.9	8.8	762,177	+1.3%	1.44
≤High School	80.2	83.3	15.9	11.0	523,423	+1.9%	2.00
Some College	82.7	85.0	14.1	10.4	711,746	+1.3%	1.12
College	86.9	87.9	8.2	4.9	1,091,345	+0.9%	0.86
≤High School							
Low Productivity	57.1	65.1	41.6	31.6	293,730	+9.4%	1.03
Med Productivity	89.0	90.6	7.3	2.8	539,185	+0.9%	2.37
High Productivity	92.7	92.7	0.7	0.3	734,667	-0.1%	2.70
Some College							
Low Productivity	69.9	74.6	28.1	20.8	425,914	+4.5%	0.83
High Productivity	95.4	95.3	0.2	0.2	997,566	+0.0%	1.49
College							
Low Productivity	80.1	84.2	16.4	9.8	661,093	+4.8%	0.72
High Productivity	93.7	91.5	0.0	0.0	1,521,622	-0.8%	1.01

Notes: "EMP (%)" is the percentage of individuals employed either part or full time. All statistics are calculated in the cross-section of individuals 25-64 years of age.

Table 21: Labor Supply Elasticities

	Age				
Transitory	**30**	**40**	**50**	**60**	
All	0.35	0.21	0.25	0.51	
≤High School	0.25	0.25	0.25	0.57	
Some College	0.45	0.28	0.41	0.72	
College	0.38	0.10	0.15	0.31	
Permanent	**30**	**40**	**50**	**60**	**Total hours**
All	0.92	0.98	1.67	2.42	1.32
≤High School	0.46	0.99	1.31	1.75	0.96
Some College	1.05	1.07	1.96	2.84	1.55
College	1.35	0.92	1.84	2.68	1.53

Notes: To calculate the labor supply elasticities, we run counterfactuals where we increase wages at all ages (permanent) or at particular ages (transitory). These transitory wage increases are anticipated, so these are Frisch elasticities. For permanent wage increases, we also report the percentage change in total lifetime hours worked.

Figures

Figure 1: Distribution of H and R, Model and Data

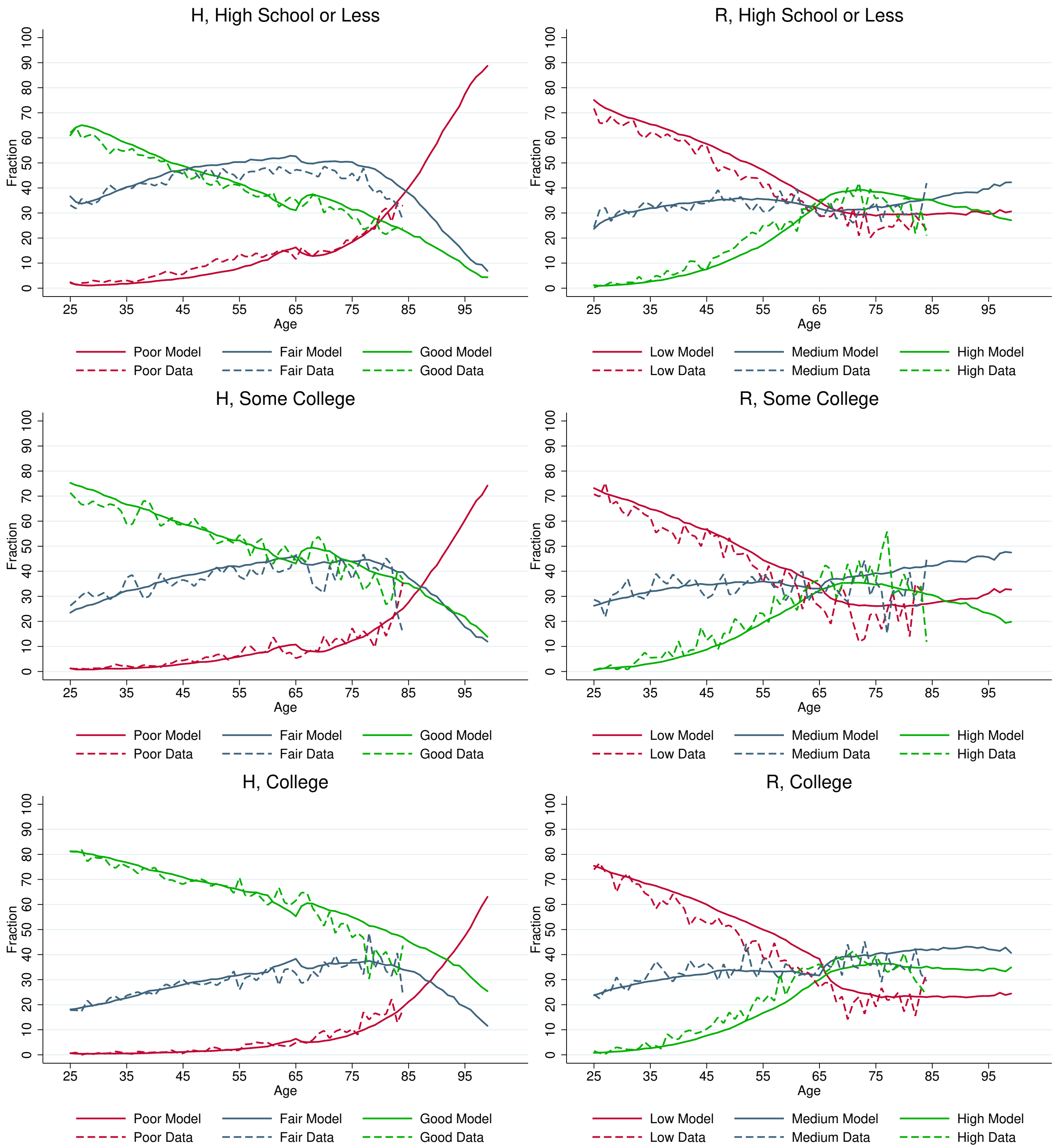
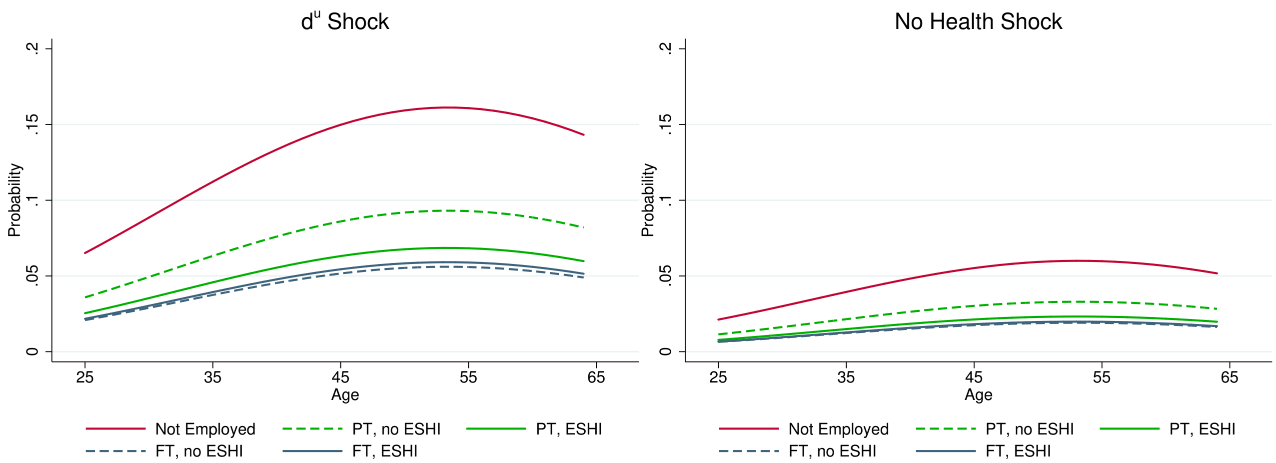


Figure 2: Selected Probabilities of Transitions from Fair to Poor Health (H), High School or Less



Note: All transitions are conditional on income quintile equal to 3.

Figure 3: Fractions with d^u, s and d^p Shocks by Age (Model and Data)

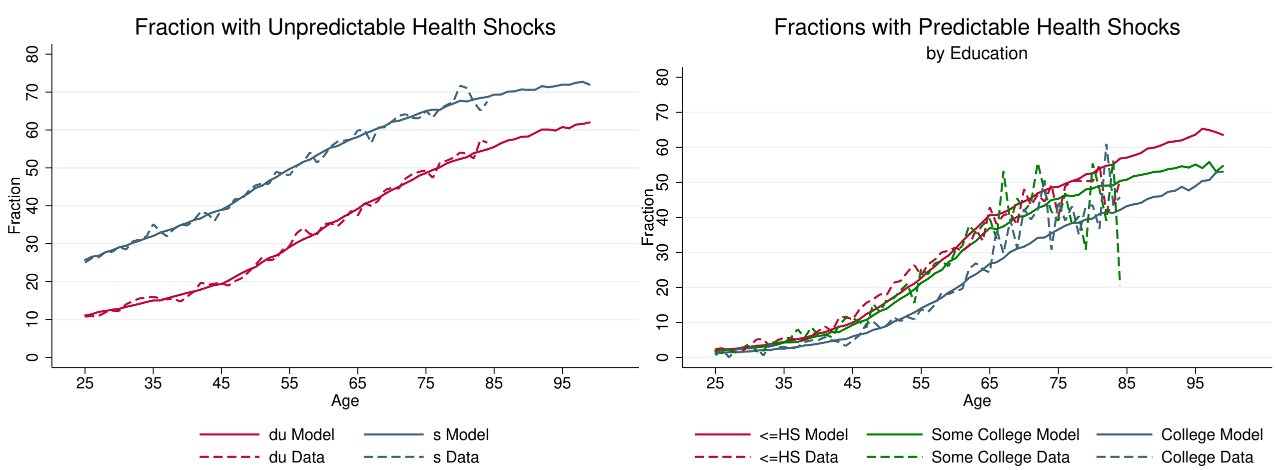


Figure 4: Distribution of Employment, Model and Data (CPS)

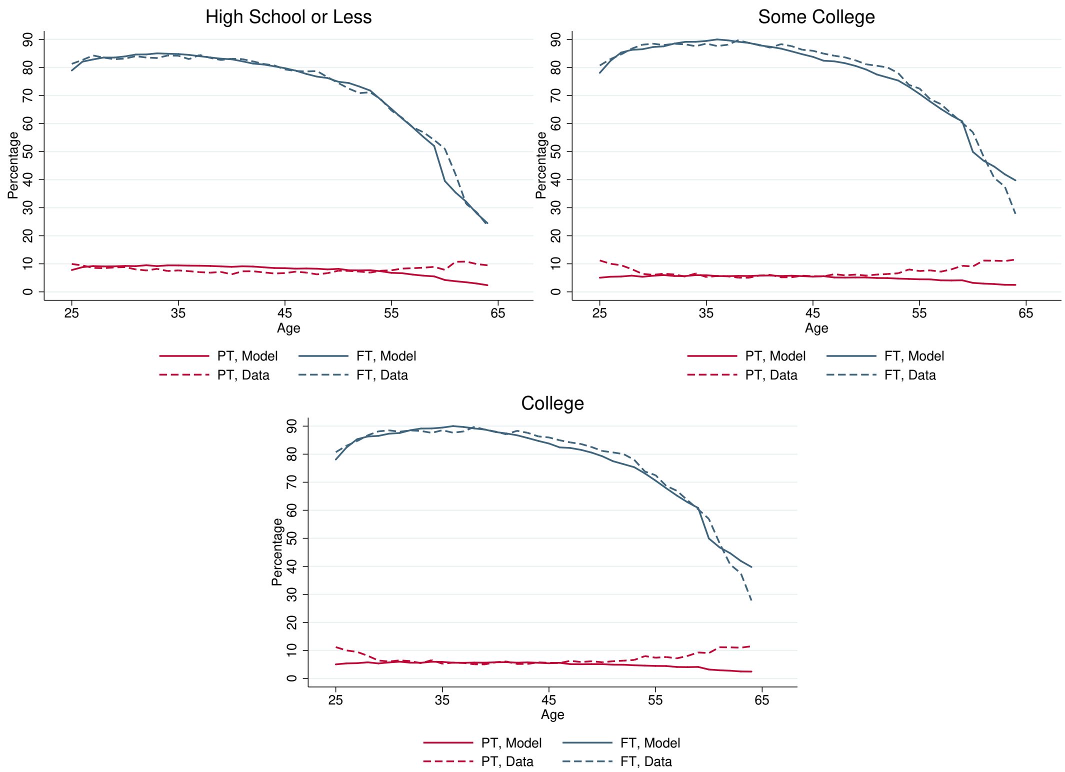
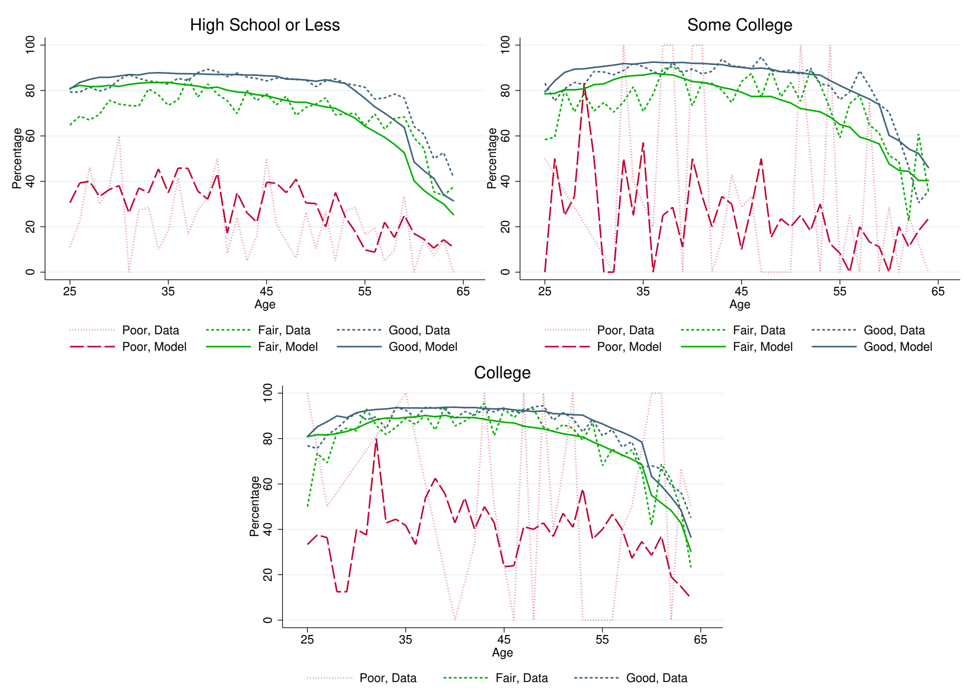


Figure 5: Distribution of FT Employment by Health and Age, Model and Data (MEPS)



Note: The figure is constructed for workers with no persistent health shocks (d^u or d^p).

Figure 6: Wage Profiles of Full Time Workers by Health, Model and Data (MEPS)

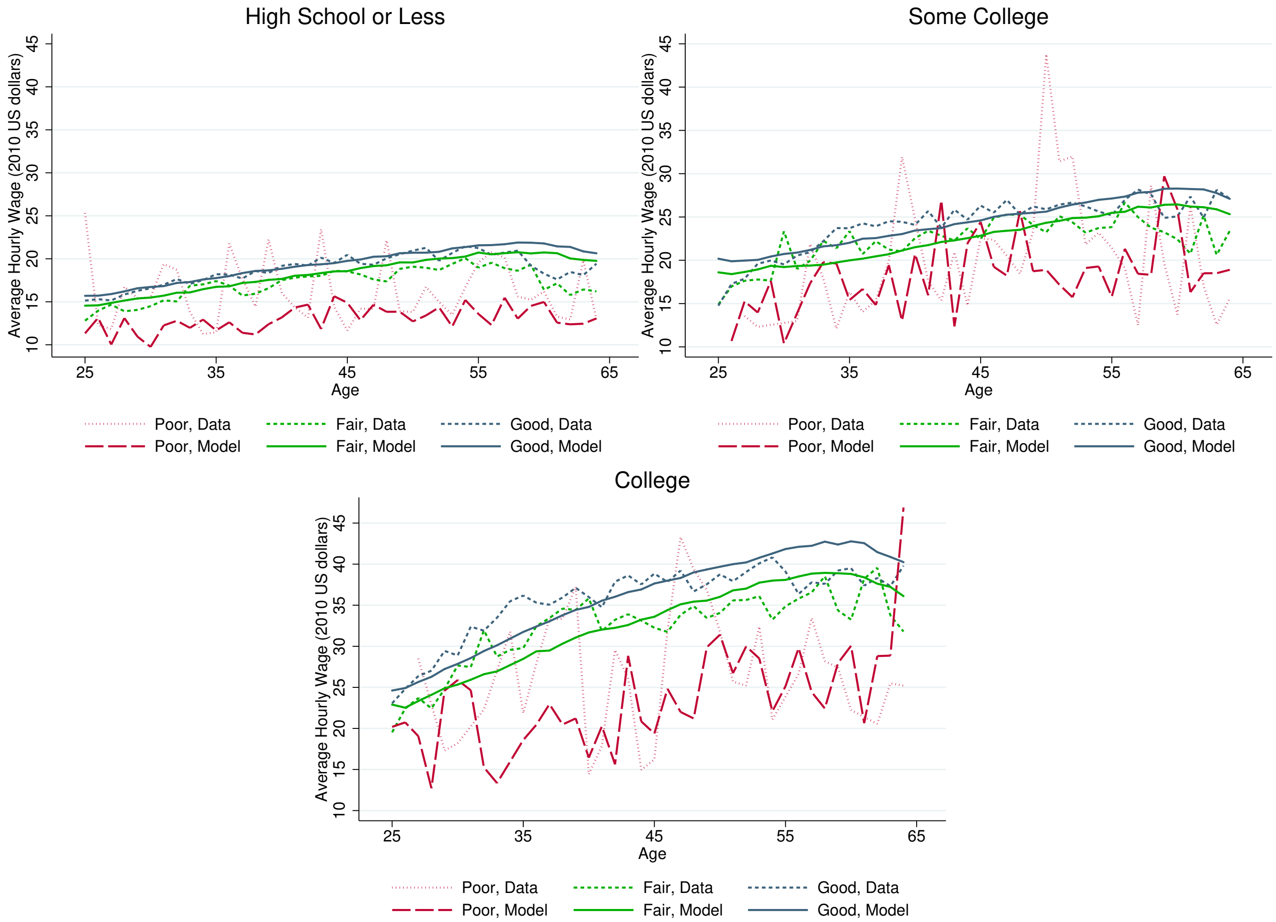
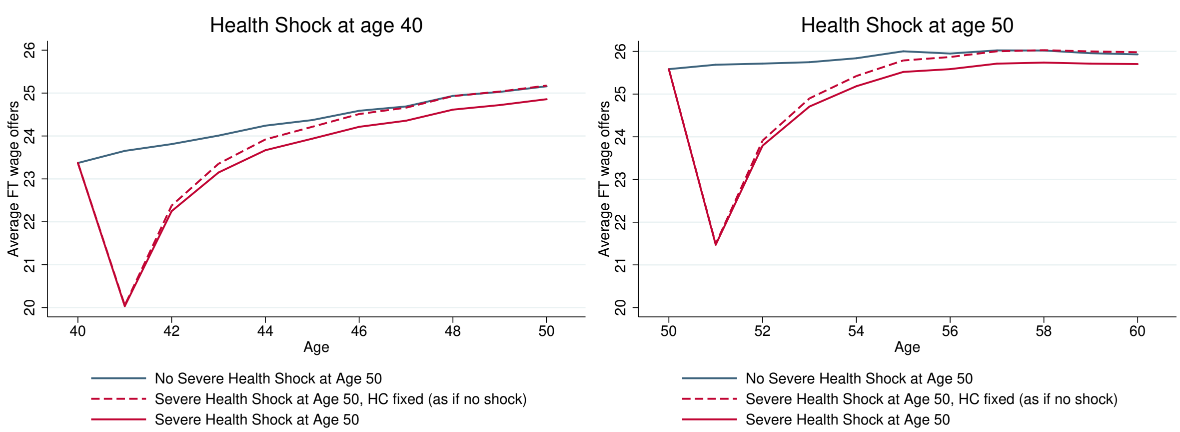


Figure 7: Effects of Severe Health Shocks on Average FT Wage Offers



Note: Severe health shocks are defined as in Section 7.1. Figures constructed for those in good or fair health at ages 40 (left panel) and 50 (right panel).

Figure 8: Income Inequality over the Life-cycle, Model and Data (CPS)

Note: Income equals earnings plus interest (both pre-tax). In the CPS, income inequality is calculated using men who are not in school or the armed forces. To reduce sensitivity of the Gini to outliers, we drop the top 2% of income observations at each age, as well as observations on employed workers with reported wage rates below the minimum wage. In the model, income is constructed using wages that include simulated measurement error.

Figure 9: Distribution of Medical Spending, Ages 25-64, Model and Data (MEPS)

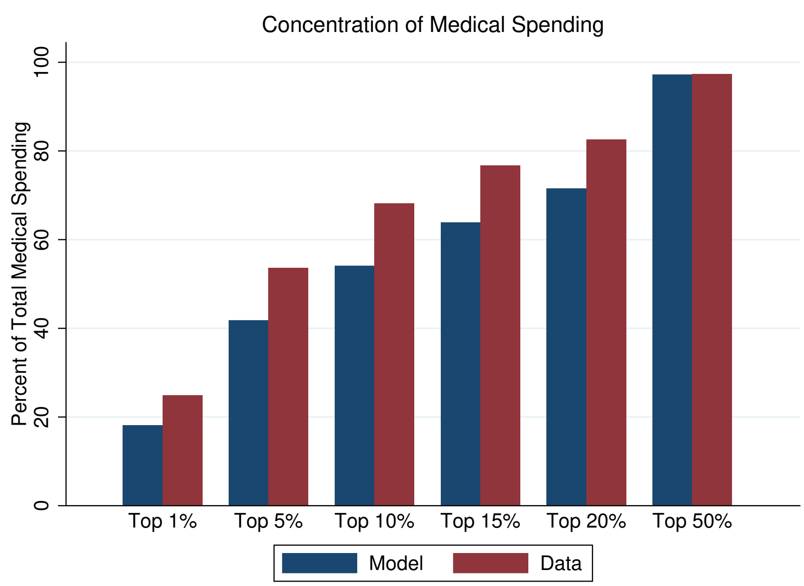


Figure 10: Income Inequality over the Life-cycle

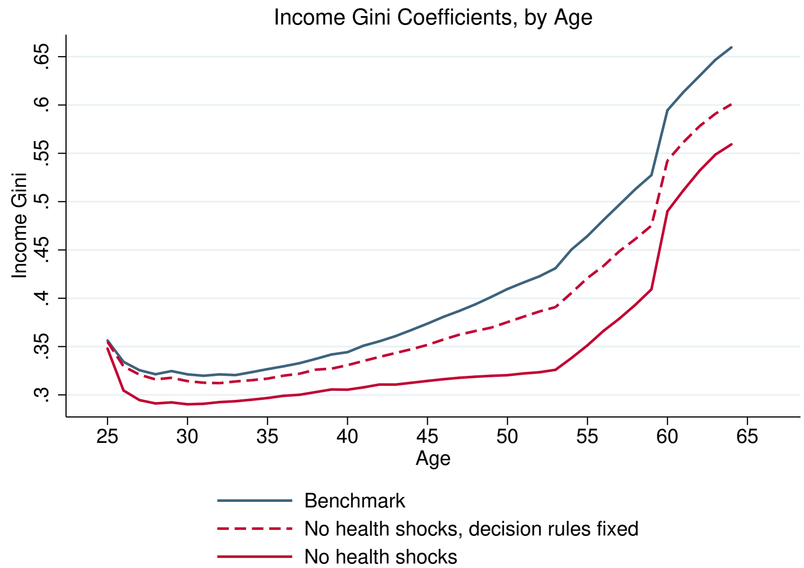
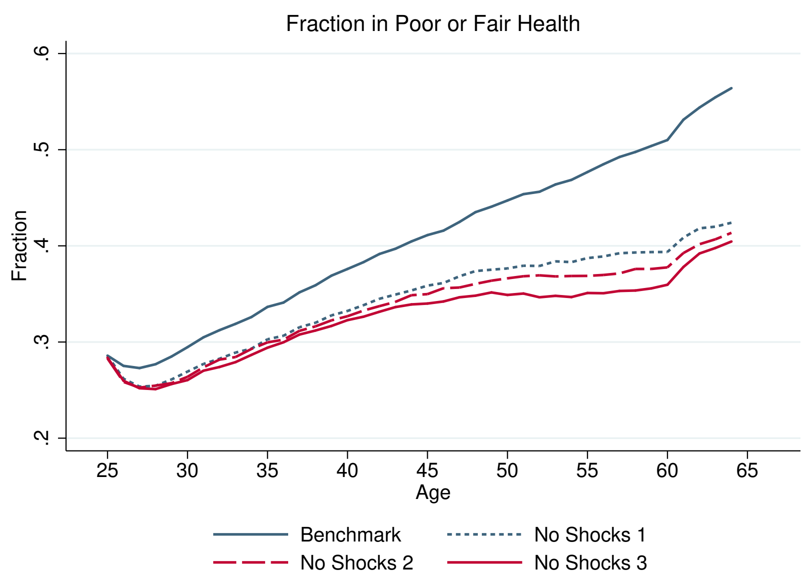
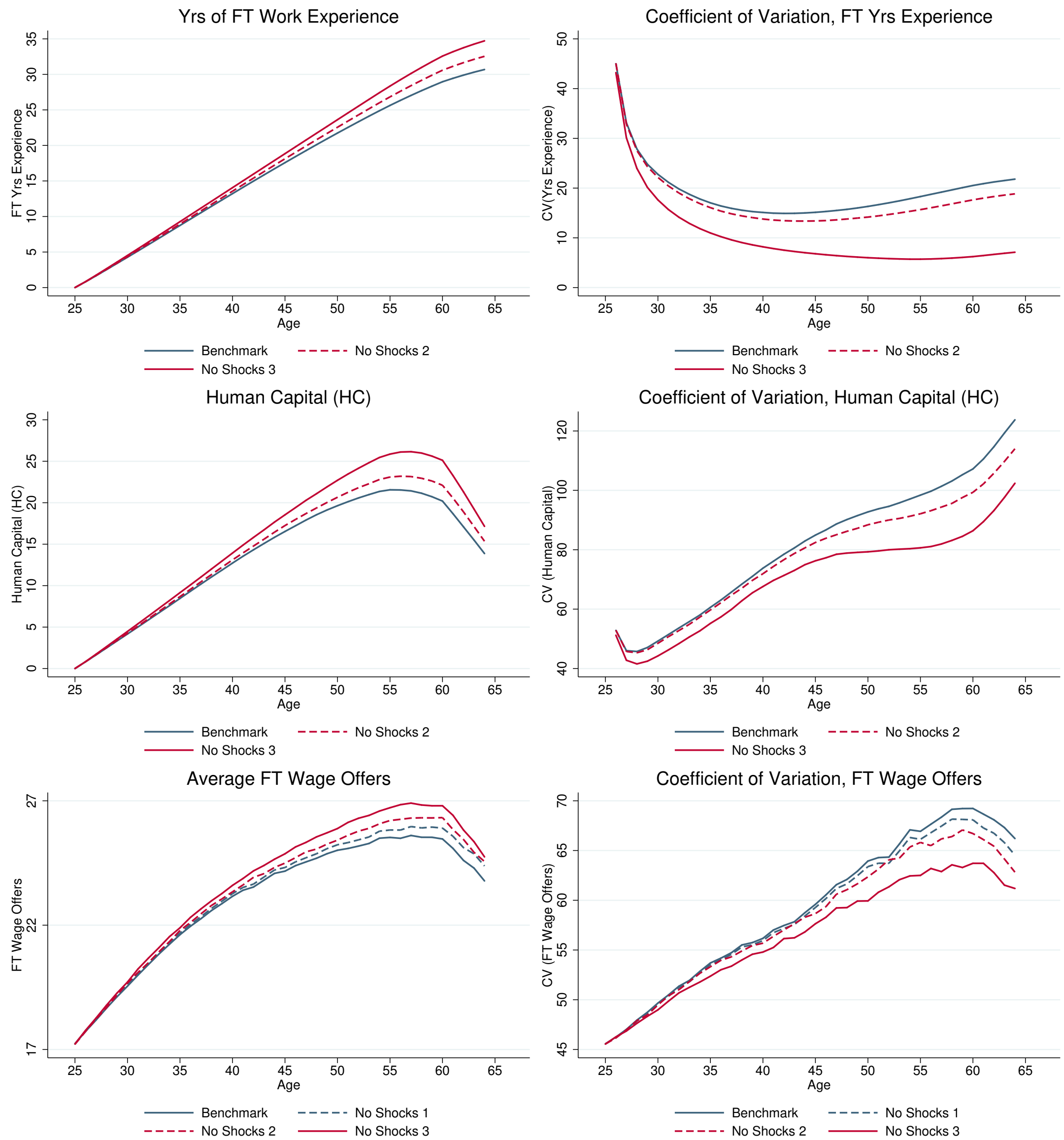


Figure 11: Effects of Health Shocks on the Distribution of H



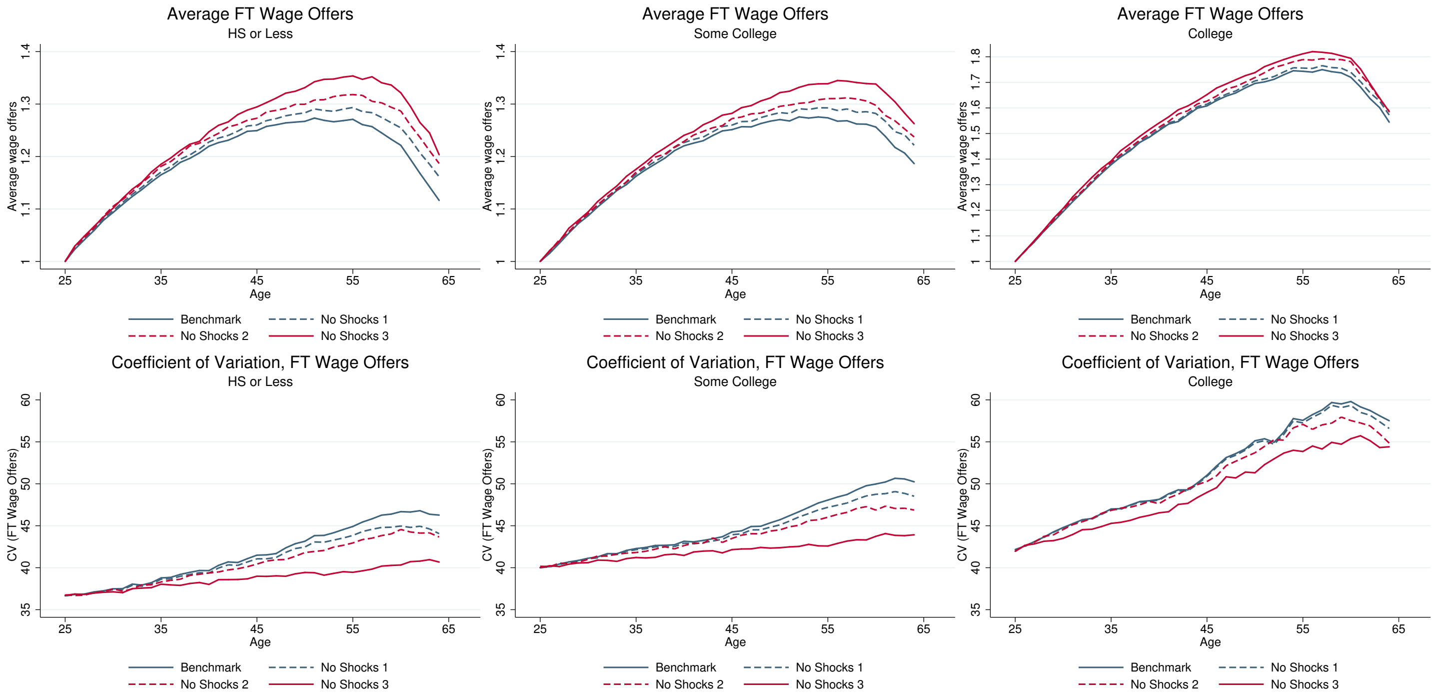
Note: In all three experiments we shut down health shocks at ages 25-64. (1) In "No Shocks 1" we hold employment, income and savings fixed at baseline values, so they cannot feedback and affect health. (2) In "No Shocks 2" we let agents adjust their labor supply and savings according to the optimal decision rules of the baseline model. (3) In "No Shocks 3" we let agents update their decision rules for labor supply and savings to reflect the new environment.

Figure 12: Effects of Health Shocks on Experience, Human Capital and Wage Offers



Note: In all three experiments we shut down health shocks at ages 25-64. (1) In "No Shocks 1" we hold employment, income and savings fixed at baseline values, so they cannot feedback and affect health. (2) In "No Shocks 2" we let agents adjust their labor supply and savings according to the optimal decision rules of the baseline model. (3) In "No Shocks 3" we let agents update their decision rules for labor supply and savings to reflect the new environment.

Figure 13: Effects of Health Shocks on Wage Offers, by Education



Note: In all three experiments we shut down health shocks at ages 25-64. (1) In "No Shocks 1" we hold employment, income and savings fixed at baseline values, so they cannot feedback and affect health. (2) In "No Shocks 2" we let agents adjust their labor supply and savings according to the optimal decision rules of the baseline model. (3) In "No Shocks 3" we let agents update their decision rules for labor supply and savings to reflect the new environment. In the figures, the mean full-time offer wage is normalized to 1.0 at age 25, within each education group. The actual means at age 25 are \$13.5, \$17.4 and \$21.4 for the High School, Some College and College groups, respectively.

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