Opportunity & Inclusive Growth INSTITUTE

FEDERAL RESERVE BANK of MINNEAPOLIS

INSTITUTE WORKING PAPER
No. 80

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November 2023

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DOI: https://doi.org/10.21034/iwp.80
Keywords: Health; Health shocks; Human capital; Income risk; Precautionary saving; Earnings inequality; Health insurance; Welfare
JEL classification: D91, E21, I14, I31

Health Shocks, Health Insurance, Human Capital, and the Dynamics of Earnings and Health*

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July 29, 2023

Abstract

We specify and calibrate a life-cycle model of labor supply and savings incorporating health shocks and medical treatment decisions. Our model features endogenous wage formation via human capital accumulation, employer-sponsored health insurance, and means-tested social insurance. We use the model to study the effects of health shocks on health, labor supply and earnings, and to assess how health shocks contribute to earnings inequality. We also simulate provision of public insurance to agents who lack employer-sponsored insurance. The public insurance program substantially increases medical usage by the uninsured, leading to improved health and life expectancy, which generates higher Social Security costs. But the program also creates positive labor supply incentives, and substantially reduces costs of social insurance, Medicaid and free care. On balance the net program cost is modest, and all agents in the model are *ex ante* better off in a balanced budget simulation. In contrast, improving access to Medicaid has perverse labor supply effects, does little to improve health, and makes almost all agents worse off in a balanced budget scenario.

Keywords: Health, Health Shocks, Human Capital, Income Risk, Precautionary Saving, Earnings Inequality, Health Insurance, Welfare
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*Capatina: Australian National University; Keane: Johns Hopkins University and UNSW. We thank Dr Philip Haywood for extraordinary assistance in classifying health shocks based on the International Classification of Diseases (ICD) codes. This research has been supported by the Australian Research Council grant FL110100247, the ARC Centre of Excellence in Population Ageing Research (CE110001029), and the John Mitchell Poverty Lab. We have received useful comments from participants at numerous conferences including the Carey Health Care conference 2023, the Econometric Society DSE conference at ANU 2022, the LAEF Conference Santa Barbara 2022, SED 2021, China Meeting of the ES 2021, the Mid-West Macro Conference 2019, the briq Workshop 2017, the IFS Welfare State Conference 2017, and seminars at JHU Economics (2022), Toulouse (2021), Wisconsin (2021), Hopkins Carey School of Business (2021), Autonoma Barcelona (2020), University of Connecticut (2019), University of Pennsylvania (2019), Temple University (2019), Atlanta Federal Reserve (2019), University of Toronto (2019), and Penn State University (2019). In particular, we are grateful for comments from Mariacristina De Nardi, Eric French, Karen Kopecky, Kai Zhao, Ponpoje Porapakkarm, Hamish Low, Victor Rios-Rull, and Hanming Fang.

1 Introduction

We embed health shocks in a life-cycle labor supply model with human capital formation, tied wage/hours/insurance offers, and medical treatment decisions. Our model includes both private and means-tested public health insurance. We use the model to assess how health shocks affect labor supply, earnings and health, and how these effects depend on the insurance environment. Our framework enables us to distinguish several channels through which health shocks affect earnings: Health shocks reduce earnings contemporaneously by generating lost work days, and they may reduce future health, which directly lowers productivity and tastes for work. Over time, health shocks also cause people to accumulate less work experience, slowing human capital accumulation and amplifying their impact on earnings.[1]

We seek to unify two approaches to modeling health in the life-cycle literature: Models in the tradition of Grossman (1972) view health spending as *voluntary* investment in health, while models like De Nardi et al. (2010) and French and Jones (2011) assume health shocks generate treatment costs that *must* be paid. We integrate these approaches by modeling agents' *choice* to treat health shocks and pay out-of-pocket (OOP) costs of treatment. OOP costs depend on health insurance coverage, which is endogenous in our model. Untreated shocks cause greater deterioration in health than treated shocks. Thus, the decision to obtain treatment, and pay the OOP cost, may be viewed as voluntary health investment.

We also extend prior work by modeling the multiple roles of health insurance. Insurance makes health care more affordable by lowering OOP costs, and helps smooth consumption in the face of health shocks. Insurance also plays a key role in giving access to care. The US has an employer sponsored health insurance (ESHI) system for those under 65. As proof of insurance is often required before treatment, working-age men who are not covered by ESHI may not have the option to treat. This plays an important role in explaining the worse health transitions of the uninsured. We also model the key features of the US system that conditional on being able to access treatment, the uninsured may have their bills paid by Medicaid or may have access to free care (i.e., an option to not pay their bills).

Our model allows us to assess how changes in the economic environment, such as providing health insurance to uninsured workers, would alter health outcomes, labor supply, human capital accumulation and earnings, as well as health care utilization and government expenses and revenues. Providing insurance to those without ESHI leads to a substantial increase in demand for care, as those who lack ESHI are intrinsically less healthy and suffer more health shocks than the insured. But it also generates substantial savings on means-tested social insurance and unpaid bills. It increases the labor supply of low skill workers, and hence tax revenue. It also improves health, and generates increased Medicare and Social Security costs due to increased life expectancy. On balance, we find the net cost of providing insurance to uninsured workers is modest, and all types of workers are *ex ante* better off in a balanced budget simulation that includes premiums and tax increases to pay for the plan.

A brief overview of our model is as follows: Working-age men begin each year with stocks of health, assets and human capital. Marital status and spouse employment/earnings are

[1] We define "human capital" as skill generated by education and work experience. "Health" also affects worker productivity in our model. The distinction is useful as it lets us assess both (i) effects of health shocks on earnings that arise because health directly affects productivity, and (ii) effects operating through human capital accumulation – that arise because health shocks cause people to accumulate less work experience.

also given, as is a man's permanent type (education, skill, latent health). The men then receive multidimensional job offers that may or may not include ESHI, from a distribution that depends on lagged employment and lagged ESHI coverage. The wage component of the offer depends on human capital, health and a transitory shock, and the disutility of working depends on health. After the employment decision is made, health shocks occur with probabilities that depend on health status. These shocks determine sick days and the level of OOP treatment cost. At this point, men who lack ESHI also draw their treatment/payment options, i.e., whether they can access treatment, and if so, whether they can treat and not pay (free care). The treatment/payment decision is then made. Finally, men make consumption/savings decisions. At the start of the next period, the individual survives with a given probability and new states are revealed (based on their laws of motion).

Some aspects of the model deserve further comment: First, to assess how health shocks impact labor supply, earnings and consumption, it is important to account for the roles of social insurance and free care. Following Hubbard et al. (1995) and 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. Workers who hit the consumption floor receive public coverage for medical expenses, approximating the means-tested Medicaid public insurance program. And following Finkelstein et al. (2018) we assume that uninsured agents may have access to free care – or, equivalently, that with some probability they can access treatment and then default on bills. In our model, the fact that treatment is a choice, the consumption floor exists, and free care may be available <u>all</u> help to shield uninsured workers from bearing the full cost of health shocks.

Second, our model of health and health shocks is more sophisticated than in prior work: Since its inception in Heckman and MaCurdy (1980) and MaCurdy (1981) the life-cycle labor supply literature has emphasized how agents respond to temporary vs. persistent and predictable vs. unpredictable wage shocks. In extending the life-cycle model to include health shocks, we recognize they can also be categorized in this way. Thus, in our model, agents are subject to health shocks that may be temporary or persistent, and unpredictable or predictable, based on risk factors such as hypertension and high cholesterol. This lets us analyze how different types of shocks affect the evolution of earnings over the life-cycle.

We calibrate our model to the U.S. white male population using the Medical Expenditure Panel Survey (MEPS) from 2000 to 2013, as well as additional data from the HRS, CPS and PSID. The MEPS contains detailed information on respondents' health status and medical conditions, which we use to construct measures of health shocks. The uninsured under-report health shocks (as they often do not treat), so we correct for this in the calibration.

Our model implies eliminating health shocks would increase the expected present value of lifetime earnings (PVE) for the average man by 11%, and reduce inequality in the PVE by 12% (as measured by the coefficient of variation). But we go beyond this calculation to quantify several channels through which health shocks affect earnings. At the broadest level, we distinguish between *direct* effects of health shocks and the *behavioral* effect of health risk:

First, we define "direct" effects of health shocks as those that arise in a given health risk environment (as determined by the probability distribution of shocks and the social insurance system). Over the life-cycle, agents experience differential exposure to health shocks due to the "luck of the draw." Those who experience more shocks tend to have reduced earnings via three channels: Reduced labor supply directly attributable to health shocks (holding job offers fixed), the knock-on effect of reduced human capital (work experience) that leads to worse job offers, and the knock-on effect of reduced health, which reduces wage offers and tastes for work. We call these the labor supply, human capital and direct health effects.

Second, we define the "behavioral" effect of health risk as the effect that arises because the risk environment influences agents' decision rules for labor supply, saving and treatment. We find two notable behavioral effects: In an environment with health risk, low-skill workers, who often lack ESHI, have an incentive to curtail their labor supply to maintain eligibility for means-tested social insurance. Conversely, health risk creates an incentive for high-skill workers to work and save more, in order to self-insure against medical expenses.

For the typical worker, if health shocks are eliminated, the labor supply, human capital, direct health and behavioral effects lead to 5.7%, 2.7%, 1.4% and 0.8% increases in earnings, respectively. For low skill workers the effects are much greater. For example, for high school men with low skill endowments, we have 10.7%, 14.8%, 1.3%, and 9.8%, respectively. This is why eliminating health shocks reduces inequality. When health shocks are eliminated, the labor supply, human capital, health and behavioral effects lead to 4.1%, 5.2%, 0.0% and 2.6% reductions in lifetime earnings inequality, respectively.

We find much of the impact of health shocks on earnings arises from the knock-on effects of reduced human capital accumulation in years following a shock. A health shock reduces work hours in the short run, and may cause workers to exit employment in the next period if health deteriorates, leading to reduced work experience. In subsequent periods this translates into lower offer wages and reduced probability of full-time offers. Low education/skill workers are more likely to exit employment following a major health shock, increasing both the total impact of the shock and the human capital effect. For example, for a typical 40-year-old male with high school or less, our model implies a major persistent health shock reduces the present value of remaining lifetime earnings by $55k$ or 11.5%. Fully 42% of this impact is due to reduced human capital accumulation after the shock. For a 40-year-old college graduate, the PVE drops by $54k$ or 5.6%, and only 34% is due to lost human capital.

Another key result is that in an environment with health risk, means-tested social insurance reduces incentives to supply labor and invest in human capital. Low-skill workers often have jobs without ESHI, so the combination of low wages, sick days and OOP costs often puts them on the consumption floor. This creates an incentive to simply rely on means-tested social insurance (the consumption floor) rather than supplying labor in the first place.[2]

Interestingly, the provision of public health insurance to agents who lack ESHI reduces this perverse labor supply dis-incentive. It increases labor supply of low-skill workers and increases tax revenue, which counteract a significant part of the cost of the program. To our knowledge this benefit of public health insurance has not been noted previously. Comparing the provision of public insurance to agents who lack ESHI with a program that enhances access to Medicaid, we find the latter is far inferior as it amplifies the labor supply dis-incentive and most agents are *a priori* worse off.

We outline the paper as follows: Section 2 reviews the literature and Section 3 presents our model. Section 4 describes our data, as well as the measurement model for correcting

[2] 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.

under-reporting of health shocks. Section 5 describes the calibration, and Section 6 discusses model fit. Section 7 presents our results on the effects of health shocks on health, labor supply earnings, and earnings inequality, and Section 8 presents our health insurance policy experiments. Section 9 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. 2022, Cole et al. 2018, and Hosseini et al. 2021). We extend this work by using a richer model of health shocks, incorporating endogenous human capital, including both ESHI and public insurance, as well as free care, and making treatment a choice.

Our work is also 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.

As health, human capital 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 major health shocks (cancer, heart and lung disease) have substantial negative effects on employment and earnings. For 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. 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. (2022), who find much larger effects of persistent shocks.

We show how Smith (1999, 2004)'s approach estimates the effect of a major health shock on workers who actually experience such a shock, which understates the effect on a typical worker. Selection arises because major health shocks are more likely to afflict workers who avoid treatment, and such workers tend to have low earnings even in the absence of a shock.

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, endogenize the medical treatment decision, and incorporate employer-sponsored and means-tested public insurance.

Our work also contributes to the literature on health insurance. The life-cycle models cited earlier emphasize its consumption-smoothing role. But Mahoney (2015) and Lockwood (2023) argue this is exaggerated in the US context, as workers who lack ESHI – i.e., the unemployed, low-wage workers and part-time workers, some workers at small firms – do not have to bear the full cost of health shocks. They can decide not to treat in non-emergency situations, in some cases they can obtain low-cost or free care from safety net providers (i.e., community health centers, urgent care clinics), and they can default on bills. We assess the impact of insurance on consumption inequality and lifetime utility in such an environment.

We contribute to a large literature that studies the effect of insurance coverage on access to care, health care utilization and health outcomes. The Institute of Medicine (2001) notes "Even though many publicly supported institutions offer free care or reduced fees and many other providers offer some charity care, people without insurance generally have reduced access to care... Uninsured adults are less likely to receive health services, even for certain serious conditions." Many studies document lower health care usage by the uninsured, even conditional on health status and health shocks: Baker et al. (2000) compare insured and uninsured people in similar health and find that even when suffering serious or morbid symptoms the uninsured go untreated 30% of the time, compared to 13% for the insured. Other notable examples are Marquis and Long (1994), Burstin et al. (1998), Schoen and DesRoches (2000), Hadley (2007) and Hoffman and Paradise (2008).

The Institute of Medicine (2002) surveys a large body of evidence showing the uninsured received less adequate care which leads to worse outcomes. They note the uninsured are much more likely to lack a regular source of care, and that the chronically ill uninsured receive inadequate ongoing treatment for their conditions. Notably, McWilliams et al. (2007b,a) show increased use of services and improved health when the uninsured become eligible for Medicare, especially among those with cardiovascular disease or diabetes. And Sommers et al. (2014) show the Massachusetts reform reduced mortality.

In the US the uninsured face not only cost barriers to treatment but direct access barriers as well: Emergency rooms are required to stabilize patients in emergency situations without asking for proof of insurance, but most needed and even urgent care is "elective" (i.e., not an immediate threat to life or limb), so it usually requires proof of insurance up front.[3] We develop a model where insurance plays both these cost-reducing and access-granting roles, and assess the importance of both for health and labor market outcomes.

Our paper is also related to the literature studying how means-tested social insurance affects labor supply (see Moffitt 1992, Keane and Moffitt 1998). 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. We also

[3] As American College of Emergency Physicians (2023) notes: "A patient is typically required to provide insurance and payment information before seeing a doctor. But, emergency departments are unique - anyone who has an emergency must be treated or stabilized, regardless of their insurance status or ability to pay."

examine how means-tested insurance reduces the importance of ESHI for low-skill workers, as it provides another way for the uninsured to avoid the full cost of health shocks.

There is a large literature studying the impact of education on health, but it faces difficult problems in assessing 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 (partly) on latent initial health and skills, which they control for using proxy variables in dynamic factor models. For instance, Hai and Heckman (2019) find "endowments" of skill and health at age 16 are positively correlated. The correlation grows with age as youth with high initial levels of skill and health invest more in both health and education, and education complements health investments.[4,5]

In contrast, our model starts at age 25, taking education and its correlation with initial health as given. Thus, we do not attempt to identify causality from education to health. We focus exclusively on explaining how education affects health transitions *after* school completion and labor market entry. We specify a health production function that depends only on lagged health, health shocks, treatment decisions and latent health type, so education does not enter directly. But education matters for health transitions because it affects investment in health (i.e., treatment decisions) via several mechanisms we explain in Section 3. Importantly, our model can explain the observed correlation between education and health transitions using these mechanisms, without education in the health production function.

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.

Our approach differs fundamentally from this literature: We assume that employment and income do not directly enter the health production function. Employment and income nevertheless matter for health in our model because they affect treatment decisions. Men with lower labor supply and earnings have lower capacity to invest in health via obtaining indicated treatment for health shocks. Hence, in an estimated health production function that omits controls for health shocks and treatment decisions, it is likely that unemployment and income will appear to be significant direct determinants of health, even if they only matter as mediators of investment decisions. We argue our approach is preferable, as it is unlikely the effects of unemployment/income in the production function are policy invariant. In contrast, effects of health shocks and treatment are plausibly invariant.

[4] In related work, García and Heckman (2021) use random assignment into early childhood education programs to document strong positive effects of education on health.

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

3 Model

In our life-cycle model agents face idiosyncratic risk to wages, employment, earnings, marital status, 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. From age 25 to 64, agents receive employment offers probabilistically each year, and decide on whether to accept or reject them. Retirement is exogenous at 65 but agents can stop working earlier. The agents are males, who are either single or married at the beginning of each period. Their health evolves stochastically over time, and they are subject to health shocks of various types with associated treatment costs. Once health shocks are revealed the agent's options depend on health insurance status. Those covered by employer sponsored health insurance (ESHI) always have access to care and choose whether to get treated and whether to pay or default on the medical bill. However, those lacking ESHI face a positive probability of not having access to treatment, and conditional on access, they may (or may not) be required to pay the bill to get treatment (i.e., default is possible probabilistically). All individuals 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.

We consider three education groups: (1) high school (HS), which includes both graduates and dropouts, (2) some college (1-3 years), and (3) college graduates.[6] Within education groups, agents are also characterized by two latent health types denoted by ε^h, where $\varepsilon^h \in \{Bad, Good\}$ and by 3 latent skill types denoted by $\varepsilon^s \in \{L, M, H\}$. As we will see below, latent health and latent skill are defined as fixed effects in the health and wage functions, respectively. We allow most model parameters to differ by education group.

3.1 The Timing of Decisions and Shocks

Agents enter the first model period (age 25) with education e, latent health ε^h, and latent skill ε^s. An agent's permanent state is thus summarized by $(e, \varepsilon^h, \varepsilon^s)$. Agents begin each annual period (i.e., age t) with stocks of assets A_t, work experience X_t, functional health H_t,

[6] 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%), which made calibrating a separate model for them impractical. So we combine them with the HS graduates (29%).

asymptomatic risk factors R_t, and marital status M_t. Lagged employment status, including health insurance coverage, is also a state variable that we denote by O_{t-1}. For married men, the spouse's employment status and income are also known. At this point (i.e., at the start of each model period) the agent dies with a probability that depends on H, e, t and M.

Working age individuals then receive an employment offer that we denote by O_t^*. The offer may be full or part-time, and with or without employer sponsored health insurance (ESHI), with probabilities that depend on lagged employment and insurance status O_{t-1}. Wage offers are determined by human capital, functional health, lagged employment status, and a stochastic component. Agents then decide whether to accept or reject the tied wage, hours and insurance offer, and their actual status is then denoted by O_t.

After employment and insurance status are determined, health shocks are realized. Then, sick days are revealed and OOP treatment costs are drawn from a distribution that depends on health shocks, insurance status, and functional health. At this point, agents must decide whether to get treatment, and, if treated, whether to pay the OOP cost or default. Lack of treatment leads to worse health transitions, while default incurs a stigma cost. Agents who lack health insurance face higher OOP costs, and their treatment/payment options - which may be restricted - are drawn probabilistically as described in Section 3.5.

Next, agents make a continuous consumption/saving decision. Those who cannot afford a minimum consumption level receive a transfer from the government. The consumption floor, which is contingent on family status, is meant to proxy for Foodstamps, disability benefits, Medicaid and other means-tested social insurance programs. Finally, transitions for health status and other next period state variables are realized, and the next period begins.

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 asymptomatic health risk (R_t). 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 affects productivity. It can take three values: poor, fair or good, $H_t \in \{P, F, G\}$. In contrast, health risk R_t captures asymptomatic risk factors that increase the probability of health shocks, but that do not affect current productivity. Key risk factors are obesity, high cholesterol and hypertension, which increase the probability of heart disease, heart attack and stroke. R_t takes two values: low and high ($R_t \in \{L, H\}$). 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 "serious" health shocks that affect the ability to function in the *current* period (year) for at least two weeks. As we discuss in Section 4, we ignore minor health events like colds. The persistence of shocks is categorized as short or long-term. For example, a broken limb is a short-term shock that affects the agent *only* in the current period. Long-term shocks, such as a stroke, have effects that last for multiple periods. Our model captures this by letting the transition probabilities for H_t depend on persistent shocks (d_t^p, d_t^u).

We also distinguish between "predictable" and "unpredictable" health shocks. Obviously predictability falls on a continuum. We call d_t^p shocks "predictable" because they are strongly predicted by education and risk factors R. We call d_t^u and s shocks "unpredictable" because they are not significantly predicted by education and only weakly predicted by R. Section 4 explains this distinction in more detail.[7]

Table 1 lists the state variables that enter the transition probabilities for H_t and R_t, the probabilities of health shocks d_t^p, d_t^u and s_t and the survival probability.

Table 1: Health Transitions and Health Shocks

Variable	Transition Probability Matrix / Probability
H_t	$\Lambda_H(H'\|H, \varepsilon^h, t, d^p, d^u, (I_\Upsilon, I_{treat}))$
R_t	$\Lambda_R(R'\|R, t, H)$
d_t^p	$\Gamma^{dp}(H, R, t, e)$
d_t^u	$\Gamma^{du}(H, R, t)$
s_t	$\Gamma^s(H, R, t)$
I_{surv}	$\varphi(H, e, t, M)$

The transition probabilities for functional health H depend on current health, latent health, age, and the persistent (long-term) health shocks d^p and d^u. If a health shock occurs ($I_\Upsilon = 1$) transition probabilities depend on treatment status (I_{treat}).[8] Notice that R only affects the transition probability for H via its influence on the frequency of health shocks.

Latent health type ε^h enters H transition function Λ_H, which we specify as an order logit, as a fixed effect. Thus, "latent health" captures unmeasured time-invariant individual characteristics that influence health transition rates. A person with good latent health might be called robust or resilient, as they have a high probability of remaining in good health as they age, even if they experience adverse shocks. The Λ_H function does not depend on education as latent health already captures any time-invariant characteristics. Section 3.7.4 describes how education is correlated with latent types.

The transition probability for R only depends on lagged R, H and age. Interestingly, health shocks and education do not have additional predictive power. The probabilities of the initial H and R states at age 25 are given by $\Gamma^R(R)$ and $\Gamma^H(H|e, \varepsilon^h)$.

Finally, the year-to-year survival probability $\varphi(H, e, t, M)$ depends on functional health, education, age and marital status.

3.3 Medical Treatment Costs and Charges

The OOP medical treatment cost is given by $OOP(ins, t, \Upsilon, H, \varepsilon^C)$. This OOP bill is to be distinguished from actual OOP payments which could be zero in the case of non-treatment or non-payment. The OOP bill depends on ESHI coverage (ins), functional health (H), current health shocks $\Upsilon_t = (d_t^p, d_t^u, s_t)$, age t, and a binary shock ε^C which determines if the person faces the "normal" OOP treatment cost for their state or a higher "catastrophic" level of cost. We assume the probability of a catastrophic shock $\delta = Pr(\varepsilon^C = 1)$ is uniform across

[7] There are very few medical conditions that are both predictable and short-term, so this category is not included in the model. All short-term (s) shocks are assumed to be unpredictable.

[8] If the individual has multiple shocks, we only allow for the choice to treat all of them or none.

the states $(H_t, \Upsilon_t, t, ins)$, but the catastrophic *level* of costs can vary across the states. We fit the OOP function to actual data on OOP costs of men with ESHI in MEPS, to capture nonlinearities in the function (deductibles, OOP maximums). For the uninsured, we assume OOP costs are equal to a 40% discount on medical charges, as we explain in Section 5.3.

Agents aged 65+ are covered by Medicare, so their $OOP(\cdot)$ is independent of ins. The OOP treatment cost is net of what ESHI or Medicare pay, but does not take into account Medicaid. As explained in Section 3.8, eligibility for Medicaid is a function of $OOP(\cdot)$.

3.4 Health Insurance

Health insurance is of three types: (1) employer sponsored (ESHI), (2) Medicare, and (3) all other forms of public insurance captured by the consumption floor. ESHI is available to a fraction of workers as we discuss in Section 3.7.1, and we define ins as an indicator for whether a worker has ESHI. Workers whose employers provide health insurance pay a (subsidized) out-of-pocket premium p^{EI}. We do not model privately purchased insurance as only a small fraction of individuals had such insurance prior to the ACA. All men 65 and over pay the Medicare premium p^{Med}, and a payroll tax τ^{Med} is paid by all workers.

The consumption floor, which captures an array of social insurance programs including Medicaid, is described in detail in section 3.8.1. To capture disability benefits in a simple way, we assume working age people in poor functional health are eligible for a higher consumption floor. This is meant to approximate benefits from the SSI and SSDI programs.

3.5 Treatment/Payment Options

An important feature of our model is that we generalize earlier work by assuming agents have treatment and payment options. Consider a man aged 25-64 who is covered by ESHI. After health shocks and OOP treatment costs are revealed, he must decide whether to treat, and, if treated, whether to pay the OOP cost or default. Failure to treat worsens H transition probabilities, while default generates a stigma cost κ, meant to capture costs of default we do not explicitly model (loss of credit rating, dealing with collection agencies, etc.).

In contrast, to capture how insurance affects access to care, we assume a man aged 25-64 who lacks ESHI may be constrained in his options. There are three possible cases: treat/pay options both available, treat option not available, default option not available. Let I_{treat} and I_{pay} denote the treatment and payment decisions, while $J(ins)$ denotes the set of possible choice sets. The choice set of the insured contains all three treatment/payment options:

$$J(ins = 1) = \big\{(I_{treat}, I_{pay}) \in \big\{(1,1), (1,0), (0,0)\big\}\big\} \tag{3.1}$$

However, those lacking ESHI have three possible choice sets:

$$J(ins = 0) = \big\{(I_{treat}, I_{pay}) \in \langle\big\{(1,1), (1,0), (0,0)\big\}, \big\{(0,0)\big\}, \big\{(1,1), (0,0)\big\}\rangle\big\} \tag{3.2}$$

The first possible choice set contains all three treatment/payment options, the second is empty (treatment not available), and the third contains only two options (treat and pay or not treat). For the uninsured, the probabilities of the three mutually exclusive cases are given by a vector of probabilities $\psi(J(ins = 0)|H, t)$ that depends on health status and age.[9]

[9] We let the probabilities depend on H and t because men who are in worse health or older are more likely to experience more serious shocks, and shock severity is likely related to treatment/payment options.

Notably, we find that a simpler model where men who lack ESHI always have all three treatment/payment options cannot fit the data. In such a model, only stigma prevents the uninsured from *always* choosing to treat/default. But this causes them to treat and pay small bills, while defaulting on large bills. The data is not consistent with such a neat division. Furthermore, we observe that men without ESHI obtain treatment at a substantially lower rate than men with ESHI. Even a very high stigma is insufficient to induce the uninsured to go untreated at such a high rate if the treat/default option is always available. And very high stigma essentially precludes defaults, which are common in fact. Thus, to fit the data, we find it necessary to *restrict the uninsured's access to care.* In fact, we calibrate stigma cost κ=0 for the uninsured, so they always accept free care when it is available.

Men who are 65 or older have Medicare coverage. To simplify the model we assume they always treat and pay the OOP cost. Thus $J = \{(I_{treat}, I_{pay}) \in (1, 1)\}$.

3.6 Marital Status

At the beginning of each period, men are either single or married, $M_t \in \{\text{Single, Married}\}$. Marital status evolves according to the transition matrix $\Lambda^M(M'|M, e, t, H, inc, O)$ with initial probability $\Gamma^M(e, H)$ at age 25. We assume that after age 65 there is no transition into marriage, and only transitions to single.

For married men of working age, the spouse's employment status ($emp^w \in \{0, 1\}$), her income (inc^w), and out-of-pocket medical costs (OOP^w) are all revealed at the start of the period. None of these are choices. The spouse is employed with probability $\Pi^w(e, t, \varepsilon^s, H)$. Her income is given by the deterministic function $inc^w(emp^w, e, t, \varepsilon^s, H)$. These functions depend on the husband's education (e), age (t), and latent skill (ε^s) to capture assortative mating. They also depend on the husband's health, as spouses can potentially adjust their labor supply in response to the husband's earning capacity. We do not model the spouse's labor supply decision, but the Π^w and inc^w functions capture observed correlations between husband characteristics and spouses' employment/income. Once the husband turns 65, the spouse stops working, and the household receives Social Security benefits (see section 3.8).

3.6.1 Spousal Health Insurance and Medical Costs

The spouse's ESHI status is given by the indicator ins^w. We assume that the spouse is covered by ESHI if she is employed or if the husband is covered by ESHI (i.e., $ins^w = 1$ if $emp^w = 1$ or $ins = 1$).[10] Her OOP medical costs are given by the deterministic function $OOP^w(ins^w, t, e)$, and these costs are always borne. The husband's age and education enter this function as these are correlated with the wife's health and age.

For simplicity, we do not allow for the possibility that married men can be covered by their spouse's insurance. We justify this assumption by noting that only 1.3% of working age men in MEPS receive insurance through a working spouse.[11] As women tend to have frequent transitions in and out of employment, they may frequently lose their ESHI, creating an extra incentive for married men to seek jobs with ESHI.

[10] In MEPS, 93% of spouses of white males aged 25-64 had ESHI from their own employer if they worked full time. So assuming employed spouses always have insurance is a good approximation. In addition, 93% of wives who lack their own ESHI – but whose husbands have ESHI – are covered by the husband's insurance.

[11] We estimate 26.5% of working age men have working spouses with ESHI, but the large majority of these men hold ESHI from their own employer.

We also abstract from modeling the spouse's decisions about medical treatment and payment of medical bills, as this would vastly complicate the model. We instead assume the household takes the wife's OOP health care costs as given and must pay them.

Denote the household ESHI premium by $p^{EI}(ins, ins^w)$. Couples where both are covered by ESHI pay a family premium that is less than twice the single premium, so $p^{EI}(1,1) < 2p^{EI}$. As Medicare is an individual plan, each spouse pays the same premium p^{Med}.

3.7 Employment and Wages

3.7.1 Employment Offers (Wage, Hours and Insurance)

In each period men aged 25-64 receive employment offers O^* characterized by a wage, number of hours, and whether the offer includes ESHI. Thus we have $O^* = \{W^*, h^*, ins^*\}$. The hours offer h^* takes one of three values, $h^* \in \{0, PT, FT\}$, where PT and FT denote part and full-time hours. After agents accept/reject their employment offer, employment and health insurance status are given by $O = \{W, h, ins\}$. We let I^O be a 1/0 indicator for whether the employment offer is accepted.

It is useful to define the categorical variable $O^{**} = \{h^*, ins^*\}$ that summarizes the five possible combinations of hours and insurance.[12] The probability of receiving each type of offer O^{**} depends on employment and insurance status in the previous period, as well as education and age. Thus we have the vector of offer probabilities $\mathit{\Pi}(O^{**}|h^*_{t-1} \cdot I^O_{t-1}, ins_{t-1}, e, t)$. For example, having a full-time job with insurance last period increases the chance of being offered such a job today. At age 25, the probability of offers is given by $\mathit{\Pi}_{t=25}(O^{**}|e)$.

When employment offers are accepted or rejected, treatment costs 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* treatment costs. For married individuals, the spouse's medical costs are deterministic and already known.

3.7.2 Hours Worked and Sick Days

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

Given the annual timing of our model, and our assumption that contractual hours are fixed annually, what we define as "sick days" incorporates the entire short-run (intra-year) labor supply response to health shocks. Thus, what we call "sick days" refers to the total reduction in annual days of work due to health shocks, which is a very different concept from the sick days that workers may be entitled to in an employment contract.[13] 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 – consistent with our definition – and also that sick days do not contribute to leisure time.

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

[12] The five possibilities are: no offer, PT offer with/without insurance, and FT offer with/without insurance.

[13] A typical US worker has 7 paid sick days per year, Bureau of Labor Statistics (2023), which are likely used up on the minor illnesses of less than two-week duration that we do not count as health shocks.

may force workers to reduce work hours. In Table 2 we present descriptive evidence supporting these modeling assumptions. We run regressions of labor market outcomes on health shocks, along with controls for lagged health and human capital, using data from the MEPS. The 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. But we see significant declines in work hours and annual earnings following all types of shocks (d^p, d^u, s). Note also that the estimated effects of persistent shocks (d^p, d^u) on hours and earnings are several times larger than those of transitory health shocks.

3.7.3 Human Capital Accumulation and the Wage Offer Function

Let X denote years of work experience, which evolves as $X_t = X_{t-1} + h_{t-1}$. The wage offer function is given by:

$$lnW^* = w(e, X, h_{t-1}, H, h^*) + \varepsilon^s + \varepsilon \tag{3.3}$$

$$\begin{aligned} w(e, X, h_{t-1}, H, h^*) = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 X^3 + \beta_4 I_{h_{t-1}=0} \\ + \beta_5 I_{H\in\{F,G\}} + \beta_6 I_{H=G} + \beta_7 I_{h^*=PT} \end{aligned} \tag{3.4}$$

where the parameters β_1-β_4 capture effects of work experience, β_5-β_6 capture effects of health, and β_7 captures any difference between full and part-time offer wages. Crucially, we allow all parameters β_0-β_7 of (3.4) to differ by education. For instance, we expect more educated workers to have faster wage growth with experience (Imai and Keane (2004)).

The function $w(e, X, h_{t-1}, H, h^*)$ combines human capital with functional health H to determine the mean of the (log) offer wage distribution. Human capital is determined by education e, which shifts β_0-β_7, and work experience X. It also depends on lagged employment status, to capture depreciation of human capital if a worker spends time in unemployment, as in Keane and Wolpin (1997). Health enters through $I_{H\in\{F,G\}}$ and $I_{H=G}$, which indicate fair/good or good health, respectively. We also let the mean of the wage offer distribution depend on $I_{h^*=PT}$, an 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 also depend on the agent's latent skill type ε^s and transitory shocks ε_t. The latent type ε^s is age invariant and discrete, as in Keane and Wolpin (1997). We specify there are three skill types (low, medium, high), and the three grid points may differ by education. Transitory wage shocks are distributed as $\varepsilon \sim N(0, \sigma^2_\varepsilon)$.

3.7.4 Correlated Unobserved Heterogeneity in Health and Skill Types

Importantly, we allow the latent skill types ε^s in 3.3 to be correlated with the latent health types ε^h that appear in the H transition function – see Section 3.2. Within each of the three education groups we allow for three latent skill and two latent health types. The type probabilities are given by $\Lambda^\varepsilon(\varepsilon^h, \varepsilon^s, e)$. De Nardi et al. (2022) adopt a similar set-up, and argue there is a strong positive correlation between skill and health types.

Our model begins at age 25, so latent skill types capture both innate skill endowments and investments in human capital prior to age 25. Similarly, health types capture both innate endowments that make some people more resilient than others, and investments in health prior to age 25 that promote resilience. Our latent health types may also capture persistent differences across agents in healthy/unhealthy behaviors. There is substantial evidence that health behaviors are persistent, cluster together, and are largely determined in adolescence (e.g., Sawyer et al. (2012)). See, e.g., Lushniak et al. (2014) on smoking, Huurre et al. (2010) and Degenhardt et al. (2013) on drinking, De Moor et al. (2011) and Van Der Zee et al. (2019) on exercise and Reilly and Kelly (2011) and Singh et al. (2008) on obesity.

3.8 Taxes, Social Security and Social Insurance

All men retire at age 65 and receive Social Security (SS). Modeling SS benefits is complex as they depend on a person's entire earnings history. We approximate the system by assuming the SS benefit depends on a person's education, latent skill and work experience at age 65, as these are highly correlated with lifetime earnings. The household level SS benefit is given by the function $SS(X_{65}, e, M, \varepsilon^s)$ that we design to capture the highly progressive nature of SS system. For married couples, the SS function only depends on husband characteristics.

For men aged 25 to 64, taxable household income y_t equals capital income plus the sum of husband and spouse labor income, minus the household's ESHI premium $p^{EI}(ins, ins^w)$, minus payroll taxes tax^{SS} and tax^{MED}, minus the tax deductible part of OOP medical expenditures d^{MED}. Taxable income for retirees is similar, except Social Security income replaces labor income. Letting I_{pay} be an indicator for paying the OOP medical bills and I_M an indicator for being married, the household's taxable income is:

$$y_{t<65} = max[0, rA + W^* \cdot h + inc^w \cdot I_M - p^{EI}(ins, ins^w) - tax^{SS} - tax^{Med} - d^{Med}] \quad (3.5)$$

$$y_{t\geq 65} = max[0, rA + SS - p^{Med} \cdot (1 + I_M) - d^{Med}] \quad (3.6)$$

The payroll (i.e., Social Security and Medicare) taxes (tax^{SS}, tax^{Med}) and the tax deductible part of OOP medical expenditures (d^{Med}) are given by:

$$\begin{aligned} tax^{SS} &= \tau^{SS} \cdot min(W^* \cdot h - ins \cdot p^{EI}, \, \overline{y}_{ss}) + \tau^{SS} \cdot min(inc^w - (1 - ins)p^{EI}, \, \overline{y}_{ss}) \\ tax^{Med} &= \tau^{Med} \cdot (W^* \cdot h - ins \cdot p^{EI}) + \tau^{Med} \cdot (inc^w - (1 - ins)p^{EI}) \\ d^{Med} &= \begin{cases} max(0, I_{pay}OOP + OOP^w - 0.075(rA + W^*h + inc^w)) & \text{if } t < 65 \\ max(0, OOP + OOP^w - 0.075(rA + SS)) & \text{if } t \geq 65 \end{cases} \end{aligned}$$

Social Security taxes are paid by each employed household member (on his/her own earnings) at the rate τ^{SS} up to the threshold earnings level of $\overline{y}_{ss}$. The ESHI premium is subtracted from the husband's taxable income if he has ESHI, and from the spouse's taxable income otherwise. The Medicare tax is similar but it does not have a maximum.

All households pay an income tax $T(y)$ given by:

$$T(y) = max(0, y - \lambda(M)y^{1-\tau(M)}) \quad (3.7)$$

where $\tau(M)$ determines the degree of tax progressivity and $\lambda(M)$ is a shift parameter that determines average taxes (as in Benabou (2002) and Heathcote et al. (2017)). We let both λ and τ depend on marital status M. Total income and payroll taxes are given by:

$$Tax = T(y) + tax^{SS} + tax^{Med} \quad (3.8)$$

Consumption is taxed at the rate τ^c which captures sales taxes.

3.8.1 Government Transfers

Following Hubbard et al. (1995), we introduce a means-tested social insurance program that guarantees a minimum household consumption level, $\bar{c}(e, I_{H=Poor}, M, t)$. The consumption floor approximates a range of benefits we do not explicitly model, such as Medicaid, Food stamps, unemployment, Social Security Disability Insurance (SSDI), and Supplemental Security Income (SSI). We let the consumption floor differ by marital status, as families are eligible for a much wider array of benefits than single men. To capture disability benefits in a simple way, we assume working-age men in poor functional health are eligible for a higher consumption floor (see Benítez-Silva et al. 1999 and Low and Pistaferri 2015). We also let the floor differ by education, as some benefits like SSDI and UI depend on previous income.

A household whose disposable income plus assets (cash on hand) minus *actually paid* OOP medical expenditures leaves them with inadequate resources to achieve the consumption floor receives a transfer tr that compensates for the difference. Disposable income is given by:

$$Y^D{}_{t<65} = rA + W^* \cdot h + inc^w \cdot I_M - p^{EI}(ins, ins^w) - Tax \tag{3.9}$$

$$Y^D{}_{t\geq 65} = rA + SS - p^{Med} \cdot (1 + I_M) - Tax \tag{3.10}$$

and, noting that it costs $(1 + \tau^c)\bar{c}$ to consume $\bar{c}$, the transfer is given by:

$$tr_{t<65} = max\{0, (1 + \tau^c)\bar{c} + I_{pay}OOP + OOP^w - Y^D{}_{t<65} - A\} \tag{3.11}$$

$$tr_{t\geq 65} = max\{0, (1 + \tau^c)\bar{c} + OOP + OOP^w - Y^D{}_{t\geq 65} - A\} \tag{3.12}$$

We emphasize that for households headed by working-age men, the OOP costs incurred by the man are a choice, as reflected by the $I_{pay}OOP$ term in (3.11). As noted in Section 3.5, men with ESHI have the full set of treatment/payment options, while options of men without ESHI may be restricted. Whenever a man has access to care, and decides to treat and pay, his household is eligible for the floor if his decision generates a positive level of $tr_{t<65}$ in (3.11).[14] As we see in (3.12), men who are 65+ always pay OOP costs.

3.9 Preferences

Agents derive utility from consumption (c) and leisure (l), and incur a stigma cost if they default on medical bills, $\kappa(ins)$, that depends on insurance status. In fact, we calibrate κ=0 for the uninsured and κ»0 for the insured.[15] Upon death agents obtain utility from bequests (U_{Beq}) and incur a death cost (ζ). The within-period utility function is given by:

$$u(c, l) = \frac{1}{1 - \sigma}[c^\alpha l^{(1-\alpha)}]^{(1-\sigma)} - (1 - I_{pay})\kappa(ins) + I_{death}(U_{beq} + \zeta) \tag{3.13}$$

We assume private consumption of married men equals household consumption C divided by the family size adjusted by the Oxford equivalence scale, $E(t, e)$.[16]

[14] If a household that pays OOP expenses sits below the floor we say it "receives Medicaid." If a household that does not pay OOP costs sits below the floor we say it "receives social insurance (SI) transfers."

[15] We explain this calibration of stigma in Section 5.4 and Appendix C.8.4. Briefly, the data suggest men with ESHI rarely default, while men without ESHI default at a high rate. Intuitively, it is plausible that stigma is low for the uninsured, who often obtain care from safety net providers who anticipate a high default rate. In contrast, the sorts of providers the insured deal with are more likely to aggressively pursue claims.

[16] The Oxford scale is 1.0 for a single person, 1.5 for a couple, plus 0.3 for each child. We assume married men have the average number of children at home that we see in the CPS, by age and education.

Our specification of leisure time accounts for time devoted to market work, time lost to illness, and time devoted to housework. We normalize the time endowment to 1, and write:

$$l = 1 - h - sd(e, H, \Upsilon) - F(I^O, H) - hw(M, h^* \cdot I^O, emp^w). \tag{3.14}$$

where I^O is the employment indicator defined in Section 3.7.1. The term $F(I^O, H)$ is a fixed cost of work that varies with health, as workers in poor health have greater disutility of work.

The term sd is sick days as defined in Section 3.7.2. Note that we subtract off sick days from leisure regardless of whether the person works. Thus, sick days generate time off work but do not provide additional leisure to workers, and they reduce leisure for non-workers.

Finally, the term hw is the time men must devote to housework, which differs by marital status, contracted work hours h^* and employment status, and the wife's employment status. We normalize $hw = 0$ for single men, so housework time is measured relative to single men.[17]

In addition, we assume a utility cost of death ζ that is incurred only in the period when the individual dies. We introduce this feature because the first term of 3.13 can be negative. This is not a problem in life-cycle models without endogenous 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 disutility of death avoids this problem.

Following De Nardi (2004), we specify the utility from leaving bequest B as:

$$U_{Beq}(B) = \theta_{Beq} \frac{(B + k_{Beq})^{(1-\gamma)}}{1-\gamma} \tag{3.15}$$

where θ_{Beq} determines the strength of the bequest motive and k_{Beq} determines the extent to which bequests are a luxury good. Agents save to smooth consumption (precautionary motive), to finance retirement, and to leave bequests.[18]

3.10 Summary of Model Mechanisms

Our model contains several mechanisms that drive the observed strong correlations between health and wealth/income. Obviously, correlation between latent health and skill types is one important factor. But this correlation subsumes a number of underlying mechanisms, as latent skill and latent health capture not only innate endowments but also investments in health and human capital at young ages, as well as persistent differences in health-related behaviors. We cannot disentangle these sources of correlation. However, having controlled for the correlation between latent health and skill types, we can isolate several potentially important causal channels that link health and wealth/income:

Channels from health to income/wealth: First, health has a direct effect on productivity, captured by β_5-β_6 in equation (3.4). Poor health reduces offer wages, which may also reduce labor supply. Second, poor health increases the disutility of work, reducing labor supply. Third, poor health increases the frequency of health shocks, which in turn generate sick days and OOP costs which may reduce income and savings. In our model all three of these channels are amplified by the human capital mechanism: if poor health reduces labor supply, it slows the rate of human capital accumulation, which reduces future wages.

[17] For example, a married man who works FT has hw=-0.20, indicating his wife is relieving him of homework duties. But a married man who is unemployed has hw=0.20, indicating he takes on extra housework.

[18] The utility function in (3.13) creates an incentive for individuals to smooth the consumption/leisure aggregate $c^\alpha l^{(1-\alpha)}$ over time, which causes consumption to drop at retirement.

Channels from income/wealth to health: The main causal channel from income/wealth to health is that agents with higher income/wealth can better afford medical treatment. Furthermore, high-skill workers are more likely to obtain jobs that provide health insurance, giving them better access to health care and lower OOP costs. For both reasons, low-skill workers are less likely to get treatment for health shocks, leading to worse health transitions.

As the model is dynamic, all these mechanisms interact over time. Anything that reduces labor supply and income will also reduce ability to get medical treatment. This in turn will reduce health, which reduces labor supply and income further, creating a vicious cycle. Anything that reduces health – i.e., any health shock – will reduce wages and employment, which further reduces ability to pay for medical care in the future.

The public/private insurance system interacts in important ways with the mechanisms of the model: In an ESHI-system, loss of employment leads to loss of insurance, reducing access and affordability of care, which may lead to worse future health, further reducing labor supply, creating a vicious cycle. And, as low-skill workers often lack ESHI, they have an incentive to curtail labor supply to maintain eligibility for means-tested transfers and public health insurance. This incentive is stronger for those who are in relatively poor health. As a result, some low-skill workers may end up "stuck" on the consumption floor.

3.11 Individual's Problem

3.11.1 Working Age Individuals

At the start of a period, an agent's state includes his permanent type (education, latent health, skill type), age, work experience, functional health, health risk, assets, employment offer, marital status and spouse employment. Letting Ω denote the state vector we have:

$$\Omega = ((e, \varepsilon^h, \varepsilon^s), t, X_t, h_{t-1}, H_t, R_t, A_t, O_t^* = (W_t^*, h_t^*, ins_t^*), (M_t, emp^w)) \tag{3.16}$$

Given Ω, an agent decides whether to accept or reject the employment offer O^*, so as to maximize the expected present value of lifetime utility. Let $I^O \in \{0, 1\}$ be an indicator for whether the employment offer is accepted or rejected. After the labor supply decision is made, health shocks and OOP medical costs are realized, including the shock ε^C that determines if expenses are "catastrophic." Conditional on a health shock, the individual draws the set of available treatment/payment options, from a distribution that depends on ESHI status. At this stage, the state of the agent is summarized by Ω, I^O, the health shocks $\Upsilon = (d^p, d^u, s)$, ε^C and the set of treatment/payment options $J(ins)$. Given these, the agent now decides whether to be treated for health shocks, and if he does, whether to pay the OOP cost or default. The treatment decision is captured by the indicator I_{treat} and the payment decision by I_{pay}. Finally, he makes the consumption/savings decision.

The agent solves the problem in three stages, working backwards:

Stage 3: First, the agent solves for the policy function for consumption conditional on Ω, all possible realizations of (Υ, ε^C), and all possible choice vectors (I^O, I_{treat}, I_{pay}). This policy function $c(\Omega, I^O, I_{treat}, I_{pay}, \Upsilon, \varepsilon^C)$ is the solution to the problem:

$$G(\Omega, I^o, I_{treat}, I_{pay}, \Upsilon, \varepsilon^C) = \max_c \{u(c, l) + \beta E_\Psi[\varphi V(\Omega') + (1 - \varphi)(\zeta + U_{Beq})]\} \tag{3.17}$$

where the expected value of the next period's state is calculated over the probabilities of all possible next period realizations of the stochastically evolving $\Psi \equiv (O^{*'}, H', R', M', emp^{w'})$

and the survival probability $\varphi = \varphi(H', e, t+1, M')$ as defined in Section 3.2, and where the maximization over c is subject to equations (3.3) to (3.15) and:

$$\begin{aligned} A' = &(1+r)A + W^{*}\cdot h\cdot I^{O} - p^{EI}(ins^{*}\cdot I^{O}, ins^{w}) + inc^{w}\cdot I_{M} + tr - (1+\tau^{c})C - Tax \\ &-I_{pay}OOP(ins^{*}\cdot I^{O}, t, \Upsilon, H, \varepsilon^{C}) - OOP^{w}(ins^{w}(ins^{*}\cdot I^{O}), t, e)\cdot I_{M} \end{aligned} \tag{3.18}$$

$$\begin{aligned} C \leq &\frac{1}{1+\tau^{c}}[(1+r)A + W^{*}\cdot h\cdot I^{O} - p^{EI}(ins^{*}\cdot I^{O}, ins^{w}) + inc^{w}\cdot I_{M} + tr - Tax \\ &-I_{pay}OOP(ins^{*}\cdot I^{O}, t, \Upsilon, H, \varepsilon^{C}) - OOP^{w}(ins^{w}(ins^{*}\cdot I^{O}), t, e)\cdot I_{M}] \end{aligned} \tag{3.19}$$

where C is household consumption and private consumption is $c = C$ for single men and $c = C/E(t, e)$ for married men. Equation (3.19) is the no-borrowing constraint.

Stage 2: Given the policy function for consumption, the agent chooses whether to treat and pay $(I_{treat}, I_{pay}) \in J(ins)$ given the state $(\Omega, I^{O}, \Upsilon, \varepsilon^{C}, J(ins))$:

$$B(\Omega, I^{O}, \Upsilon, \varepsilon^{C}, J(ins)) = \max_{I_{treat}, I_{pay} \in J(ins)} G(\Omega, I^{O}, I_{treat}, I_{pay}, \Upsilon, \varepsilon^{C}). \tag{3.20}$$

Stage 3: The agent chooses whether to accept or reject the employment offer by solving:

$$V(\Omega) = \max_{I^{O}} E_{(\Upsilon, \varepsilon^{C}, J(ins))}\left\{B(\Omega, I^{O}, \Upsilon, \varepsilon^{C}, J(ins))\right\}. \tag{3.21}$$

Here the expectation is taken over the probabilities of all possible Υ, ε^{C} and $J(ins)$.

3.11.2 Retired Individuals

At age 65 all men must retire. Then, from ages 65 to 100, consumption is the only choice variable. An agent's state is given by education, latent skill and health type, years of experience at age 65, age, health, health risk, assets, marital status, health shocks and medical cost shocks. Letting Σ denote the state vector we have:

$$\Sigma = (e, \varepsilon^{s}, \varepsilon^{h}, X_{65}, t, H, R, A, M, \Upsilon, \varepsilon^{C}) \tag{3.22}$$

If a man is married we assume the spouse must also retire at 65, and that she is also eligible for SS and Medicare. The agent maximizes the expected present value of lifetime utility by solving the problem:

$$V(\Sigma) = \max_{c}\left\{u(c) + \beta E\varphi V\left(\Sigma'\right)\right\} \tag{3.23}$$

subject to equations (3.6),(3.7),(3.10),(3.12)-(3.15) and:

$$A' = (1+r)A + SS(X_{65}, e, M, \varepsilon^{s}) + tr - (1+\tau^{c})C - OOP - OOP^{w}\cdot I_{M} - p^{Med}(1+I_{M}) - T(y) \tag{3.24}$$

$$C \leq \frac{1}{1+\tau^{c}}[(1+r)A + SS(X_{65}, e, M, \varepsilon^{s}) + tr - OOP - OOP^{w}\cdot I_{M} - p^{Med}(1+I_{M}) - T(y)] \tag{3.25}$$

The solution algorithm is described in Appendix H.

4 Data and Variable Construction

Our main data source 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 18, covering years 2000 to 2013. We stop in 2013 as the ACA created important changes in the environment. Panels 1-4 are dropped as some key variables are not available before 2000. Our sample consists of white males aged 25 years or older. We also use the CPS, HRS and PSID to construct other statistics used in the analysis.

Here we summarize the construction of our health variables using MEPS. Appendix A provides a more detailed description. In Appendix F we describe data patterns for Blacks and Hispanics, and explain why data limitations, as well as the need to expand our model to fully capture key aspects of their behavior, both preclude us from modeling them here.

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

An important advantage of MEPS is that it contains detailed information on respondents' medical conditions. The conditions and procedures reported by respondents are recorded by interviewers as verbatim text, which is then converted by professional coders into three digit ICD-9 codes.[19] This allows us to identify the different types of health shocks in our model:

We categorize each of the 989 ICD-9 codes 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 coded a medical condition as causing having a *long-term productivity loss* if it has an impact on productivity for at least 2 weeks per year for two or more years. We say a condition causes a *short-term productivity loss* if it has an impact for at least 2 weeks in the year it occurs, but no effect in subsequent years. If a condition affects productivity for less than two weeks, we ignore it. This rules out short-term 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.

Appendix A Table 6 shows how we map ICD-9 conditions that satisfy different combinations of these four criteria into 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. 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^p_t, d^u_t, 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 two years of interviews in each panel.

4.2 Constructing Health (H)

Our functional health measure (H) combines: 1) self-reported health, 2) self-reported mental health, 3) activities of daily living (ADL) limitations, 4) instrumental activities of

[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.

daily living (IADL) limitations, and 5) a set of eight physical functioning limitations that we combine into a single score.[21,22] Self-reported physical and mental health range from 1=poor to 5=excellent. The ADL and IADL variables are binary indicators for presence of any limitations. All five variables are standardized using data on all men 25 and over.

We conduct factor analysis on these five standardized variables and find they all 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. Finally, we discretize this continuous measure into three categories corresponding to poor, fair and good functional health.[23] Appendix B Figure 7 shows how H varies with age. Of course, the fraction of people in good health declines with age. There is a strong correlation between education and health even at young ages: At age 25, 82% of college types are in good health, compared to only 63% of high school types. At age 65 the corresponding fractions are 65% and 40%.

4.3 Constructing Asymptomatic Health Risk (R)

We construct R using conditions that do not effect current productivity but that predict future health conditions and/or long-term productivity (see Appendix A Table 6). Specifically, we first construct five variables: 1) an indicator for essential hypertension, 2) an indicator for disorders of lipoid metabolism, e.g., high cholesterol, 3) the count of all other ICD codes that enter R, 4) a measure of excessive BMI, and 5) a measure of low BMI. All five measures are standardized using data on all men 25 and over. We then take a weighted sum of these variables where the weights are based on the relative importance of each variable for predicting the health shocks d^p (see Appendix A for details). Hypertension, high cholesterol and obesity are the most important factors. Finally, we discretize this measure into two categories corresponding to low and high risk.

4.4 Measurement Model

Under-reporting of medical conditions is a potentially important issue. Health shocks (d^p, d^u, s) and risk factors R are likely to be under-reported for people who do not seek treatment, which is more common for those who have low income/education or who lack health insurance.[24] In contrast, functional health H is constructed from self-reported measures, so we assume it is not subject to *systematic* measurement error for these groups.

In the MEPS, conditions are reported when the respondent was diagnosed by a doctor in the past and the condition is "current," or the condition was associated with a particular medical event or with disability days, or the condition was reported as "bothering" the respondent during the interview period. Thus, a condition may or may not be recorded in the MEPS if a person was not formally diagnosed.[25]

[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] Hosseini et al. (2022) also construct a measure of health based on a set of health deficits.

[23] Good health corresponds to values of H above the median (among all males aged 25+). Poor health corresponds to values at least one standard deviation below the mean. Fair health is the interval in between.

[24] For example Wherry and Miller (2016) find that the ACA Medicaid expansion was associated with increased rates of diagnosis for diabetes and high cholesterol.

[25] A condition such as back pain could be reported even if a person never seeks formal medical care. But a condition such as diabetes must be formally diagnosed before a person is aware of it and can report it.

To make the model consistent with the data, we assume health shocks d^p, d^u, and s are correctly measured for the treated. However, if an agent has a health shock and decides not to treat ($I_{treat} = 0$), we assume the shock is only recorded with probability $\eta(\Upsilon)$. This probability is shock specific (i.e., persistent shocks may be reported more often).

Recall from Section 3.2 that the true shock probabilities in the model are given by $\Gamma^{dp}(\cdot)$, $\Gamma^{du}(\cdot)$, and $\Gamma^{s}(\cdot)$. Letting $\tilde{\Gamma}^{dp}(\cdot)$, $\tilde{\Gamma}^{du}(\cdot)$, and $\tilde{\Gamma}^{s}(\cdot)$ denote the observed (i.e., under-reported) shock frequencies, we have:

$$\begin{aligned}
\tilde{\Gamma}^{d^p}(\cdot) &= \Gamma^{d^p}(\cdot)\big\{P(I_{treat}=1|d^p=1)+P(I_{treat}=0|d^p=1)\eta(d^p)\big\} \\
\tilde{\Gamma}^{d^u}(\cdot) &= \Gamma^{d^u}(\cdot)\big\{P(I_{treat}=1|d^u=1)+P(I_{treat}=0|d^u=1)\eta(d^u)\big\} \\
\tilde{\Gamma}^{s}(\cdot) &= \Gamma^{s}(\cdot)\big\{P(I_{treat}=1|s=1)+P(I_{treat}=0|s=1)\eta(s)\big\}
\end{aligned} \tag{4.1}$$

where $P(I_{treat} = 1|\Upsilon)$ is the probability of treatment as determined by the structural model (see equation (3.20)).

We treat under-reporting of health risk differently because R is based on a set of highly persistent conditions. For example, whether high cholesterol has been diagnosed is unlikely to be primarily determined by whether a person is treated for one particular shock. Instead, we assume those covered by ESHI or Medicare report R correctly, while, among those lacking insurance, only a fraction $\eta^R(ins)$ of people with high R report it.

5 Calibration

Our model is calibrated to US data from 2000 to 2013. Major provisions of the ACA came into force in 2014 in many of the most populous states. This changed the structure of the problem in important ways, so we do not use more recent data. We focus on civilian, non-institutionalized white males aged 25+ and over who are not in school.

Appendices B, C, D and E describe the calibration in great detail. Here we give a broad overview, mainly aimed at giving intuition for how key model parameters are identified.

First, we can estimate some parameters in a first stage outside the structural model. These are disability benefits, social security and pension benefits, tax function parameters, employer health insurance premiums, survival probabilities, stochastic processes for marriage and family size, as well as processes for spousal employment, income and medical costs.

We also make two key assumptions that: (i) insured men treat health shocks with probability close to one, and (ii) health shocks and risk factors are reported accurately for the insured. This allows us to estimate the stochastic processes for health shocks, health risk, sick days and medical treatment costs outside the model using data on insured men.

The functions that we estimate outside the model generate exogenous variation in agents' budget and time constraints that help to identify the remaining parameters that we calibrate internally. We also fix some key parameters based on prior literature: The weight on consumption in the Cobb-Douglas utility function ($\alpha = 0.4$), the intertemporal substitution parameter ($\sigma = 2.0$), the discount rate (β=0.97) and the interest rate (r=4.5%).

The key structural parameters we calibrate internally are those that govern: the health process, reporting error in health shocks and health risk, the probabilities the treatment and payment options are available to the uninsured, the job and wage offer processes, the transfers available to non-disabled men, and the distribution of latent health and skill types. We now give an overview of the calibration process, focusing on the parameters we calibrate internally, and in all cases referring the reader to Appendices B, C, D and E for details.

5.1 Probabilities of Health Shocks and R Transitions

We assume men covered by ESHI, DI or Medicare almost always get treated for serious health shocks, and hence they do not under-report health conditions in MEPS. Later, we verify that our calibrated model indeed implies those with *ex ante* insurance choose to (almost) always get treated, so our assumption is internally consistent.[26] Given this, we estimate the probabilities of health shocks $\Gamma^{dp}(H, R, t, e)$, $\Gamma^{du}(H, R, t)$, and $\Gamma^{s}(H, R, t)$ and the transition probability for health risk $\Lambda_R(R'|R, t, H)$ directly from the MEPS data using the sub-sample of individuals with *ex ante* insurance (ESHI, DI or Medicare).[27,28] We specify these functions as binary logits.

As described in section 4.4, our measurement model specifies that men who are not treated under-report medical conditions. Having pinned down the true frequencies of health shocks and high R, the measurement model parameters $\eta(\Upsilon, H)$ and $\eta^R(ins)$ play an important role in matching the frequencies of observed health shocks $\tilde{\Gamma}^{dp}$, $\tilde{\Gamma}^{du}$, $\tilde{\Gamma}^{s}$ and high R in MEPS for the uninsured. The key identifying assumption is that, conditional on H, R, t and (for d^p) e, the true frequency of health shocks and high R does not differ by insurance status *per se*. This rules out *ex ante* moral hazard.[29] Thus, our model attempts to explain observed differences in frequencies of health shocks and high R between the insured and uninsured based on (i) sorting into insurance, and (ii) different frequencies of seeking treatment.[30]

5.2 Health Transition Probabilities

Functional health is discrete in our model, with three ordered levels, $(Poor, Fair, Good)$. So we specify the H transition function $\Lambda_H(H'|H, \varepsilon^h, t, d^p, d^u, (I_\Upsilon, I_{treat}))$ as an ordered logit. The logit index is compared to two thresholds to determine which of the three possible H levels is realized. For the good latent health type the logit index is shifted upward, making it more likely to exceed the upper threshold (which implies good health).

The H transition function must be estimated inside the model for three reasons: (1) we do not observe latent health types so there is unobserved heterogeneity and hence endogeneity, (2) the health shocks (d_t^p, d_t^u, s_t) are under-reported for those who are not treated, and (3) the decision to treat, which enters the H function, is endogenous.

[26] It is also consistent with the model to estimate the transition probability $\Lambda_R(R'|R, t, H)$ using data on the privately insured, as we assume the insured correctly report R.

[27] This allows us to avoid the extra computational burden of estimating these functions inside the model. More importantly, it avoids concerns about identification that would arise if we treated the true frequency of health shocks as unobserved.

[28] Medicaid may provide insurance *ex post* if the cost of health shocks pushes a person below an income threshold. Hence, the frequency of health shocks conditional on Medicaid greatly exaggerates the frequency of shocks among otherwise similar people (in terms of H, R, t) who do not receive Medicaid. For this reason, we exclude Medicaid recipients when estimating the probabilities of health shocks.

[29] Khwaja (2001) and Fang et al. (2007) show that insurance has two opposite effects in a dynamic model: First, insured agents have less incentive to take care of their health - ex ante moral hazard. But second, insured agents expect to live longer, creating an incentive to preserve their health to avoid disutility from poor health in old age. They find these effects roughly cancel out. This is a key justification for our decision to ignore *ex ante* moral hazard. Other papers finding *ex ante* moral hazard is not important in the health insurance context are Newhouse and Group (1993) and Courbage and De Coulon (2004).

[30] Prior evidence suggests sorting in health insurance is important. In particular there is strong evidence of advantageous selection into private insurance – see Fang et al. (2008) and Capatina (2020).

We calibrate the parameters of the Λ_H function as described in Appendix B.5. We run descriptive ordered logit models of health on lagged health, age, education and health shocks using both the MEPS and simulated data. We consider both a simple logit and a logit with latent types in the intercept. In the simulated data we treat latent types as unknown, health shocks as mis-reported, and non-treatment as unobserved, so the estimates obtained from the simulated data suffer from the same biases as those obtained from MEPS. We then calibrate the structural model parameters so the parameters of the descriptive logit models are similar in the MEPS and simulated data. We also match H transition rates by age/education.

Two aspects of identification of the H function are worth noting: First, persistence in health status can be generated by either latent health types or the lagged health status that enters the H transition function. Fundamentally, what distinguishes these two sources of persistence is whether d-type shocks have long run effects on health. That is, in a model where persistence in health status is due only to heterogeneity, and where lagged health does not enter, d_t shocks would not affect health beyond period $t+1$. In a such a model the agents would have little incentive to treat shocks.[31] See Appendix B.5.2.3 for further discussion.

Second, the effect of non-treatment is identified from the difference in health transitions between those with ESHI vs. those lacking ESHI or public insurance, as we discuss in Appendix B.5.2.4. For example, as we see in Appendix Table 23, the probability of staying in good H from one year to the next is 8pp higher for those with ESHI at age 45. The rate at which uninsured men go untreated is pinned down by differences in medical charges by insurance status (see section 5.4). Given this rate, the coefficient on I_{treat} in Λ_H is calibrated so the model matches the difference in H transitions by insurance.

Aside from non-treatment of health shocks, another reason the uninsured might have worse H transitions is simply that they are more likely to be the bad latent health type. However, our calibrated model implies that bad latent health types often end up on Medicaid. As a result, the fraction of men with bad latent health is almost identical within the group with ESHI and the group that is completely uninsured. Hence, it is non-treatment that primarily drives the difference in H transitions between those with ESHI and the uninsured.[32]

5.3 Medical Expenditures

We estimate the OOP treatment costs for men aged 25-64 covered by ESHI outside the model using data on OOP payments of privately insured men in the MEPS. The evidence suggests that men with ESHI get treated at a high rate, and rarely default on medical bills, which implies a negligible bias in our estimates.[33] Similarly, we assume that men aged 65+ treat and pay at a high rate, as they are covered by Medicare, so we also estimate their OOP treatment costs directly from the OOP expenditures observed in the MEPS.

However, for the uninsured rates of non-treatment and default are substantial (see Appendix C.8), so we need a different approach: For men aged 25-64 who do not have ESHI,

[31] An additional (more subtle) source of persistence arises because a d_t shock may reduce health status at $t + 1$. This increases the probability of health shocks at $t + 1$, which then affect health at $t + 2$.

[32] A difference also arises as the uninsured have worse R and hence more d^p shocks, but this effect is minor.

[33] Starting in 2013-14, the MEPS includes medical debt variables. "PYUNBL" measures if the respondent or anyone in his family currently has any medical bills that the family was unable to pay. In 2013-14, among white men with ESHI, only 3% responded "Yes." Given that these bills could be old or from other family members, it is likely that only a very small fraction of the respondent's current bills are not paid.

we set OOP equal to a fraction (60%) of the average total health care *charges* estimated for those with private insurance in the MEPS. People with ESHI never pay these charges, as insurance companies negotiate substantial discounts with providers (and furthermore, their OOP costs are only a fraction of these discounted charges). But the uninsured can also negotiate discounts on provider charges. To capture this, we assume those not covered by ESHI have OOP equal to 60% of charges, following Lockwood (2023) and Mahoney (2015).

5.4 Treatment and Payment Options

An important and novel aspect of our model is that the uninsured may be constrained in their treatment/payment options. As we described in Section 3.5, if a health shock occurs, working-age men who lack ESHI face one of the three possible choice sets in equation (3.2): (1) all treat/pay options available, including treat/not pay, (2) no access to treatment, (3) treatment is an option but one must pay (no default option). Understanding how we identify and calibrate the choice set probabilities is important for understanding our framework.

In Section 3.5 we explained why a model where men who lack ESHI *always* have all three treatment/payment options, and only stigma prevents them from always choosing treat/not pay, cannot hope to fit the data.[34] Hence, we adopt a model without stigma where men without ESHI probabilistically face one of the three choice sets in (3.2).

Central to our ability to identify the three choice set probabilities is that medical charges are observed in the MEPS for anyone who treats, *regardless* of whether they pay. Hence, the frequency that the uninsured have negligible charges conditional on a reported health shock, and the difference in medical charges between insured and uninsured, both inform us about how often the uninsured go untreated. And data on OOP spending of the uninsured relative to their discounted charges informs us about how often they default.

First, we explain why a model with only choice sets (1) and (2) does not suffice: If the uninsured lacked access to care with some probability, we could calibrate that probability to match the lower level of charges observed for the uninsured, and/or the frequency with which the uninsured have a shock but no significant charges. But in such a model treated agents would always default. Hence, with only choice sets (1) and (2), we would be unable to explain why the uninsured do have significant observed OOP expenditures, or why they often go on Medicaid (i.e., the consumption floor) to pay medical bills. Of course, we could introduce a high stigma to induce some agents who face choice set (1) to pay, but we then get the counterfactual prediction that they only pay small bills. Thus, to match the patterns in the data, we need to introduce a probability of choice set (3), where the uninsured can treat but must pay. This allows us to generate cases where the uninsured pay large bills.

Aside from enabling us to fit the data, we argue that the existence of all three choice sets is realistic. In the US, proof of insurance is often required before treatment, generating a lack of access for the uninsured and motivating choice set (2). At the same time, the uninsured often have the option to treat and not pay – e.g., in charity clinics or in emergency rooms in life-threatening situations where treatment must be administered without proof of insurance – motivating choice set (1). And there are many contexts where treatment requires payment in advance, such as simply filling a prescription, motivating choice set (3).

[34] Such a model cannot explain two key facts: First, we do observe the uninsured paying large bills, often by going on Medicaid. Yet small bills often go unpaid. Second, the uninsured often go untreated, despite the fact that treatment followed by default (or, equivalently, free care) is often available, and default is common.

To calibrate the three choice set probabilities, we target four statistics: (i) how often the uninsured do not treat, as measured by how often they have negligible charges[35] despite having shocks, (ii) the difference in charges between the insured and uninsured, which also reflects how often the uninsured do not treat, (iii) how often the uninsured pay bills conditional on treatment, as indicated by paying a significant fraction of charges,[36] and (iv) average OOP payments divided by discounted medical charges for the uninsured who treat.

Let $P(T)$ denote the probability of treatment, and $P(Pay|T)$ denote the probability of payment conditional on treatment. These two targets pin down the choice set probabilities that we denote by $P(J)$. To see why, note that an uninsured man who draws choice set (1) will always treat and not pay, as stigma is zero. If he draws (3) he treats with probability $P(T|3)$, which is determined by the rest of the model, so for present purposes we treat it as known.[37] So the probability an uninsured man treats is $P(T) = P(1) + P(T|3)P(3)$, and the probability he pays is $P(Pay|T) = 1 - P(1)/[P(1) + P(T|3)P(3)]$. Given measures of $P(T)$ and $P(Pay|T)$ we can back out $P(1)$ and $P(3)$, which gives $P(2)$. In practice, as we use four targets, the two probabilities are over-determined, so we cannot literally solve these two equations to find the $P(J)$. The calibration achieves a balanced fit to all four targets.

We give details of the calibration in Appendix C.8. Table 35 reveals the uninsured are much more likely to have negligible charges given a health shock, and Figure 10 shows average charges of the uninsured are much lower than for the insured. Both statistics indicate non-treatment for shocks is common among the uninsured, implying lack of access is common. Overall, we estimate that uninsured men only treat 60% of the time, while our model generates a 62% rate, see Table 37. That table also reveals that only 42% of completely uninsured men pay their bills, and the ratio of OOP payments to discounted charges is only 25%, so default is common. Our model predicts 42% and 30% respectively, so the fit is good.

As we see in Appendix C Tables 38 to 40, our estimated treatment rates for the uninsured are higher for men who are older or in worse health. For example, 48% of uninsured men in good health have negligible charges conditional on health shocks, compared to 40% and 16% of those in fair and poor health. Hence, we calibrate separate choice set probabilities by health status and age. This reflects that the nature of shocks may vary: e.g., the chance a shock generates a trip to the ER may be higher for men who are older or in poor health.

5.5 Latent Type Probabilities

Within each of the three education groups we allow for three latent skill types and two latent health types. The matrix $\Lambda^{\varepsilon}(\varepsilon^h, \varepsilon^s, e)$ gives the probabilities of each of the 18 types. We assume that within each education group, the three latent skill types have equal mass. We calibrate the probability of being the good latent health type within each education-skill group, $Prob(\varepsilon^h \mid \varepsilon^s, e)$, by targeting correlations between health and a set of variables that are correlated with latent skill, i.e., employment, income, and wealth, separately by education. Details are provided in Appendix C Section 9.

[35] We define negligible charges as <\$500/year, which is low given that undiscounted charges are typically very high. In MEPS, health shocks may go unrecorded if one goes untreated. But in our simulated data we classify shocks as observed/unobserved, and we match statistics conditional on *observed* shocks with MEPS.

[36] We classify a person as not paying if OOP is less than 75% of *discounted* charges (i.e., 45% of charges).

[37] Our model implies $P(T|3)$ is 87%, 91%, 94% for men in poor, fair and good health respectively. These probabilites are high because treatment is valuable. The bulk of non-treatment is generated by lack of access.

Appendix C Figures 14-16 (left panels) plot the fraction of men in fair/poor health by age, conditional on employment. There is a wide gap between the health profiles of employed vs non-employed men. Similarly, we find that men in good health have significantly higher incomes than men in fair/poor health, even conditional on full-time employment status, age and education – see Appendix C Table 47. Finally, using the HRS we find that, at ages 56-60, within each education group, the bottom wealth terciles contain very high fractions of individuals in poor and fair health, while the top tercile contains high fractions in good health – see Appendix C Table 48.[38] All three patterns suggest a strong positive correlation between latent health and latent skill. Our model captures these patterns well.

5.6 Fixed Cost of Work and Hours of Homework

The time constraint in equation (3.14) contains fixed costs of work $F(I^O, H)$ and hours of homework $hw(M, h^* \cdot I^O, emp^w)$. We calibrate these parameters to target hours of work conditional on health, marital status and spouse's employment status. As we see in Appendix C Section 10 Figure 20, the probability of working full-time is strongly increasing in health status. Of course, these employment patterns are affected by many channels, including how wages vary with health and how the consumption floor varies with H. These channels do generate substantial differences in employment by H. But we find that, without fixed costs of work that vary with H, the employment profiles are slightly too high in the model relative to the data, particularly for men in poor health.

We calibrate the levels of homework hw to match differences in employment levels between married and single men, and between married men whose spouses do or do not work. As we see in Appendix C Table 51, married men work much more than single men. This is partly due to selection: Our stochastic process for marriage implies that men who have higher income and greater labor force attachment are more likely to become married. But we find that this alone does not explain the large employment gap between married and single men. Thus, our calibrated model explains this gap as arising, at least in part, because married men lose less leisure than single men when they work full time.

5.7 Bequest Function

Bequest utility (3.15) contains three parameters θ_{Beq}, k_{Beq} and γ we calibrate to match the distribution of assets at ages 55-60 in the HRS. The parameter k_{Beq} determines the wealth level at which the bequest motive becomes operative, so we calibrate it by targeting the fraction of individuals with "negligible" assets at ages 55-60. To calibrate θ_{Beq} and γ we target the 25th, 50th and 75th percentiles of the asset distribution at ages 55-60, conditional on assets above the "negligible" threshold. See Appendix C Section 10.4 for details.

5.8 Stigma Cost of Default on Medical Bills

As discussed in detail in Appendix C Section 8.4, we decided to set the stigma cost $\kappa(ins)$ of not paying medical bills to zero for the uninsured. For those with ESHI we calibrate a high enough κ so less than 3% default on bills, consistent with evidence from the MEPS that we discussed in Section 5.3.

[38] De Nardi et al. (2022) argue that ex-ante health heterogeneity is important in explaining the large wealth heterogeneity at retirement.

5.9 Hours Worked and Sick Days

We set contractual weekly work hours to hrs^{FT}=40 and hrs^{PT}=20. These are median hours of full and part-time workers in good health with no health shocks in MEPS.[39]

In our model contractual hours are reduced by sick days, $sd(e, H, \Upsilon)$, which we estimate directly from MEPS. As we explain in Section 3.7.2 we conceptualize sick days as the total reduction in annual days of work due to health shocks, not merely the "sick days" that workers may be entitled to in an employment contract. Thus, as we discuss in Appendix B.7, we estimate sick days as the difference in hours worked between men with and without health shocks, conditional on H and education, among those with ESHI. The long-term shocks d^p and d^u generate substantial sick days. For example, for workers in poor/fair health with HS or less, a d^u shock reduces work hours by about 8 hours per week (or about 416 annually).

5.10 Job and Insurance Offer Probabilities

Job offer probabilities $\Pi(O^{**}|h^*_{t-1}{\cdot}I^O_{t-1}, ins_{t-1}, e, t)$ depend on lagged employment and insurance status, education and age. We calibrate them to match: (1) yearly transition rates for full-time employment and ESHI coverage among men aged 30-55 in MEPS, and (2) observed employment/age profiles (FT and PT, with and without ESHI), by education, constructed using CPS data. As we show in Appendix D Section 11 Tables 57-58, full-time employment and insurance coverage are highly persistent, while transition rates into full-time employment and insurance coverage are low. Thus, we calibrate that men who worked full-time and who had ESHI in the prior period receive offers with those features with very high probability. Conversely, men who did not work full-time or have insurance in the prior period are unlikely to receive such offers in the current period.

5.11 Offer Wage Function

We only observe wages of men who *choose* to work so estimates of the wage offer function are subject to selection bias if estimated directly from observed wage data in a first stage. Thus, we use our structural model to implement a selection correction. We simulate data from the model, add measurement error, generate the distribution of accepted wages, and match features of the distribution of accepted wages in the simulated vs. actual data.

If we interpret our structure as a complex selection model – i.e., an expanded version of Heckman (1974) – then identification (aside from functional form) relies on exclusions that R_t, A_t, M_t, emp^w_t, 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 work experience, lagged work status and taxes affect after-tax wage offers but not preferences.

As we explain in detail in Appendix D Section 12, the features of the accepted wage distribution that we target are: (1) average wages of full-time workers in good health in MEPS, broken down by 5-year age groups and education, (2) wage differences by health and education for full-time workers in MEPS at ages 40-50, (3) differences between full- and part-time wages at ages 30-55 in the CPS, (4) average wages within terciles of the wage distribution of full-time workers in the CPS, conditional on education, and (5) the variance of log wages for full-time workers in good health in the CPS.

[39] We define "not employed" as annual hours worked less than 520, "part-time" as annual hours between 520 and 1,500, and "full-time" as annual hours of 1,500+.

Finally we also target features of the distribution of fixed effects obtained from wage regressions estimated on the PSID. These are informative about the dispersion of the fixed skill types in the offer wage function. We use the PSID because it is a much longer panel so it enables us to get more information about individual heterogeneity.

5.12 Consumption Floor and Disability Benefits

The consumption floor $\bar{c}(educ, I_{H=Poor}, M, t)$ for men in poor health is calibrated outside the model using data on disability benefits – see Appendix D Section 13 for details. For men in fair and good health, we calibrate the consumption floor by targeting the fraction of men who receive government transfers in the CPS, by education, marital status and age. We classify individuals as receiving transfers if they report having public health insurance or receiving any of the following types of incomes: disability, welfare, or SSI.

As we see in Appendix D Table 70, the calibrated consumption floors for single men in fair/good health are quite low – only about one-third of the levels of disability benefits for single men. For married men in good/fair health, the consumption floor is scaled up considerably, reflecting that families are eligible for a much wider range of benefits. As we see in Tables 71-74, the model matches accurately the fractions of single men and families receiving DI benefits and social transfers, conditional on education.

6 Model Fit

The model provides a good fit to a large number of statistics from the MEPS, CPS, HRS and PSID, as we discuss in great detail in Appendices B though E that describe calibration. Here we list the statistics that we match and for which we obtain a good fit:

1) Appendix B (Health Related Model Inputs): health over the life cycle conditional on education, health transition rates by age and education, health transition rates conditional on health shocks, ordered logit models for health (with and without latent health types), health transitions conditional on insurance status, health shock frequencies by health status and ESHI, high risk (R) status by ESHI and age,

3) Appendix C (Choice Sets, Latent Types, Preferences): fraction with negligible charges conditional on health shocks for uninsured (i.e., rates of not treating), OOP payment rates of the uninsured who treat, OOP/discounted charges ratio for the uninsured, treatment and payment rates of the uninsured conditional on health and age, health care charges by age conditional on insurance status and education, as well as:

Health status conditional on employment by education/age, health status among workers by ESHI/education/age, income conditional on education/health, health conditional on wealth/education, employment by age conditional on health/education, employment conditional on marriage and spouse employment, percentiles of assets conditional on education,

4) Appendix D (Labor Market Constraints): transition rates between employment and insurance coverage states (conditional on education), employment rates by age conditional on education, employment and insurance status by age conditional on education, fractions with ESHI by education, health and employment status, mean wages by age and education of FT workers in good health, mean wages by health and education of FT workers, ratio of PT to FT wages conditional on education, percentiles of fixed effects from wage regressions run on the PSID, terciles of the wage distribution of FT workers conditional on education,

variance of log wages by age conditional on education, fraction of men receiving DI and non-DI benefits (conditional on education and marital status), and the fraction of men receiving social transfers conditional on age and education.

There are some processes that we calibrate outside the model, so we fit them well by construction: In Appendices B.3, B.4 and B.6 we fit the frequencies of health shocks and R and the distribution of medical costs conditional on health shocks (and other state variables) for working-age men with insurance, and for men aged 65+, and in Appendix E (Demographics, Family Structure and Spousal Variables) we fit survival probabilities, family size by age, marital status transitions, spousal employment and income and spousal medical costs.

6.1 Fit to Key Untargeted Statistics

In the remainder of this section we discuss our fit to some key statistics that were not targeted in the calibration (i.e., untargeted moments).

6.1.1 Selection into Employer-Sponsored Insurance

One important pattern is selection of workers into employer-sponsored health insurance by health status. We did not target this in calibration, but getting it right is crucial for counterfactuals where we provide insurance to the uninsured, as the cost and health impact of such a policy depends on the distribution of health status among the uninsured.

Figure 1, from Appendix C.9, examines this issue for high school men.[40] It shows the share of men in fair/poor health by age, *conditional* on employment (left) and ESHI (right). On the left, we see employed men tend to be in much better health than non-working men at all ages. We target this pattern, and capture it accurately, including the improvement in health of non-employed men at ages 55 to 64 that arises from selection into retirement.

The right panel of Figure 1 shows there is advantageous selection, as workers with ESHI tend to be healthier. The fraction of men in fair/poor health is about 15 to 20 percentage points higher among the uninsured, a gap that grows slowly with age. Our model provides an excellent fit to this advantageous selection pattern even though it was not explicitly targeted.

In Appendix C.9 we show advantageous selection arises for two reasons: First, men in good health are *relatively* more likely to accept jobs with insurance than men in poor health. ESHI is less valuable for men in poor health, as they can often rely on DI or free care. So social transfers crowd out private insurance. Second, and far more quantitatively important, is simply that men in poor health are much less likely to accept any job offer. And they are less likely to be offered jobs with ESHI in the first place, due to low labor force attachment.

6.1.2 Health Transitions Conditional on Education, Income and Insurance

Our structural model of health transitions is very simple, as health only depends on lagged health, health shocks (and whether they are treated), age, and a man's latent health type (good vs. bad) – see Table 1. But in the data, education, income and insurance are highly correlated with health transitions. Can our model generate these patterns?

To address this question, Table 3 presents results from a descriptive ("kitchen sink") ordered logit regression of health (H) on lagged H, education, d^p and d^u shocks, a dummy for ESHI, income quintiles and a cubic in age, estimated for ages 25-64. The first column

[40] The patterns for Some College and College groups are similar, but have more noise as the fractions of men without ESHI are much smaller.

shows the results using MEPS data, while the second column shows results using simulated data from the structural model. To make these regressions comparable, we include only reported (not actual) health shocks in the simulated data regression.

The similarity between the estimates obtained from the data vs. the model is remarkable, particularly as these regression coefficients were not targeted in calibration. Nevertheless, the simulated data regression implies positive "effects" of education, income and insurance on health that are very similar to those obtained from MEPS.

Thus, the mechanisms of the structural model are successful in generating the observed correlations between education, income, insurance and health that we see in the data. The distribution of latent types by education and skill works together with the endogenous treatment and work decisions to generate better H transitions for those who are more educated, have higher income, and have insurance. In this sense, our model provides an explanation for the well-known positive associations between health, education, income and insurance. But of course, the model is silent on why latent health is correlated with education.

6.1.2.1 Mechanisms Connecting Education, Income, Insurance and Health

The last three columns of Table 3 explore in more detail the mechanisms through which the structural model generates these key associations. In the simulated data it is possible to observe latent health types, true shocks and untreated shocks. Controlling for these variables sheds light on the mechanisms of the model:

In the third column we control for latent health type. As we see, this essentially eliminates the association between education and health transitions, indicating that this association is largely driven by the positive correlation between education and latent health types – see Appendix C.9 Table 45. The coefficients on income are also rendered much smaller, but they are still significant. And the coefficient on insurance actually increases.

In the fourth column we control for untreated health shocks, and we include actual rather than measured health shocks (but we do not control for latent health type). This essentially eliminates the association between insurance coverage and health transitions. Thus, we see that this association is driven by the fact that the insured are more likely to get treatment for health shocks. The coefficients on income are only slightly attenuated compared to column (2), while the coefficients on education increase slightly.

Finally, in the last column we control for both latent health type and untreated shocks, and include actual rather than reported shocks in the model. This eliminates the association of health transitions with education, income and insurance coverage.[41] Thus, to explain all three associations we need to account for both latent health types and treatment decisions.

6.1.3 Earnings Inequality over the Life Cycle

Much of our analysis concerns how health shocks contribute to earnings inequality, so it is important that our model capture observed patterns of inequality in the data. Figure 2 shows how our model fits data on earnings inequality. The figure plots the Gini coefficient for labor earnings by age in the CPS vs. the model. As we see, the income Gini increases very slowly from age 25 to 50, and then it increases at a rapidly accelerating rate from 50 to 64. This pattern was not targeted in calibration, yet we fit it quite well.

[41] The coefficient on some college is small but marginally significant. This is not surprising given the very large sample size in the simulated data regression.

7 Results: Effects of Health Shocks on Key Outcomes

7.1 Effects of Major Health Shocks on Earnings

We first 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 30%, of which 19% are severe by our definition, giving a 5.7% annual frequency of severe d^u shocks.[42] We find on average a cumulative (non-discounted) earnings loss of $42.8k 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.[43]

This $42.8k loss is calculated for individuals who experienced a severe d^u shock in the benchmark model. But the chance a shock is "severe" (i.e., it causes health to deteriorate) depends on endogenous treatment: An untreated d^u shock is "severe" 40% of the time at ages 50-60, while a treated d^u shock is "severe" only 14% of the time. Therefore the sample of men with a severe d^u shock at age 50 contains a disproportionately high fraction of those who do not treat. These men are likely to lack ESHI and have low-earnings even in the absence of shocks, so their earnings losses caused by the shocks are relatively small.

In contrast, if we calculate the earnings loss by comparing a case where *everyone* experiences a severe shock at age 50 vs. an experiment where no one experienced such a shock, the loss is much higher ($\$59.8k$). The selection effect works to lower the estimated loss. We can call these the "selected on shocks" (SOS) and the average effect, respectively.

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. Table 4 reports both the SOS (top panel) and average (bottom panel) effects for different types of workers at different ages. Here we focus on the average effects. For example, for a college type man at age 40, a major health shock reduces the PV of remaining lifetime earnings by $\$53.9k$ or 5.6%.[44] Notice that lifetime FT equivalent work years decline by 0.84 years.

Impacts of health shocks are much greater in percentage terms for less educated workers. For example, for a typical man with a high school or less education, a major health shock at age 40 reduces the PV of earnings by $55.0k or 11.5%. The loss in FTE work years is a substantial 1.89 years. For older workers the impacts are less in absolute terms (because they are nearing the end of the working life at age 65), but much larger in percentage terms.

Table 4 also shows the part of the impact of health shocks due to reduced human capital accumulation in the years after the shock. In Section 7.2 we explain this decomposition.

[42] We focus on d^u shocks as they are more common. We obtain very similar results for predictable persistent shocks d^p. For men aged 50-60 the annual frequency of d^p shocks is 23%, of which 18% are severe by our definition, giving a 4.1% annual frequency of severe d^p shocks. The frequency of a severe shock of either type is 8.3%. See Appendix B Table 14 for frequencies of severe shocks by education and age.

[43] 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.

[44] 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%.

7.2 How Human Capital Amplifies the Impact of Health Shocks

Human capital *amplifies* the impact of health shocks, as a decline in labor supply caused by a shock slows accumulation of human capital, causing job offers to deteriorate, generating a feedback loop. Human capital depends on work experience and lagged employment status, which both affect multimensional job offers (wage, ESHI, hours). Hence, the human capital feedback loop operates via two channels: First, a decline in labor supply slows accumulation of work experience, which reduces future wage offers. Second, if a worker exits employment after a shock, future employment offers deteriorate: next period it is harder to get a full-time job offer with ESHI, so non-employment or employment in a bad job can be persistent.

We can assess the importance of these two human capital mechanisms in generating the total effect of a health shock by running simulations where we shut down the human capital feedback loop. To do this we hold the levels of experience (X) and lagged employment ($I_{h_{t-1}}$) that enter the offer wage function (3.4) and the job offer probabilities (see Section 3.7.1) fixed at the levels that prevailed in a baseline simulation where no major health shock occurred. We report these results in Figure 3. The figure shows the impact of a major health shock at age 40, which we define as a d^u shock that causes a deterioration in H in the next period.

The upper left panel of Figure 3 shows the effect on offer wages. The solid blue line is the baseline path where no major d^u health shocks occur at age 40. Then we consider two simulations where all men experience such a shock at age 40: The solid red line shows the total effect, while the dashed blue line shows the effect if human capital (i.e., work experience and lagged employment status) is held fixed (as on the baseline path).

We see that a major health shock leads to a sharp decline in wage offers in the year after the shock (about 10%). Over time effects diminish: the mean offer is 5.2%, 3% and 1.9% below its baseline level after 3, 5 and 8 years, respectively. But even if we hold human capital fixed the offer wage is still 4.4%, 2.2% and 1.1% below its baseline level after 3, 5 and 8 years, respectively, due to the direct effect of health. Thus, the extent to which human capital amplifies the impact of a health shock via the offer wage channel is modest.

The lower left panel of Figure 3 examines effects of a major health shock on full-time employment. Here the story is very different: Probability of full-time employment drops by 12 percentage points one year after the shock, as the decline in health directly reduces tastes for work (eqn 3.14) and offer wages (eqn 3.3). Recovery to pre-shock level is extremely slow: Even after 8 years employment is 7.8 pp below baseline. In contrast, if we fix human capital along its baseline path, the probability of full-time employment almost returns to baseline after 5 or 6 years. *Thus, the main channel via which human capital amplifies the impact of health shocks is employment; i.e., slow return to full-time employment after the shock.*

The employment mechanism is clarified in the upper right panel of Figure 3, which shows the fraction of workers who receive full-time job offers by age. We've seen that a shock at age 40 causes a 12 percentage point drop in employment at age 41. Because the probability of getting a full-time offer depends on lagged employment, this means fewer workers receive full-time offers at age 42. As we see in the upper right panel of Figure 3, the fraction of workers who receive a full-time job offer at age 42 declines by 11 percentage points relative to the baseline. Offer probabilities then recover very slowly.[45]

[45] Amongst the subset of workers who do exit employment at age 41, the probability of receiving a full-time job offer at age 42 is low. This makes it difficult to return to full-time employment after a health shock.

While lower job offer probabilities are a key factor that generates the slow recovery of employment following a health shock, they are not the whole story: Returning to the bottom left panel of Figure 3, the dotted red line shows that employment takes a few years to return to its baseline path even if job offers are held fixed as in the baseline. This is because after a major health shock health status is reduced. This lowers both tastes for work and offer wages until health status recovers, and this in turn reduces worker's probability of accepting full-time offers (even if they are received). At age 42 (two years after the shock) about 2/3 of the drop in employment is due to reduced health and 1/3 due to reduced offer probabilities. At later ages, as health recovers, reduced offer probabilities are the main factor.

The bottom right panel of Figure 3 shows the effects of a major health shock on labor earnings. Earnings are lower by 12%, 7% and 5% after 3, 5 and 8 years, respectively. The persistence is primarily due to the employment channel, with a small contribution from wage offers. Earnings drop less than full-time employment as some workers shift to part time.

Finally, we return to Table 4, which reports how major health shocks affect the present value of earnings for different types of workers. In the bottom panel, we see that for a typical college man a major health shock at age 40 reduces PV of remaining lifetime earnings by \$54.9k, and the human capital feedback channel accounts for 34% of this effect. Lifetime work years decline by 0.84 years, but if we shut down the human capital channel the decline is only 0.41 years. *The human capital mechanism is stronger for less educated workers*: For a typical high school man, a major health shock at age 40 reduces PV of remaining lifetime earnings by \$55.0k, and the human capital feedback channel accounts for 42% of this effect. As we show in Section 7.5, the human capital channel is more important for low skill men as they are more likely to exit employment, and slower to return, following major shocks.

7.3 Effects of Health Shocks on Key Outcomes

Here we examine the impact of health shocks (d^u, d^p, s) on some key outcomes in our 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, but we hold the perceived risk of health shocks (and hence decision rules) unchanged.

To be more precise, in these experiments, agents behave *as if* they expect to draw health shocks from the distributions Γ^{dp}, Γ^{du}, and Γ^{s}, so decision rules are unchanged. This allows us to examine what we call "direct" effects of health shocks. Later, in Section 7.5, 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.

In the baseline model simulation, reported in the first row of table 5, average annual sick days are 16.42. This may seem high, but it is important to understand that what we call "sick days" refers to the total reduction in annual days of work due to health shocks, so it is a very different concept from the sick days that workers may be entitled to in an employment contract.[46] Given the annual timing of our model, and our assumption that contractual hours are fixed annually, what we define as "sick days" incorporates the entire short-run (intra-year) labor supply response to health shocks.[47]

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

[47]Consistent with this idea, when we process the data, a worker who is employed at the start of the year and who experiences a mid-year health shock that causes him to leave employment for several months would be recorded as having a large number of sick days.

The second row of Table 5 first compares the baseline to an experiment where men never receive serious health shocks (s, d^u or d^p) at working ages (25-64). Our model predicts this would reduce total annual medical costs from \$4,618 to \$1,132, on average. We emphasize this is total cost, not just OOP.[48] Total cost does not drop to zero when we eliminate serious health shocks, as people with no shocks still have minor illnesses, prescriptions, preventive care, etc. We also predict that the fraction of working age men in good health would increase from 60% to 75%, and the probability of survival to 65 would increase from 82% to 87%.

The productivity effects of eliminating health shocks are substantial: Sick days of 16.4 per year are eliminated, which translates into about a 6% increase in work days for employed workers. The employment rate increases from 88% to 91%, so combining the intensive and extensive margin effects, the increase in total hours is about 10%. The mean offer wage increases by 2.6% (from \$23.60 to \$24.22). Notice that the impact on total hours is 4 times greater than the impact on offer wages, indicating that the impact of health shocks on earnings operates more through employment and hours than through wages.

The bottom panel of Table 5 gives results for men with a high school education (or less). In the baseline, these men have higher medical costs, more sick days, and a lower fraction in good health than more educated men. Eliminating health shocks has a large positive effect on the employment rate of high school men, which increases by 5 percentage points, compared to 3.2 points for all men. And the lifetime full-time equivalent work years of high school men increases by 5 years, compared to 3.5 years for all men. *It is a common theme of our results that health shocks have large effects on employment of low-skill men.*

Table 5 also reports the effect of eliminating the "unpredictable" shocks (d^u, s). This leads to almost as large a reduction in medical costs and sick days as eliminating all shocks. This is not because unpredictable shocks are more severe, but because they are much more prevalent.[49] Eliminating unpredictable shocks leads to a increase in FT equivalent lifetime work years of 2.8, and eliminating the d^p shocks leads to an additional increase of 0.7 years.

Finally, we 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. Decision rules are again held fixed. Giving all men low health risk has modest effects at working ages. The probability of having a d^p shock falls by 31%. However, as only 14% of working-age men experience a d^p shock in any given year, the overall benefit of reducing R is modest. In the bottom row of Table 5, we see that average medical costs decrease by \$548 and the fraction of men relying on social insurance decreases from 6.5% to 5.9%. The probability of living to age 65 increases from 82% to 83%.

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.

[48] Recall we estimate the medical charges function using data on insured men in MEPS (see Appendix B Section 6.2). For the insured we set total medical costs to 60% of charges, reflecting negotiated discounts. For the uninsured we also set total medical costs to 60% of charges (assuming they can obtain the same discount), using the charges function estimated on the insured.

[49] The most prevalent shocks are transitory s shocks (45% of working age individuals experience these each year), followed by d^u (24%) and lastly by d^p (17% for HS, 14% for Some College, and 10% for College).

7.4 Decomposing Sources of Earnings Inequality

Next we use our model to assess the contributions of initial conditions and health shocks to earnings inequality. We generate simulated life-cycle histories from the benchmark model, and calculate the present value of lifetime earnings (PVE) at age 25 for each simulated agent. Then, similar to Keane and Wolpin (1997), we regress the PVEs on initial conditions (i.e., education, latent skill type, latent health type, and initial H and R at age 25).

Table 6 row 1 presents the R^2 from this regression, both run separately by education and for all education groups combined. The combined results imply that 83.9% of the variance in the PVE across agents can be explained by initial conditions at age 25, primarily education and fixed productivity type, similar to results in Keane and Wolpin (1997).

What is the contribution of health shocks to inequality in the PVE? To assess this, we add a set of variables designed to capture the impact of health shocks throughout the working life. We include the number of times the agent experienced each of the eight possible combinations of the three shocks (d^u, d^p, s),[50] separately for when they are treated and untreated. We also enter 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. And we include the number of years the person spent in good, fair or poor health. Finally, to control for mortality shocks, we include the number of years prior to age 65 when the individual died, if positive. We were unable to find additional health variables that significantly improved the fit of our PVE regression.

When we include this array of health and health shock measures, the R^2 of our PVE regression increases to 91.6% – see Table 6 row 2. Thus, initial conditions (at age 25) and health shocks together can "explain" (or predict) 91.6% 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 91.6% - 83.9% = 7.7%. Thus, the "luck of the draw," whereby agents with the same initial conditions experience different health shock realizations, contributes at least 8% to the variance of PVE.

Next, Table 6 row 3 presents regressions that only control for initial health and the array of health variables, while omitting education, latent skill and latent health. Here, we find that initial health and health shocks explain 37.3% of the variance in the PVE across all agents. Combining results from rows (2) and (3), this means the initial conditions can *independently* explain 91.6 - 37.3 = 54.3% of the variance of the PVE.

The remaining 91.6 - 54.3 - 7.7 = 29.6% of variance in PVE cannot be attributed uniquely to either factor, as it 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-type and the incidence of health shocks.[51]

This discussion highlights the limitation of using a regression decomposition of PVE to assess the importance of health shocks for earnings inequality. Unfortunately it does not tell us how to allocate the 29.6% covariance term to initial conditions vs. subsequent health shocks and treatment decisions. The counterfactuals in Section 7.5 provide an alternative way to evaluate the role of health shocks in generating inequality.

[50] This allows the health shocks to have different effects when they occur in combination.

[51] 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.

The results in Table 6 that look *within* education groups reveal that health shocks can explain much more of the variance of PVE within the high school group (38%) than within the college group (16%). The counterfactuals in Section 7.5 shed light on why health shocks generate more earnings inequality among less educated workers.

7.5 Effects of Health Shocks on Earnings and Earnings Inequality

We now conduct counterfactuals to assess how health shocks affect the present value of lifetime earnings. Specifically, we remove health shocks from the model and simulate agents' life-cycle histories in the new environment. First, we consider the *total* effect of eliminating health shocks. Later, in Section 7.5.1, we decompose the total effect into the various channels through which health shocks affect earnings.

Table 7 reports the mean present value of lifetime earnings (PVE), both in the baseline model and in counterfactuals where we eliminate health shocks for working-age men.[52] The left-most column shows the baseline results: The mean PVE is $\$774k$, with a standard deviation of $\$385k$, implying a coefficient of variation of 0.497. The great heterogeneity of the PVE across education/productivity types is evident: The mean PVE ranges from only $\$318k$ for low-skill high school types to $\$1,508k$ for high-skill college types. (Of course, this is why initial conditions are so important in the regressions of Section 7.4.)

The right-most column of Table 7 shows the change in the mean PVE when health shocks are eliminated at working ages. For all workers the PVE increases by 10.7%. But the impact on low-skill workers is far greater. For the low-skill high school type, the total effect is to increase the PVE by a very substantial 37.0% (or $116k). In contrast, for high-productivity college workers, eliminating health shocks only increases the PVE by 6% (or $88k).

These results imply that health shocks contribute importantly to earnings inequality. Table 8 reports the coefficient of variation (CV) of the PVE, both in the baseline and in counterfactuals where we eliminate health shocks. As we see in the right-most column, the coefficient of variation decreases by 12.0% when we eliminate health shocks, from 0.497 in the baseline to 0.438. The Gini inequality measure (not reported) decreases by 12.7% from 0.278 to 0.242. *Thus, our model implies that health shocks generate about 12-13% of the inequality in present value of lifetime earnings for white men.* Notice this is 50% bigger than the 8% figure we obtained using the regression decomposition in Section 7.4. The regressions do not capture the behavioral response to reduced health risk.

Table 9 reports rates of employment and social insurance receipt. In the baseline, the overall employment rate is 87.7%, and eliminating health shocks increases this to 92.4%. But, as we see in the lower part of Table 9, baseline employment rates are much lower for low-skill workers. Only 71.5% of low-skill HS types work, and 25.5% receive means-tested social insurance. Eliminating health shocks increases their employment rate to 92.3%, and reduces the fraction who receive social transfers to 2.7%. Notably, the removal of health shocks eliminates most of the differences in employment rates across education/skill groups. Thus, *most of the increase in earnings for low-skill workers, and hence most of the reduction in inequality, arises via increased employment.*[53]

[52] Eliminated health shocks for men aged 65+ leads to an increase in average lifespans of 5 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.

[53] As we will see in Section 7.5.1, the role of higher wages is modest.

Returning to Table 8, it is notable that baseline inequality is much greater *within* lower-skill groups. For example, the CV is .421 for low-skill HS workers vs. only .206 for high-skill HS workers. This is mainly because health shocks generate more earnings inequality *within* the low-skill group: When health shocks are eliminated, the CV for low-skill HS workers drops by 49.8%, to .211, while that for the high-skill HS workers only drops by 10.1%, to .185. Health shocks generate so much inequality within low-skill groups because *low-skill workers who are adversely affected by health shocks have a high probability of exiting employment*.

7.5.1 Mechanisms: How do health shocks affect earnings and inequality?

Next we explore the mechanisms through which health shocks affect earnings and earnings inequality. In our model, health shocks affect earnings in four ways: First, there is the labor supply effect: Health shocks generate reduced hours in the impact period, and, if they cause health to deteriorate, they reduce tastes for work in future periods. Second, there is the human capital effect: Reduced hours and employment have a knock-on effect on future offer wages and job offer probabilities. Third, there is a productivity effect: Health shocks may cause worse health, which directly lowers productivity and hence wages. Fourth there is a behavioral effect: Existence of health risk alters decision rules for labor supply and savings.

To isolate the behavioral effect we run a simulation where we eliminate health shocks, but we hold decision rules fixed as in the baseline model simulation.[54] This gives the "direct effect" of health shocks, which is the sum of the (i) labor supply, (ii) human capital and (iii) productivity effects listed above. Comparing the results of this "direct effect" simulation with the "total effect" simulation (where we eliminate health shocks and *also* let decision rules adapt to the lower risk environment) reveals the behavioral effect of health risk. In Table 7, columns (4) and (5) report the behavioral and total effects, respectively.

Next, we decompose the "direct effect" into the (1) labor supply, (2) human capital and (3) health productivity effects by running a set of counterfactuals that hold different sets of endogenous variables fixed as in the baseline simulation. The "labor supply effect" captures changes in labor supply and earnings that are *directly* attributable to better health (i.e., fewer lost days due to illness, higher tastes for work). To isolate the "labor supply effect" we eliminate health shocks but hold offer wages and job offers fixed as in the baseline.

The "health productivity effect" is the additional effect that arises because better health directly improves productivity (i.e., wage offers). We obtain this by modifying the previous counterfactual to allow offer wages to improve due to improved health (while continuing to hold job offers and the experience terms in the offer wage function fixed).

Finally, the "human capital effect" is the additional effect that arises because elimination of health shocks causes workers to get more work experience: This leads to better job and wage offers, which (i) directly raises earnings, and (ii) leads to additional increases in labor supply. This "human capital effect" is obtained by modifying the previous counterfactual to also let work experience adjust (so all endogenous variables are free to adjust).[55]

[54] As we explained in Section 7.3, this counterfactual eliminates the "luck of the draw" whereby agents with the same initial conditions experience different health shock realizations. But agents in this counterfactual continue to make decisions as if they face the same risk of health shocks as in the baseline.

[55] Thus the "human capital effect" is the difference between (i) the direct effect simulation (where all endogenous variables are free to adjust) and (ii) a simulation where job offers and the experience terms in the offer wage function are held fixed as in the baseline. (Note: In each case decision rules are held fixed.)

We present this decomposition in Table 7, which reports the labor supply, human capital, productivity, behavioral and total effects in columns (1) to (5), respectively. For all workers, eliminating health shocks increases the PVE by 10.7%, and we attribute 5.7% to the labor supply channel, 2.7% to the human capital channel, 1.4% to the effect of health on productivity, and 0.8% to the behavioral effect. However, there is a great deal of heterogeneity in the magnitudes of these effects across different types of workers.

A striking result in Table 7 is that reduced labor supply due to health shocks has a much bigger impact on low-education and low-skill workers. For example, among the low-productivity high school types, health shocks reduce lifetime earnings by a substantial 10.7% via the labor supply channel. Importantly, they lose an additional 14.8% due to the knock-on effects of reduced human capital accumulation. This is due to *both* reduced offer wages and lower probabilities of full-time job offers, but the employment channel is more important (as we show below). The behavioral effect of eliminating health risk is also substantial, as it reduces lifetime earnings by 9.8%. But the direct impact of health on wages has a minor effect of only 1.3%. The combined impact of all four channels is 36.6%.

In contrast, among college men health shocks only reduce lifetime earnings by 3.9% via the labor supply channel.[56] The extra knock-on effect of reduced human capital accumulation is only 1.3%, precisely because the reduction in labor supply is minor, so it generates little deterioration in job and wage offers. The direct impact of health shocks on wages is similar to what we see for low-skill workers (1.5%). But in the behavioral effect of eliminating health risk is much smaller and of opposite sign. Eliminating health risk causes college men to work slightly *less*, as they have less incentive to accumulate precautionary savings. The combined impact of all 4 channels is to reduce PVE by 6.5%.

Next, in Table 8, we analyze how health shocks contribute to inequality in the present value of lifetime earnings through each of the four channels. For all workers, eliminating health shocks reduces the coefficient of variation in the PVE by 12.0%. We attribute 4.2% to the labor supply channel, 5.2% to the human capital channel, and 2.6% to the behavioral effect. In contrast, because the direct productivity effect on offer wages is similar for all types, it contributes essentially nothing to inequality. The human capital channel is so important because, as we saw in Table 7 the knock-on effect of health shocks via reduced human capital accumulation is much more important for low-skill workers. The main reason is that low-skill workers are much more likely to exit employment after a major health shock, and, as we show in Section 7.5.2, they are slow to return to full-time employment after health shocks, primarily due to reduced offer probabilities that make it difficult to return.

7.5.2 Mechanisms: How do health shocks affect employment and transfers?

We now return to Table 9 and assess the mechanisms through which health shocks affect employment and social insurance in more detail. The four columns show: (1) the baseline, (2) the effect of removing health shocks while holding human capital and decision rules fixed, (3) the "direct effect" that holds only decision rules fixed, and (4) the "total effect" that also lets decision rules adapt. Thus, the "human capital effect" is the difference between columns

[56] Health shocks are less important for the hours of high-skill workers for three main reasons: (1) high-skill workers tend to be in better health and hence face fewer health shocks, (2) better-educated workers face fewer predictable health shocks and have fewer sick days conditional on health shocks, and (3) better educated and higher productivity workers are less likely to exit employment after health shocks.

(3) and (2), and the "behavioral effect is the difference between columns (4) and (3). The difference between columns (2) and (1) combines what we call the "labor supply" and "health productivity" effects. Here we call this the "labor supply" effect for convenience, as we find the "health productivity" effect on employment and social transfer receipt is uniformly small.

As we see in Table 9, for all workers the elimination of health shocks increases the employment rate by 4.7 points (from 87.7% to 92.4%), and we attribute 0.9 points to the labor supply channel, 2.4 points to the human capital channel, and 1.4 points to the behavioral channel. It is interesting the human capital effect is almost three times larger than the labor supply effect. This reflects the pattern we saw in the lower left panel of Figure 3. When health shocks are eliminated but job offers are held fixed, employment recovers to its baseline level quickly (dashed red line). But, when we factor in the knock-on effect of reduced labor supply on job offers, the recovery in employment becomes very gradual (solid red line).

The decomposition for social transfers is different. For all workers elimination of health shocks reduces transfer receipt from 6.6% to 1.5%, and we attribute 2.0 points to the labor supply channel, 1.9 points to the human capital channel, and 1.2 points to the behavioral channel. The labor supply effect is relatively more important here, because a large share of transfers occur in the same period as the health shock, due primarily to the impact of lost work days that reduce consumption in the impact period.

There is substantial heterogeneity in the impact of health shocks across types of workers. It is particularly interesting to focus on the low-skill high school type: As we see in Table 9, eliminating health shocks increases their employment rate by 20.8 points (from 71.5% to 92.3%) and we attribute 3.2 to the labor supply channel, 10.1 points to human capital channel, and 7.5 points to the behavioral channel. Effects on transfers are also large: their SI receipt drops by 22.8 points (from 25.5% to 2.7%) and we attribute 6.4 to the labor supply channel, 8.8 to the human capital channel, and 7.6 points to the behavioral channel.

Thus, we find that both human capital and behavioral effects are much larger for low-skill workers. Figure 4, which expands the employment panel of Figure 3 by education, shows clearly why the human capital channel is so much more important for low-skill workers. The immediate drop in high school workers' employment rate in the year following a major health shock at age 40 is much greater than for college workers (i.e., 20 vs. 7 points). In subsequent years, if we hold human capital fixed as in the baseline (dashed red line), so job and wage offers do not deteriorate due to lost work experience, employment recovers quite quickly to its baseline rate for workers of all skill levels. But when we factor in the knock-on effect of reduced work experience, the employment rate decline for high school men becomes much more protracted: After 8 years (age 48) their employment rate is still reduced by 10 points, compared to only 3 points for college workers.

The very persistent effect of major health shocks on job offers, employment and earnings for low-skill men who exit employment following such a shock is a key finding of our analysis. Interestingly, Rose and Shem-Tov (2023) find that *exogenous* job exits lead to very persistent drops in earnings and employment for low-skill men in the ACS data linked with the Census Bureau LEHD data. It is likely that exits generated by health shocks would have even more persistent effects, as worse health makes return to the labor market more difficult.

As we have seen, the behavioral effects of health risk on earnings and employment are only substantial for low-skill workers. The behavioral effect arises because, in the baseline model, low-skill high school men have an incentive to curtail their labor supply and human capital accumulation so as to maintain eligibility for social insurance.[57] Thus, in an environment with 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).

One reason this moral hazard effect is so strong for low-skill high school workers is that they are relatively unlikely to get a job offer with insurance (only 48% get such an offer), so working provides relatively low protection against health shocks (through access to treatment and lower OOP) compared to other groups. In Section 8 we explore how provision of public insurance for the uninsured reduces this moral hazard effect.

Finally, we also see in Table 9 that for high-skill workers the behavioral effect of eliminating health risk is to slightly *reduce* labor supply. This is because high-skill workers are unlikely to use transfers to help pay medical costs. They instead rely on employer-provided insurance or they self-insure via saving. Removing health risk reduces the need for precautionary saving, and reduces the attractiveness of jobs that offer insurance. For both reasons, removing health risk slightly reduces the incentive of high-skill workers to supply labor.

7.6 Health Types and the Effect of Health Shocks

Next we examine how effects of health shocks on lifetime earnings differ by latent health type (ε^h). In Table 10 we see the present value of lifetime earnings is far greater for the good latent health type ($958k) than the bad type ($551k). Much of this difference arises because the good latent health type also tends to be better educated and have higher productivity. If we condition on education the difference remains substantial – e.g., $744k vs $494k within the high school group. Once we conditional on education, about 2/3 of the remaining gap arises because the bad health type also tends to be low productivity. According to the PVE regression from Table 6 row 1, which controls for education and productivity types, the impact of being the bad latent health type on the PVE is -$76k for HS men, -$80k for some college men, and -$131k for college men.

Notice that earnings inequality is far greater within the bad latent health type. For example, in the high school group, the coefficient of variation is .482 within the bad type compared to only .276 within the good type. The rate of employment within the bad health type is 11 points lower than for the good health type (81.5% vs. 92.8%) and the rate of social transfer receipt is much higher for the bad health type (12.9% vs. 1.5%).

The elimination of health shocks increases the expected present value of earnings of the bad health types by 15% to 24%, compared to only about 6% to 7% for the good health types. As we see in Table 10, when health shocks are eliminated the employment rate of the bad health type increases by 10 percentage points, while that of the good type is almost unchanged. Thus, eliminating health shocks almost eliminates the employment gap between the two groups. But it only eliminates about 1/3 of the PVE gap. This is because the good health types still tend to have higher wages, as they are more likely to be the high skill type.

Eliminating health shocks greatly reduces the degree of earnings inequality within the bad health type, while only slightly reducing inequality within the good health type. For example, within the high school group, the coefficient of variation of lifetime earnings falls

[57]Health shocks reduce the incentive of low-skill workers to work, as the combination of low wages, sick days and OOP health care costs is likely to push them unto the consumption floor anyway. Given the risk, they might as well decline employment, take leisure time, and rely on the consumption floor.

from .482 to .365 for the bad health types when health shocks are eliminated, while it only falls from .276 to .267 within the good type. Thus, the vagaries of health shocks contribute much more to lifetime earnings inequality within the bad health type. This is partly because the bad latent health types have more shocks, but the more important factor is that they are more likely to exit employment when they do have shocks - which in turn is due to the fact that they tend to be lower income and more reliant on the consumption floor.

7.7 Health Shocks and the Present Value of Lifetime Consumption

Finally, we examine how health shocks affect consumption inequality. Table 11 reports results on the present value of lifetime consumption (PVC) for men, in a calculation where married men receive household consumption deflated by the equivalence scale. In the baseline simulation, the coefficient of variation (CV) and Gini for the PVC are .392 and .221.[58]

Eliminating health shocks lowers the CV to .355 and the Gini to .199. Thus health shocks account for 10% of lifetime consumption inequality by both measures. In each case, roughly one-quarter of the effect arises from the behavioral response to health risk. Recall that health shocks account for 12%-13% of PVE inequality. It is interesting that health shocks generate less consumption than earnings inequality. This is perhaps surprising, given that the reduction in earnings generated by health shocks translates into reduced consumption, and, on top of that, health shocks generate OOP treatment costs that also reduce consumption. One reason is that earnings losses are personal, while consumption losses are shared within families, and hence they are mitigated relative to earnings losses. A second reason is that earnings losses are mitigated by the progressive tax/transfer system.

Turning to heterogeneity by types, we see that eliminating health shocks increases the PVC for high school workers by $54k or 13.3%, while increasing that of college workers by only $35k or 5%. It is striking that health shocks have a larger impact on less-educated workers even in absolute terms. This is because they tend to be in worse health and have more health shocks, and, as we saw in Section 7.1, low-skill workers are much more likely to exit employment following major health shocks. Also, HS men are less likely to be married, so earnings losses and OOP costs translate more directly into personal consumption.

Within the high school group, eliminating health shocks reduces the CV from .354 to .305, and the Gini from .203 to .174. Thus, by both measures, health shocks account for 14% of lifetime consumption inequality in the high school group. Roughly one-third of the effect arises from the behavioral response to health risk.

[58]This compares to .497 and .278 for the PVE. Several factors lower consumption relative to earnings inequality: (i) the tax/transfer system and Social Security benefit rules are progressive, (ii) higher earners leave much larger bequests, (iii) the liquidity constraint prevents high-skill workers from borrowing against future income, and discounting emphasizes consumption at early ages in the PVC calculation, and (iv) higher income men are more likely to be married, and married men share a large fraction of earnings with spouses and children. Comparing Tables 7 and 11 we see, for example, that the highest skill men keep only 59% of lifetime earnings for personal consumption, while the lowest skill men keep 86% (after transfers to the government and spouses/families and heirs). Note: In the cross-section consumption inequality is reduced by consumption smoothing, but that is irrelevant for the present values of earnings and consumption.

8 Providing Public Health Insurance to the Uninsured

In this section we use our model to simulate the impact of providing government funded health insurance to uninsured workers. In the baseline environment 39% of working age men lack employer provided health insurance (ESHI).[59] Rates of ESHI coverage vary greatly by age, education and full or part-time employment status, and our model provides a good fit to these patterns (see Appendix D.11). Among working age men, the fractions of high school, some college and college types with ESHI are 54%, 60% and 69%, respectively.

In our experiment we leave employer-sponsored insurance untouched, meaning that the probabilities job offers come with employer-sponsored insurance are unchanged. But we require all men who end up uninsured to participate in a government-funded health insurance program. This is similar in spirit to the initial idea of the ACA, which sought to leave the employer-sponsored system in place while organizing the uninsured into a large risk pool that could access a subsidized insurance plan, with mandated participation.[60,61]

Participants in the mandatory public plan pay an annual premium equal to the single employee's share of the typical employer-sponsored plan premium in the benchmark ($810), and this is tax deductible. Once the public plan is implemented, the men who participate face the same OOP treatment costs and have the same treatment/payment options as those covered by ESHI. The stigma associated with treating and not paying is also the same. Since our analysis is focused on the male population, we do not give the extra insurance to spouses – we keep their OOP unchanged and they do not pay additional premiums.

We present the results of the experiment in Table 12. The top panel shows how introducing the new public insurance program affects medical costs by source of payment. The program has a gross annual cost of $1,307 per working age man (or $3,282 per participant).[62]

[59]This is close to the data: in the CPS, 37% of working age white men were not covered by a group health plan provided by their own employer, and in the MEPS, 40% of respondents do not have ESHI through their job. 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.

[60]If we were instead 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.

[61]Large firms in the US are required to provide insurance to full-time workers, so it is employees of small firms and the unemployed who often lack insurance. We do not model the employer side of the market, but in our model the full-time offers with (without) insurance are implicitly coming from the large (small) firms. The ACA included tax penalties to prevent large firms with more than 50 employees from dropping their employer-sponsored insurance plans. We assume a similar guarantee is in place in our experiment, so large firms cannot drop insurance when the public plan is introduced. Furthermore, we find the probability that workers accept offers with insurance is almost unchanged in our experiment, which is consistent with our assumption that it does not create incentives for large firms to change their wage and insurance offers.

Introduction of the public plan could make jobs without insurance more attractive, creating an incentive for the roughly 45% of small firms that do offer insurance to drop it (Aizawa and Fang (2020)). But our experiment only generates a very small increase in the fraction of offers without insurance that are accepted (from 81.1% in the baseline to 83.9% in the experiment). This creates little incentive for small firms to drop insurance or offer lower wages in equilibrium.

[62]We assume the treatment cost borne by the government is $OOP - 0.6 * Charges$, so the government does not negotiate a better discount than what the uninsured obtained in the baseline model.

However, a substantial part of this cost is covered by reduced spending on Medicaid and DI, which drops from \$372 to only \$42 per capita. There is also a substantial drop in unpaid bills, from \$465 per working age man in the benchmark to only \$48. We assume unpaid bills are ultimately paid by agents in some form (higher taxes, higher medical costs for the insured), so this is also be counted as a cost saving. Note how average OOP costs and ESHI-covered costs are essentially unchanged in the experiment. This is because we left the existing ESHI system intact, and there is very little change in the composition of who is covered by ESHI.

Summing up all the cost components, total medical expenditures per capita increase by \$528, from \$2,586 in the benchmark to \$3,114 in the experiment. This is a 20% increase, implying a substantial "moral hazard" effect of providing insurance. Most of this increase in medical expenditures (\$408 of \$528) is due to an increase in the rate of treatment for health shocks.[63] As we see in the "health outcomes" panel of Table 12, the fraction of men who treat conditional on a shock increases from 80% to 99%. Per capita untreated medical costs drop from \$643 to \$42. It is interesting that untreated costs drop more (\$601) than medical spending increases (\$528). This occurs because people get healthier.

As we see in the "health outcomes" panel of Table 12, the provision of public insurance for the uninsured has important health benefits. The fraction of working age men in good health increases from 60 to 66% and the fraction of those experiencing any health shock in a given year decreases from 59.9% to 58.4%. Life expectancy increases by 0.7 years.

Table 13 shows how providing public insurance affects medical spending and sources of payment for insured vs. uninsured working-age men. The insured are little affected, although they do have a slight drop in total healthcare costs because the population is healthier. Men without employer-provided insurance have treatment costs of \$2,556 per person in the baseline, but they only pay \$506 of this (20%), the rest being covered by Medicaid or free care (unpaid bills). When the public insurance plan is introduced we see a substantial increase in spending by the initially uninsured from \$2,566 per person in the baseline to \$3,966 in the experiment. This is a 54% increase, implying a very large "moral hazard" effect. This mostly reflects an increase in the rate of treatment for men who lack ESHI from 55% in the baseline to 98% in the experiment,[64] causing the latent cost of untreated shocks to drop from \$1624 to only \$52.[65] OOP spending of the initially uninsured actually increases slightly, as their increased rate of treatment slightly outweighs their reduced cost per treatment. The cost of the public plan is \$3,282 per uninsured person, but savings of \$832 on Medicaid and \$1,052 per person on unpaid bills counterbalance 57% of this.

The "labor market outcomes" panel of Table 12 shows how the introduction of the public program improves labor market outcomes. The mean offer wage increases by 0.9%, the employment rate increases by 1.1%, and the present value of lifetime earnings increases by 1.9% or \$15k.[66] Introduction of public health insurance also reduces the fraction of working-

[63] The rest of the increase (\$120) arises because the newly insured also spend more in the state where no "significant" health shocks (d^p, d^u, s) occur. This is due to spending on preventive care, minor health events, etc. In the experiment, we assume the level of spending of the newly insured in the no-significant-shock case rises to the same level as we see for those covered by ESHI in the benchmark.

[64] Among those lacking ESHI, 65% experience a health shock annually.

[65] There is also an increase in spending on preventive care, minor illness, etc., by formerly uninsured men who face no shocks.

[66] The increase in the employment rate from 87.7% to 88.7% is primarily driven by a small increase in the fraction of job offers without ESHI that are accepted, from 81.1% in the baseline to 83.9% in the experiment.

age men who rely on social insurance (the consumption floor, including Medicaid, disability, Foodstamps, etc.), from 6.6% in the benchmark to 5.4% in the experiment. And earnings inequality is reduced as the coefficient of variation of the present value of lifetime earnings drops from 0.497 to 0.481.

The expected present value of household consumption (PVC) increases from $800k to $810k.[67] The increase is less then the $15k increase in the present value of earnings primarily because the expected present value of health insurance premiums is $5.6k. Consumption inequality is reduced, as the coefficient of variation of the PVC drops from 0.425 to 0.415.

8.1 Budgetary Impacts

Finally, the two "government expenditures and revenues" panels at the bottom of Table 12 summarize how the public insurance program affects all aspects of the government budget. The first panel focuses on households with working-age heads, while the second considers all households in the model, including those where the head is 65+.

Government tax revenues collected from households with working-age male heads increase from $15,403 to $15,530 per household in the experiment.[68] This 1% increase in tax revenue arises due to the increase in labor supply. The program also raises $323 per household in premiums, so the total increase in revenue is $450 per household (2.9%). Total spending on social insurance declines by $412 per household, a substantial cost saving equal to 2.7% of baseline revenue. Most of this is due to the $330 decline in Medicaid and DI expenditure that we saw in the top panel, although there is also a decline in other social transfers. Furthermore, there is a substantial decline in unpaid bills, which we count here as a government saving.[69] Together, the increase in revenue ($450), and declines in social insurance payments ($412) and unpaid bills ($417) make up for almost all of the $1,307 per household cost of the new public health insurance plan, which costs the government $28 per working-age household.

However, this calculation ignores the fact that government expenditures on Medicare and Social Security for those aged 65+ increase because life expectancy increases by 0.7 years. The bottom panel of Table 12 considers all households in the model, including those where the head is 65+. As we note, the increase in Social Security and Medicare costs is $204 per model household. Overall, once we factor in the impact of these additional costs, as well as other changes in social insurance costs, the introduction of the public insurance plan costs the government $237 per household. This extra cost can be covered by increasing the consumption tax from 5.7% to 6.5%.

We argue this change is small enough that we do not miss much by assuming away changes in the offer wage distribution that might occur in equilibrium. The fraction of job offers with ESHI that are accepted decreases very slightly from 98.4% to 98.3%. Lifetime labor supply increases from a mean of 30.6 full-time years in the baseline to 31.4 years in the experiment (a 2.6% increase).

[67] In this calculation, we include individual consumption of single men, and total household consumption for married men. Alternatively, we could give married men only their equivalence scale-adjusted share of household consumption. In that case, the expected present value of lifetime consumption for an individual man increases from $459k to $464k.

[68] In our model the number of men aged 25-64 is equal to the number of male-headed household with heads aged 25-64, so "per working age man" and "per household with a working age male head" are equivalent here.

[69] As Finkelstein et al. (2019) note, 60% of Medicaid costs go to cover free care: "Medicaid is best conceived of as consisting of two separate parts: a monetary transfer to external parties who would otherwise subsidize the medical care for the low-income uninsured, and a subsidized insurance product for recipients."

Our analysis takes into account the moral hazard effects of enhanced insurance coverage on total medical expenditures as well as the costs generated by longer life expectancy. But there is one potential cost we do not consider: If provision of public insurance increases demand for medical services, it may increase their price. Hence, our experiment may understate the cost of providing public insurance. We address this issue in Appendix G (Sensitivity) Table 106, where we assume the program-induced 20% increase in demand for health care by working-age agents, which translates into a 10.8% increase in total spending,[70] generates a 5% increase in prices. This only increases the net cost of the program by \$58 per capita, although, for men covered by ESHI, it also increases the sum of OOP and insurer cost by \$81 per capita. All agents are still better off *ex ante* in a balanced budget simulation.

It is interesting to compare our analysis with an accounting exercise that mechanically assesses the cost of the public insurance plan without any behavioral response. Uninsured men make the same treatment decisions as in the baseline, but their OOP is now set *as if* they had ESHI, and the government pays the difference.[71] We calculate that public insurance spending would be \$856 per person aged<65. This is much *less* than the \$1307 increase in Table 12, as there is no moral hazard effect. The government saves \$325 on Medicaid, and the public plan collects \$321 in premiums per person <65, of which Medicaid pays \$53.

Thus, net spending on the public plan would be \$263 per person under 65, which is more than the \$28 reported in Table 12. But the cost per household of all ages is \$190, which is less than the \$237 in Table 12.[72] So by accounting for behavioral responses we get a *higher* cost estimate, in large part due to increased Social Security and Medicare spending.

8.2 Heterogeneity in Impacts of Public Insurance

Table 14 shows how introduction of the public insurance plan affects different education, skill and health types. We report the results of a balanced budget simulation where premiums are combined with an 0.8 pp increase in the consumption tax to pay for the plan. As we see, for workers with high school education or less, the employment rate increases by 1.7 percentage points, and the present value of lifetime earnings increases by 3.6 percent. For more educated workers the increases in earnings are more modest (i.e., 1.5 and 0.9 percent for some college and college workers, respectively). This explains why the provision of public insurance reduces the coefficient of variation in the present value of lifetime earnings from .497 in the baseline to .481 in the experiment – see Table 12.

The lower panels of Table 14 show the impact on particular skill and health types within each education group. Effects are much larger for those with low productivity and/or bad latent health. For example, among high school men, 32% have low productivity and bad latent health. Within this group, the employment rate rises by 3.5 pp, earnings increase by 6.3%, reliance on social insurance drops by 3.6 pp, and the fraction in good health increases by 8 pp. The large positive effects on labor supply, earnings and health of low-skill poor-health types is why inequality falls.

The last column of Table 14 shows how introducing public insurance for the uninsured affects the present value of lifetime utility for each of the 18 types in the model. Notice that

[70] According to CMS working-age people accounted for 54% of US healthcare spending in 2014.

[71] We assume men who defaulted in the baseline continue to default here. The government already bears that cost in the baseline, so it is a wash if they cover it now.

[72] As the ratio of households with heads of all ages to households with heads under 65 is 1.38.

all 18 types experience an increase in the PV of lifetime utility, despite the tax increase, so *ex ante* we achieve a Pareto improvement. *Ex post*, some agents may end up worse off because they are lucky and experience no health shocks, and/or no periods where they lack employer provided insurance, yet they have to pay taxes to support the insurance plan. We also emphasize that this experiment is in steady state (i.e., all agents are born into a world where the public insurance plan exists). If the plan where implemented at a point in time then some agents, such as the already retired, would be worse off along the transition path.

8.3 Improving Medicaid Accessibility

An alternative to providing public insurance for the uninsured is a policy of improving access to Medicaid. In our model we assume the uninsured may sometimes be unable to access treatment, reflecting the fact that proof of insurance is required for many procedures. This reflects the fact that during our sample period (pre-ACA) Medicaid access was very limited in most states for non-disabled working-age single men or couples without children.

Here we conduct an experiment where Medicaid guarantees access to treatment for any uninsured man who is unable to attain the consumption floor after paying medical expenses. In such a case Medicaid pays only the excess of treatment cost beyond what drives the person down to the consumption floor.[73] (In contrast, the ACA Medicaid expansion did *two* things: It extended access to single men and women without children, and it also raised the means-tested eligibility threshold, making higher income households eligible.)

An increase in the consumption tax by 1.4 percentage points would be required to pay for this Medicaid accessibility policy. If it is implemented, Medicaid receipt increases from 3.7% of working age men in the benchmark to 7.3% in the experiment, while all social insurance receipt increases from 6.6% to 10.1% (Note that SI receipt exceeds Medicaid receipt as one can be on the consumption floor due to low income in the absence of health shocks).

A striking result is that improved access to Medicaid has strong labor supply disincentive effects. Aggregate employment falls by 3.1 percentage points. The decline is concentrated among men of the bad latent health type, especially if they are also the low productivity type. This subgroup of the high school, some college and college men have their employment drop by 10.5, 14.1 and 18.0 percentage points, respectively.

Strikingly, this Medicaid policy reduces the present value of lifetime utility for 17 out of 18 types. We clearly see the superiority of a public health insurance plan for all men who lack employer provided insurance over a policy of improved access to Medicaid – a program whose receipt is conditional on low income. The point is that the former policy encourages labor supply while the later policy discourages it.

Furthermore, the public insurance plan leads to a much greater improvement in health than improved Medicaid access: The fraction in good health increases by 5.9 percentage points compared to an increase of only 0.9 points when Medicaid access is improved. This is because the public plan covers shocks that do not drive agents down to the consumption floor, while under Medicaid such shocks may go untreated, causing health to deteriorate. (Notice that universal insurance increases the treatment rate from 80% to 99% in the total population under 65, but the Medicaid access experiment only increases it to 83%.)

[73] This change only affects men who drew the "no access" choice set in the baseline. Men who drew the "can treat if pay" and "can treat and then pay or default" choice sets already had the option to treat and rely on Medicaid to pay any treatment costs in excess of what would drive them to the consumption floor.

8.4 How Does Insurance Affect Health and Earnings?

In this section we explore in more detail the mechanisms through which public insurance affects health and earnings. The first two rows of Table 16 compare the baseline with the results from the public insurance experiment where we do not change the consumption tax. We then present results from three experiments that elucidate the mechanisms through which public insurance affects behavior.

In the first experiment we completely eliminate the OOP cost of health shocks.[74] Notice that eliminating the costs of treatment only increases the rate of treatment from 80.1% to 81.7%. This is because, in our model, it is lack of access to treatment by the uninsured, not cost *per se*, that mainly drives non-treatment. When access to treatment is available, the uninsured almost always treat (as they often have the option to default and obtain free care, or to rely on Medicaid). As cost is not the main barrier to treatment, eliminating cost generates relatively modest improvements in health.

Elimination of OOP costs has a positive effect on labor supply. This is greater for low-skill workers. As we see in the bottom panel of Table 16, for high school workers the employment rate increases from 84.8% to 85.9%, and transfer receipt drops from 10.2% to 8.2%. This illustrates the "moral hazard" effect of social insurance: Low skill workers have an incentive to curtail labor supply to maintain eligibility for means tested transfers that protect against high OOP costs. Elimination of OOP costs removes this labor supply disincentive.

The next row of Table 16 reports an experiment where we give all uninsured men access to treatment. Specifically, we shift the probability mass of the "cannot treat" choice set to the "can treat if pay" choice set. Here we are not allowing any more or less free care for the uninsured than in the baseline - we are only providing more access to treatment for those who are willing to pay. This increases the rate of treatment from 80.1% to 96.6%, which is almost as high as when we provide public insurance to the uninsured (99.2%). This illustrates that lack of access rather than cost is the main barrier to treatment. The higher rate of treatment causes the fraction in good health to increase substantially, from 60% to 65.2%. This, in turn, raises the employment rate by 0.5 points and raises PVE by 1%.

Finally, we consider an experiment where Medicaid guarantees access to care for anyone whose medical expenses would put them on the consumption floor.[75] In contrast to those experiments that give universal access to all workers who lack employer-sponsored insurance, or that guarantee access to anyone willing to pay, expansion of Medicaid access has perverse labor supply effects. The employment rate drops by 2.2 points, and transfer receipt increases by 2.5 points. Furthermore, it only increases the treatment rate from 80% to 83% (compared to 96.6% when everyone has access to treatment). The problem is that, to rely on Medicaid, one typically must have poor health and/or fairly low earning capacity to begin with. Expected lifetime earnings drop by $10k or 1.3%, and earnings inequality increases. Consistent with our results in Section 8.3, making Medicaid benefits more accessible is an inferior and highly distortionary way to improve access to health care.

[74]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.

[75]This experiment is the same as in Section 8.3, except here we do not impose a balanced budget.

9 Conclusion

We have built health, health shocks and health insurance into a life-cycle labor supply model with human capital, and explored the implications for labor supply, earnings and health. Rather than restate our main conclusions, which are summarized in the introduction and Section 7, we seek to draw some general lessons we have learned from modeling health.

First, in the US context, providing access to care is a key aspect of insurance, while its role in smoothing consumption is relatively less important at least for low-skill workers. The reason is that workers who lack ESHI do not bear the full cost of health shocks. They can decide not to treat in non-emergency situations, in some cases they can obtain low-cost or free care from safety net providers (i.e., community health centers, urgent care clinics) or rely on Medicaid, and they can default on bills[76] – see Mahoney (2015), Lockwood (2023).

The access role of insurance is vital as non-emergency treatment generally requires proof of insurance. As Institute of Medicine (2001) notes: "Because hospital emergency departments are legally required to assess and stabilize all [emergency] patients... without regard for ability to pay, they are the *only* providers who cannot turn uninsured patients away for lack of a source of payment." But the scope of this mandate is very limited:[77] Most needed and even urgent care is elective (i.e., non-emergency), and is hence difficult to obtain without proof of insurance. And, as the Institute of Medicine (2002) explains, another key role of insurance is to give access to a regular source of care (i.e., a regular physician), which is especially important for people with chronic conditions to receive adequate care.[78]

Consistent with this analysis, our model implies that providing men who lack ESHI with guaranteed access to care has substantial benefits in terms of health outcomes, labor supply and human capital accumulation. Reducing the uninsured's OOP cost of treating health shocks has positive but much more modest effects. Of course, providing insurance to uninsured individuals plays both roles. The fraction of working-age men in good health increases by 6 points, the employment rate increases by 0.7 points, and the present value of lifetime earnings increases by 1.8%. The gains are greater for high school men (7 points, 1.7 points, 3.6%), and even greater for low-skill high school men (8 points, 3.5 points, 6.3%).

Second, comparing our results to an alternative simpler model where agents *always* treat and pay health shock costs, Capatina et al. (2020), we find ignoring treatment decisions and free care leads one to exaggerate the consumption risk created by health shocks (by ignoring other margins on which agents can adjust). This causes one to exaggerate the incentives that health risk creates for workers to curtail labor supply to maintain eligibility for means-tested

[76] According to CMS, 55% of an emergency physician's time is spent providing uncompensated care. See Federal Register 67(251) Dec. 31, 2002 and https://www.acep.org/administration/reimbursement/the-impact-of-unreimbursed-care-on-the-emergency-physician.

[77] As Institute of Medicine (2001) notes: "The federal Emergency Medical Treatment and Active Labor Act ... requires hospital emergency rooms to assess and stabilize all patients with a life- or limb-threatening or emergency medical condition or those who are about to give birth. Hospitals are not required to provide continuing care after the patient has been stabilized..."

[78] As Institute of Medicine (2002) notes: "Health insurance is effective in improving receipt of appropriate health care in part because it increases access to a regular source of care," and "A patient with an ongoing relationship with a health care provider is more likely to receive appropriate medical attention and services early in the development of an illness or disease process rather than only once the condition has become acute or difficult to treat."

transfers. This incentive is important, but the simpler model exaggerates it.

Furthermore, if one fails to model endogenous treatment, or the access role of insurance, one is left with no structural explanation for why the uninsured have worse health transitions. To explain this, one is forced to adopt a reduced form of the health production function where insurance/income enter directly. This makes it difficult to do credible counterfactuals, as it is unlikely the effects of insurance/income in the production function are policy invariant.

Third, we find the contribution of health shocks to earnings inequality in the aggregate is about 12% to 13%. Health shocks generate inequality primarily because they reduce earnings and labor attachment of low skill workers, while having much smaller effects on high skill workers. Furthermore, within the subset of low-skill low-education men, the contribution of health shocks to inequality is very substantial. Both luck and behavior are important: Low-skill workers who are lucky enough to avoid major health shocks have substantially higher lifetime earnings, as such shocks often drive low-wage workers out of the labor market and onto means-tested transfers. In addition, even just the risk of health shocks makes it optimal for a significant fraction of low-skill men to rely on transfers (including Medicaid) rather than work, increasing earnings inequality within the low-skill group.

Finally, universal insurance has important advantages over means-tested Medicaid in terms of labor supply incentives, health outcomes, and welfare. The Institute of Medicine (2002) explained that Medicaid is fundamentally inferior to ESHI because it does not provide continuity of access: "Medicaid coverage tends to be intermittent, with adults gaining or losing coverage as their income, employment, or health status changes... As a consequence of the intermittency of Medicaid coverage, adults identified as covered by Medicaid at one point in time may not achieve the benefits that continuous health insurance coverage can provide."[79] We show, in addition, that Medicaid generates important work disincentives, as receipt is contingent on low income. This contrasts sharply with the positive labor supply incentives we find for non-contingent provision of public insurance to all men who lack ESHI.

An important limitation of our paper is the focus on white males. We plan extensions to women and minorities in ongoing work. Extension to women is very ambitious, as we must model fertility and costs of pregnancy. Our preliminary work on Black and Hispanic men, described in Appendix F, suggests that extension to these groups is is also difficult, for two reasons: First, the MEPS samples of Blacks and Hispanics are fairly small, making calibration difficult. Second, their behavior differs from whites in important ways: Blacks and Hispanics report fewer health shocks, treat a much lower fraction of reported shocks, and have worse health transitions than whites even conditional on insurance, health, education and income. We believe key factors driving these differences are the well-documented barriers to access for minorities even conditional on ESHI, discussed in Allen et al. (2017); Tarlov et al. (2010); Wang et al. (2008); Kang-Kim et al. (2008); Lurie and Dubowitz (2007); Cunningham and Kemper (1998); Bashshur et al. (1994) among others. Capturing these barriers requires significant extension of our model.

[79]The Institute of Medicine (2002) also states that "The programmatic features of Medicaid that contribute to worse health related outcomes among its enrollees include provider participation and payment levels and limited coverage periods.... Low provider payment rates, in both the fee for-service and the capitated sectors, reduce access to health care services for Medicaid enrollees... [who] often find themselves limited to much the same set of overtaxed safety-net providers as uninsured adults, with concomitant delays in getting appointments and referrals to specialists and little continuity of care..."

Tables

Table 2: Wages, Hours and Earnings Regression Results, MEPS

Dependent Var	Log Wage	Weekly Hours	Annual Earnings
Mean	3.105	35.328	81.128
SD	0.562	19.440	39.084
s	0.005**	-0.300**	-0.792***
	(0.003)	(0.134)	(0.294)
d^p	-0.009**	-0.675***	-2.302***
	(0.005)	(0.210)	(0.443)
d^u	-0.001	-1.049***	-1.892***
	(0.003)	(0.163)	(0.348)
Lagged Dep. Var.	0.927***	0.767***	0.730***
	(0.003)	(0.004)	(0.004)
Education			
Some College	0.017***	0.796***	2.631***
	(0.003)	(0.166)	(0.346)
College	0.046***	1.455***	6.940***
	(0.003)	(0.151)	(0.325)
Initial Health			
Fair	0.010	4.055***	11.309***
	(0.012)	(0.314)	(0.630)
Good	0.017	5.014***	14.166***
	(0.012)	(0.326)	(0.654)
R2	0.903	0.671	0.663
Observations	19,285	30,896	29,726

Standard errors in parentheses

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

Notes: Estimated using MEPS, years 2000-2013, on white males, and using data from interviews 1 and 3 which are approximately 1 year apart. 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 3 in MEPS, and keeping only those with hourly wages greater than half of the minimum wage. The Weekly Hours regression is estimated on all individuals including those with zero hours. The earnings regression includes non-employed workers, and incorporates a Box-Cox transform of annual earnings, with lambda = 0.323. Earnings are measured at the annual level, so the dependent variable is earnings in the second year of interview and here shocks are also measured in the second year while health is measured in round 3, roughly at the beginning of the second year of interview. If we drop controls for health and health shocks, the R-squared of the three regressions decline to 0.903, 0.666 and 0.655, respectively.

Table 3: Ordered Logit Regression, H, ages 25-64, MEPS Data and Model

	Data	Model (1)	Model (2)	Model (3)	Model (4)
H = Poor	-4.483***	-4.571***	-4.406***	-5.374***	-5.225***
	(0.105)	(0.018)	(0.019)	(0.020)	(0.020)
H = Fair	-1.818***	-1.709***	-1.589***	-1.836***	-1.708***
	(0.041)	(0.007)	(0.007)	(0.007)	(0.007)
Some College	0.128***	0.199***	0.027***	0.205***	0.021**
	(0.049)	(0.008)	(0.008)	(0.008)	(0.009)
College	0.353***	0.449***	0.008	0.492***	0.012
	(0.049)	(0.008)	(0.009)	(0.009)	(0.010)
d^p shock	-0.726***	-0.769***	-0.802***	-0.840***	-0.885***
	(0.057)	(0.010)	(0.010)	(0.010)	(0.010)
d^u shock	-0.675***	-0.776***	-0.812***	-0.923***	-0.973***
	(0.046)	(0.008)	(0.008)	(0.008)	(0.008)
ESHI	0.446***	0.588***	0.643***	-0.032***	0.010
	(0.050)	(0.007)	(0.007)	(0.008)	(0.008)
Inc: 1st	-0.301***	-0.234***	-0.037***	-0.210***	0.008
	(0.064)	(0.011)	(0.011)	(0.011)	(0.011)
Inc: 2nd	-0.100*	-0.152***	-0.029***	-0.137***	-0.003
	(0.061)	(0.010)	(0.010)	(0.010)	(0.010)
Inc: 4th	0.093	0.099***	0.039***	0.073***	0.005
	(0.064)	(0.010)	(0.010)	(0.010)	(0.011)
Inc: 5th	0.191***	0.135***	0.055***	0.087***	-0.004
	(0.067)	(0.011)	(0.011)	(0.012)	(0.012)
Latent health = Bad			-0.917***		-1.005***
			(0.008)		(0.008)
Not treat shock				-1.703***	-1.751***
				(0.011)	(0.011)
Cubic Age	Yes	Yes	Yes	Yes	Yes
Shocks correctly measured	No	No	No	Yes	Yes
Pseudo R^2	0.271	0.263	0.278	0.305	0.322

Standard errors in parentheses

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

Note: The cutoffs are omitted.

Table 4: 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		
A. SOS Effect							
HS or Less							
30	-12,502	-2.4	-22,333	-4.3	44.0	-0.37	-0.77
40	-18,751	-4.0	-36,597	-7.9	48.8	-0.50	-1.23
50	-25,214	-7.9	-36,066	-11.3	30.1	-0.62	-0.99
60	-21,606	-21.0	-24,865	-24.2	13.1	-0.54	-0.62
Some College							
30	-14,134	-2.1	-27,156	-4.0	48.0	-0.33	-0.77
40	-19,669	-3.4	-27,917	-4.9	29.5	-0.43	-0.63
50	-22,242	-6.1	-33,772	-9.2	34.1	-0.52	-0.88
60	-20,259	-18.3	-24,931	-22.5	18.7	-0.41	-0.51
College							
30	-17,725	-1.6	-29,428	-2.7	39.8	-0.18	-0.47
40	-25,414	-2.7	-37,020	-3.9	31.4	-0.27	-0.56
50	-32,641	-5.2	-38,603	-6.2	15.4	-0.35	-0.48
60	-27,797	-13.3	-31,325	-15.0	11.3	-0.30	-0.35
B. Average Effect							
HS or Less							
30	-20,414	-3.7	-46,520	-8.4	56.1	-0.66	-1.97
40	-31,823	-6.7	-55,006	-11.5	42.1	-0.91	-1.89
50	-40,812	-12.3	-59,495	-18.0	31.4	-1.05	-1.66
60	-31,485	-30.0	-37,229	-35.4	15.4	-0.77	-0.91
Some College							
30	-20,538	-3.1	-50,036	-7.4	59.0	-0.55	-1.65
40	-29,055	-5.1	-49,996	-8.7	41.9	-0.70	-1.44
50	-33,293	-8.7	-48,837	-12.8	31.8	-0.72	-1.18
60	-26,659	-21.8	-32,418	-26.5	17.8	-0.55	-0.68
College							
30	-25,641	-2.4	-56,115	-5.2	54.3	-0.37	-1.10
40	-35,551	-3.7	-53,859	-5.6	34.0	-0.41	-0.84
50	-42,045	-6.5	-50,788	-7.9	17.2	-0.43	-0.63
60	-38,700	-18.1	-46,246	-21.7	16.3	-0.45	-0.58

Notes: In Panel A, we consider individuals who experience a severe d^u shock (causing a drop in H) in the benchmark simulation at the indicated age, and compare their earnings to a scenario where the shock does not occur. In Panel B, we compare counterfactuals where either (i) all men experience a severe d^u shock at the indicated age or (ii) no man experiences such a shock at the indicated age. In the "HC Fixed" scenario we hold human capital fixed at the levels that arise in the scenario where the health shock does not occur.

Table 5: The Importance of Health Shocks in the Benchmark Model

	Med Costs	Sick days	Surv to 65 (%)	Good H (%)	Emp (%)	Yrs Worked	SI (%)	Wage Offer
All Men (25-64)								
Benchmark	4,626	16.42	82.06	59.95	87.74	30.65	6.56	23.60
No s, d^u, d^p	1,127	0.00	87.09	74.76	90.99	34.17	2.67	24.22
No s and d^u	1,670	3.61	85.60	70.81	90.43	33.49	3.28	24.10
Low R	4,069	14.35	82.68	61.54	88.41	31.18	5.94	23.68
HS or Less								
Benchmark	5,160	22.50	78.04	49.93	84.77	28.52	10.18	17.55
No s, d^u, d^p	1,130	0.00	85.22	67.69	89.82	33.56	3.98	18.35
No s and d^u	1,810	4.75	83.01	62.61	88.93	32.56	5.00	18.18
Low R	4,481	19.79	79.07	51.79	85.87	29.27	9.11	17.68

Notes: Data are simulated from the Benchmark model, with the indicated health shocks shut down at ages 25-64, but with decision rules unchanged. Medical Costs are equal to 0.6·Charges. Sick days are full time days per year assuming a working day of 8hrs.

Table 6: Explaining the Variance of the Present Value of Lifetime Earnings

	R^2 from PV Earnings Regressions			
Independent Variables Included	**<=HS**	**SC**	**College**	**All**
1. Initial conditions (IC)	0.677	0.741	0.788	0.839
2. IC + Health, health shocks, treatment	0.827	0.866	0.885	0.916
3. Health, health shocks, treatment	0.378	0.285	0.162	0.373

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 health and skill types (ε^h and ε^s) and H and R at age 25. In the "All" column (that combines education groups), the initial condition also includes education and its interactions with latent types, 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 (and treatment status in rows 3 and 5) at the time of occurrence.

Table 7: Effects of Health Shocks on Present Value of Lifetime Earnings (PVE)

	Baseline PVE	**Lab Sup Effect**	**Hum Cap Effect**	**Health Effect**	**Behavior Effect**	**Total Change**
		(1)	(2)	(3)	(4)	(5)
All	773,607	5.72	2.73	1.41	0.78	10.65
≤High School	562,440	8.73	4.78	1.57	2.80	17.88
Some College	686,287	5.57	3.04	1.02	0.22	9.85
College	1,080,767	3.94	1.33	1.48	-0.22	6.54
≤High School						
Low Productivity	317,861	10.74	14.82	1.26	9.80	36.61
Med Productivity	548,271	9.23	4.26	1.64	2.15	17.28
High Productivity	821,246	7.62	1.24	1.65	0.52	11.03
Some College						
Low Productivity	420,611	6.41	7.13	0.90	1.88	16.32
Med Productivity	667,130	5.59	2.66	1.04	-0.20	9.09
High Productivity	971,121	5.19	1.53	1.06	-0.22	7.56
College						
Low Productivity	694,205	4.34	3.13	1.47	-0.44	8.50
Med Productivity	1,039,861	3.97	0.97	1.51	-0.17	6.29
High Productivity	1,508,236	3.74	0.75	1.47	-0.15	5.81

Note: The table presents the mean (across simulated agents) of the present value of earnings (PVE). This is expressed in 2010 dollars in the Benchmark and as a percentage change from the Benchmark in the subsequent columns. Columns numbered (1)-(3) present the direct effects of health shocks decomposed into the labor supply effect, the human capital effect and the health productivity effect. Column (4) presents the behavioral effect (due to decision rules adapting), and column (5) presents the total effect from a simulation where health risk is eliminated and decision rules adapt.

Table 8: Effects of Health Shocks on Inequality in Lifetime Earnings (CV of PVE)

	Baseline CV	**Lab Sup Effect**	**Hum Cap Effect**	**Health Effect**	**Behavior Effect**	**Total Change**
		(1)	(2)	(3)	(4)	(5)
All	0.497	-4.15	-5.23	0.01	-2.62	-11.98
≤High School	0.454	-4.76	-9.45	0.03	-7.32	-21.50
Some College	0.395	-3.35	-6.30	-0.03	-1.97	-11.65
College	0.350	-1.65	-3.13	-0.19	0.80	-4.17
≤High School						
Low Productivity	0.421	-6.47	-16.88	-0.03	-26.44	-49.83
Med Productivity	0.268	-11.51	-9.54	-0.54	-6.19	-27.78
High Productivity	0.206	-8.01	-1.52	-0.65	0.11	-10.07
Some College						
Low Productivity	0.331	-7.19	-15.30	-0.18	-13.49	-36.17
Med Productivity	0.193	-10.24	-10.73	-0.58	1.75	-19.80
High Productivity	0.184	-8.11	-4.97	-0.47	1.57	-11.98
College						
Low Productivity	0.230	-4.85	-12.76	-0.59	2.52	-15.67
Med Productivity	0.155	-6.34	-4.72	-1.01	4.18	-7.88
High Productivity	0.139	-4.70	-3.27	-0.88	2.19	-6.66

Note: The table presents the coefficient of variation (CV) of the PVE for the Benchmark and the percentage change from the Benchmark in the subsequent columns. Columns numbered (1)-(3) present the direct effects of health shocks decomposed into the labor supply effect, the human capital effect and the health productivity effect. Column (4) presents the behavioral effect (due to decision rules adapting), and column (5) presents the total effect from a simulation where health risk is eliminated and decision rules adapt.

Table 9: Effects of Health Shocks on Employment and Social Insurance

	Employment (%)				Social Insurance (%)			
	Baseline	No Health Shocks			Baseline	No Health Shocks		
		DR+HC Fixed	Dec Rule Fixed	Total Effect		DR+HC Fixed	Dec Rule Fixed	Total Effect
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
All	87.7	88.6	91.0	92.4	6.6	4.6	2.7	1.5
≤HS	84.8	86.2	89.8	93.0	10.2	7.0	4.0	1.4
Some College	86.8	87.7	90.1	90.7	6.6	4.8	2.9	2.1
College	91.7	92.0	92.9	92.7	2.4	1.7	1.0	1.2
≤HS								
Low Skill	71.5	74.7	84.8	92.3	25.5	19.1	10.3	2.7
Med Skill	89.5	91.1	91.9	93.4	4.0	1.3	1.0	0.6
High Skill	93.2	92.7	92.8	93.5	1.1	0.7	0.7	0.7
Some College								
Low Skill	79.3	80.8	86.3	88.6	15.7	12.5	7.3	4.6
Med Skill	89.8	90.4	91.6	91.3	2.8	1.4	0.8	0.9
High Skill	91.3	91.7	92.2	92.0	1.3	0.6	0.4	0.7
College								
Low Skill	88.5	89.2	91.5	91.1	6.0	4.3	2.5	2.7
Med Skill	92.8	92.9	93.3	93.0	0.8	0.5	0.4	0.5
High Skill	93.9	93.9	94.1	93.9	0.3	0.2	0.1	0.3

Notes: The table presents the full-time employment rate and rate of government transfer receipt for working age men. The first column shows the baseline simulation. The next three columns show counterfactuals where we eliminate health shocks at working ages: (i) holding human capital (HC) and decision rules (DR) fixed as in the baseline, (ii) letting human capital adjust, and (iii) letting both adjust.

Table 10: Effects of Removing Health Shocks, by Latent Health Type

	PV Earnings		**CV of PVE**		**Emp. Rate**		**SI Rate**	
Latent Health	**Baseline**	**No HS**	**BL**	**No HS**	**BL**	**No HS**	**BL**	**No HS**
Bad (45%)	550,937	+20.44%	0.500	0.397	81.5	91.9	12.9	2.1
Good (55%)	958,310	+5.98%	0.380	0.372	92.8	92.8	1.5	0.9
By Education								
≤High School								
Bad (73%)	493,572	+23.79%	0.482	0.365	81.2	92.9	13.7	1.6
Good (27%)	744,096	+7.55%	0.276	0.267	93.9	93.3	1.1	0.7
Some College								
Bad (48%)	605,406	+15.58%	0.444	0.371	81.7	89.4	11.6	3.2
Good (52%)	760,947	+5.63%	0.329	0.319	91.4	91.8	2.0	1.0
College								
Bad (11%)	828,200	+15.40%	0.419	0.351	82.9	90.4	10.1	2.8
Good (89%)	1,113,545	+5.69%	0.332	0.327	92.9	93.0	1.4	1.0

Note: The mean (across simulated agents) of the present value of earnings (PVE) is expressed in 2010 dollars. CV denotes the coefficient of variation. Rates of employment and social insurance (SI) receipt are calculated in the cross-section of men aged 25-64. BL denotes the Baseline model; No HS denotes the counterfactual where health shocks are removed.

Table 11: Health Shocks and Inequality in the Present Value of Lifetime Consumption (PVC)

	Baseline			**No Health Shocks Decision Rules Fixed**			**No Health Shocks Total Effect**		
	PVC	**CV**	**Gini**	**Δ(PVC)**	**CV**	**Gini**	**Δ(PVC)**	**CV**	**Gini**
All	533,693	0.392	0.221	8.25	0.364	0.205	8.14	0.355	0.199
By Education									
≤High School	407,585	0.354	0.203	12.13	0.323	0.184	13.28	0.305	0.174
Some College	495,389	0.301	0.171	8.01	0.285	0.161	7.38	0.278	0.158
College	707,977	0.264	0.150	5.72	0.258	0.146	5.00	0.257	0.145
By Productivity									
≤High School									
Low Productivity	274,596	0.249	0.135	16.11	0.223	0.115	19.88	0.178	0.089
Med Productivity	399,629	0.226	0.121	12.65	0.194	0.101	13.69	0.184	0.094
High Productivity	548,561	0.201	0.106	9.76	0.185	0.097	9.67	0.181	0.095
Some College									
Low Productivity	353,897	0.210	0.108	9.46	0.184	0.089	9.53	0.166	0.080
Med Productivity	490,972	0.167	0.087	8.05	0.149	0.076	7.11	0.145	0.073
High Productivity	641,299	0.179	0.094	7.17	0.167	0.086	6.39	0.163	0.084
College									
Low Productivity	520,694	0.157	0.078	6.18	0.144	0.068	5.55	0.144	0.069
Med Productivity	710,475	0.142	0.071	5.57	0.134	0.066	4.87	0.132	0.065
High Productivity	892,761	0.154	0.081	5.57	0.149	0.078	4.77	0.146	0.076

Note: The mean (across simulated agents) of the present value of consumption (PVC) is expressed in 2010 dollars in the baseline simulation, and as a percentage change in the two counterfactuals. CV denotes the coefficient of variation.

Table 12: Mandatory Public Health Insurance

	Benchmark	Public HI	Change
Average Annual Medical Expenses (per man) - Ages 25-64			
Costs covered by New Public Insurance Program	0	1,307	
OOP Costs - Paid by Individuals	515	517	
Costs covered by ESHI	1,234	1,200	
Costs covered by Medicaid/DI	372	42	
Unpaid Bills	465	48	
Total (sum of all above expenditures)	2,586	3,114	528
Average costs of untreated health shocks	643	42	
Health Outcomes:			
Fraction who treat conditional on shock, ages 25-64	80.1	99.2	
Fraction experiencing a health shock, ages 25-64	59.9	58.4	
Fraction in Good Health, ages 25-64	60.0	65.9	
Life Expectancy	77.5	78.2	
Labor Market Outcomes:			
Mean Wage Offer	23.60	23.82	
Employment Rate	87.7	88.7	
FT Years of Work	30.64	31.39	
PV of Lifetime Earnings (thousands)	774	789	
Coefficient of variation PV Earnings	.497	.481	
PV of Lifetime Consumption (thousands)	800	810	
Coefficient of variation PV Consumption	.425	.415	
Receive social insurance benefits, working ages (%)	6.6	5.4	
Government Revenues and Expenditures (per household)			
Households with working age male heads only:			
Tax Revenues	15,403	15,530	
Public Health Insurance Premiums	0	323	
Public Health Insurance Payments	0	-1307	
Social Insurance Payments	-953	-541	
Unpaid Medical Bills	-465	-48	
Government Surplus (per household) - head age 25-64	13,985	13,957	-28
Government Revenues and Expenditures (per household)			
Households with heads of All Ages (all model households):			
Tax Revenues	12,901	12,962	
Social Security + Medicare (net of Medicare premiums)	-10,630	-10,834	
Social Insurance Payments (other)	-790	-477	
Public Health Insurance (Payments minus premiums)	0	-708	
Unpaid Bills	-336	-34	
Government Surplus (per household) - All ages	1,145	908	-237

Table 13: Medical Costs by ESHI, Ages 25-64, Benchmark and Public Insurance

	Total cost	By Source of Payment					Cost of
	of treated	OOP (Self)	ESHI	Medicaid	Unpaid	Public	untreated
Benchmark							
No ESHI	2,556	506	0	937	1,113	0	1,624
ESHI	2,606	522	2,043	1	39	0	0
All	2,586	515	1,234	372	465	0	643
Public Insurance							
No ESHI	3,966	517	0	105	61	3,282	59
ESHI	2,550	517	1,994	1	39	0	31
All	3,114	517	1,200	42	48	1,307	42

Table 14: Mandatory Public Health Insurance, by Latent Types, Balanced Budget

	EMP		SI		PV Earnings		% Good H		PV Uti
Skill/Health Type	**Bench**	**Public**	**Bench**	**Public**	**Bench**	**Public**	**Bench**	**Public**	**Public**
	%	pp Δ	%	pp Δ		% Δ	%	pp Δ	% Δ
All	87.7	0.7	6.6	-0.8	774	1.8	60.0	5.9	0.33
≤High School	84.8	1.7	10.2	-1.8	562	3.6	49.9	7.0	0.39
Some College	86.8	0.2	6.6	-0.5	686	1.5	59.5	6.0	0.34
College	91.7	-0.3	2.4	0.1	1,081	0.9	71.8	4.8	0.22
≤High School									
Low, Bad (31.7%)	70.6	3.5	26.5	-3.6	313	6.3	40.5	8.0	0.23
Low, Good (1.7%)	89.4	0.0	6.3	0.2	401	1.6	70.5	6.6	0.11
Med, Bad (24.2%)	87.7	2.9	5.2	-2.6	525	7.2	42.2	6.9	0.64
Med, Good (9.1%)	94.1	-0.3	0.9	-0.1	610	1.2	71.9	6.6	0.05
High, Bad (16.7(%)	92.1	0.2	1.5	-0.4	791	2.3	42.8	6.0	0.71
High, Good (16.7%)	94.3	-0.6	0.7	0.0	852	1.0	71.3	6.5	0.28
Some College									
Low, Bad (19.0%)	71.9	1.6	23.6	-2.0	379	3.5	42.4	7.5	0.40
Low, Good (14.3%)	88.8	-1.2	5.6	1.0	476	0.2	73.4	6.0	0.17
Med, Bad (16.0%)	86.9	1.2	5.1	-1.8	625	3.1	45.2	5.9	0.44
Med, Good (17.3%)	92.3	0.0	0.8	-0.1	706	1.0	73.4	5.5	0.23
High, Bad (13.0%)	89.5	0.0	2.6	-0.5	911	1.7	45.0	5.5	0.59
High, Good (20.3%)	92.5	-0.3	0.5	0.1	1,009	0.6	73.6	5.5	0.24
College									
Low, Bad (6.0%)	76.5	0.7	17.4	-0.7	587	1.8	44.4	6.0	0.31
Low, Good (27.3%)	91.1	-0.6	3.6	0.4	718	0.5	74.9	5.0	0.07
Med, Bad (3.8%)	89.3	0.2	2.5	-0.6	961	1.6	46.4	4.7	0.25
Med, Good (29.5%)	93.3	-0.2	0.6	0.0	1,050	0.9	75.3	4.6	0.29
High, Bad (1.7%)	90.8	0.9	1.9	-0.6	1,394	2.2	47.3	4.9	0.63
High, Good (31.7%)	94.1	-0.3	0.3	0.1	1,514	0.8	75.2	4.5	0.25

Notes: The table presents statistics from the experiment in which we give public health insurance to those previously uninsured aged 25-64 and the consumption tax increases to balance the government budget. All statistics are calculated in the cross-section of individuals 25-64 years of age. PV Earnings are expressed in thousands of dollars. The table shows the percentage increase in PV earnings and PV utility relative to the benchmark when individuals have public health insurance. Employment, social insurance recipiency rates and fraction in good health are shown as percentage point changes relative to the benchmark.

Table 15: Medicaid Guaranteed Experiment, by Latent Types, Balanced Budget

	EMP		SI		PV Earnings		% Good H		PV Uti
Skill/Health Type	**Bench**	**Public**	**Bench**	**Public**	**Bench**	**Public**	**Bench**	**Public**	**Public**
	%	**pp** Δ	%	**pp** Δ		% Δ	%	**pp** Δ	% Δ
All	87.7	-3.1	6.6	3.5	774	-1.8	60.0	0.9	-0.29
≤High School	84.8	-3.6	10.2	4.2	562	-2.2	49.9	1.3	-0.28
Some College	86.8	-3.5	6.6	4.2	686	-2.2	59.5	1.1	-0.24
College	91.7	-2.2	2.4	2.3	1,081	-1.3	71.8	0.4	-0.34
≤High School									
Low, Bad (31.7%)	70.6	-10.5	26.5	12.3	313	-11.3	40.5	3.7	-0.19
Low, Good (1.7%)	89.4	-2.6	6.3	3.2	401	-2.3	70.5	1.5	-0.30
Med, Bad (24.2%)	87.7	-0.7	5.2	0.7	525	-0.9	42.2	0.2	-0.33
Med, Good (9.1%)	94.1	0.0	0.9	0.1	610	0.0	71.9	0.1	-0.33
High, Bad (16.7(%)	92.1	-0.2	1.5	0.1	791	-0.1	42.8	0.1	-0.30
High, Good (16.7%)	94.3	-0.1	0.7	0.0	852	0.0	71.3	0.1	-0.33
Some College									
Low, Bad (19.0%)	71.9	-14.1	23.6	16.9	379	-15.6	42.4	4.3	0.03
Low, Good (14.3%)	88.8	-4.5	5.6	5.3	476	-3.4	73.4	1.4	-0.28
Med, Bad (16.0%)	86.9	-1.1	5.1	0.7	625	-0.9	45.2	0.3	-0.30
Med, Good (17.3%)	92.3	-0.1	0.8	0.1	706	-0.1	73.4	0.1	-0.35
High, Bad (13.0%)	89.5	-0.2	2.6	0.3	911	-0.2	45.0	0.2	-0.31
High, Good (20.3%)	92.5	-0.1	0.5	0.2	1,009	-0.1	73.6	0.1	-0.33
College									
Low, Bad (6.0%)	76.5	-18.0	17.4	19.3	587	-19.3	44.4	2.9	-0.10
Low, Good (27.3%)	91.1	-3.9	3.6	3.9	718	-3.3	74.9	0.8	-0.39
Med, Bad (3.8%)	89.3	-1.0	2.5	0.8	961	-1.0	46.4	0.1	-0.33
Med, Good (29.5%)	93.3	-0.2	0.6	0.2	1,050	-0.1	75.3	0.1	-0.34
High, Bad (1.7%)	90.8	0.0	1.9	0.2	1,394	0.0	47.3	0.1	-0.32
High, Good (31.7%)	94.1	-0.1	0.3	0.1	1,514	-0.1	75.2	0.0	-0.34

Notes: The table presents statistics from the experiment where we allow all those who qualify for the consumption floor to treat health shocks at ages 25-64 and where the consumption tax increases to balance the government budget. All statistics are calculated in the cross-section of individuals 25-64 years of age. PV Earnings are expressed in thousands of dollars. The table shows the percentage increase in PV earnings and PV utility relative to the benchmark. Employment, social insurance recipiency rates and fraction in good health are shown as percentage point changes relative to the benchmark.

Table 16: How Does Public Insurance Affect Health and Earnings?

	Treat	Pay	Good H	EMP	SI	PVE	CV
All Men (25-64)							
Benchmark	80.1	86.2	60.0	87.7	6.6	774	0.497
Public Insurance	99.2	98.3	65.9	88.7	5.4	789	0.481
Zero OOP	81.7	-	60.4	88.4	5.3	777	0.489
Everyone can treat	96.6	89.0	65.2	88.2	6.1	785	0.490
Medicaid Access	83.0	87.4	60.8	85.5	9.1	764	0.516
High School or Less (25-64)							
Benchmark	77.4	84.0	49.9	84.8	10.2	562	0.454
Public Insurance	98.6	97.1	56.9	86.8	8.0	584	0.424
Zero OOP	79.9	-	50.6	85.9	8.2	569	0.437
Everyone can treat	94.7	87.2	55.7	85.9	9.1	577	0.441
Medicaid Access	81.4	85.5	51.2	82.3	13.1	554	0.476

Notes: The percentage who treat is conditional on having a health shock. The percentage who pay is conditional on having a shock and treating. PV Earnings are in thousands of dollars. The last column presents the coefficient of variation of PV earnings. All statistics are calculated in the cross-section of individuals aged 25-64.

Figures

Figure 1: Fractions in Poor/Fair Health, by Employment and ESHI, HS or Less, Model and Data

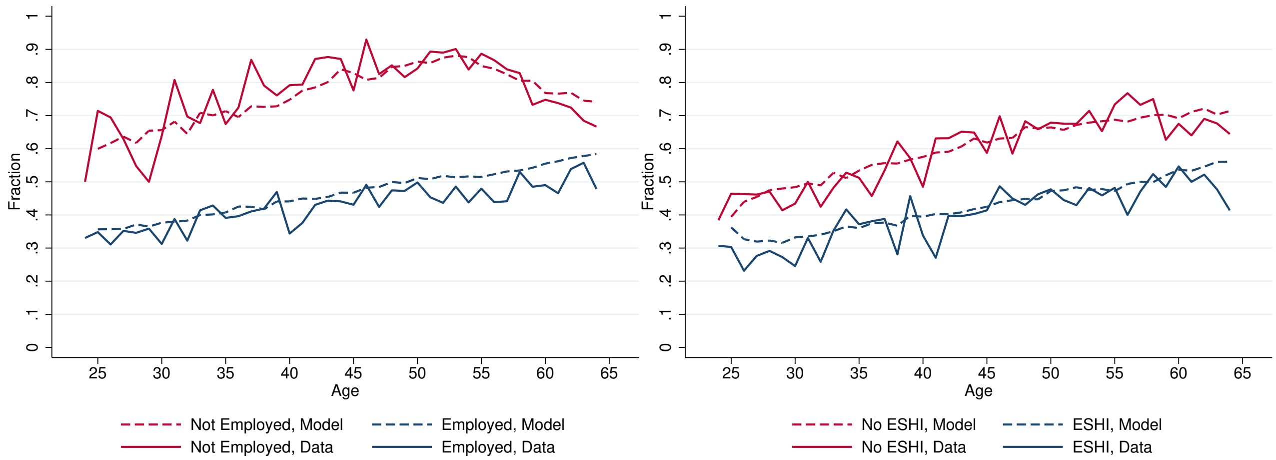
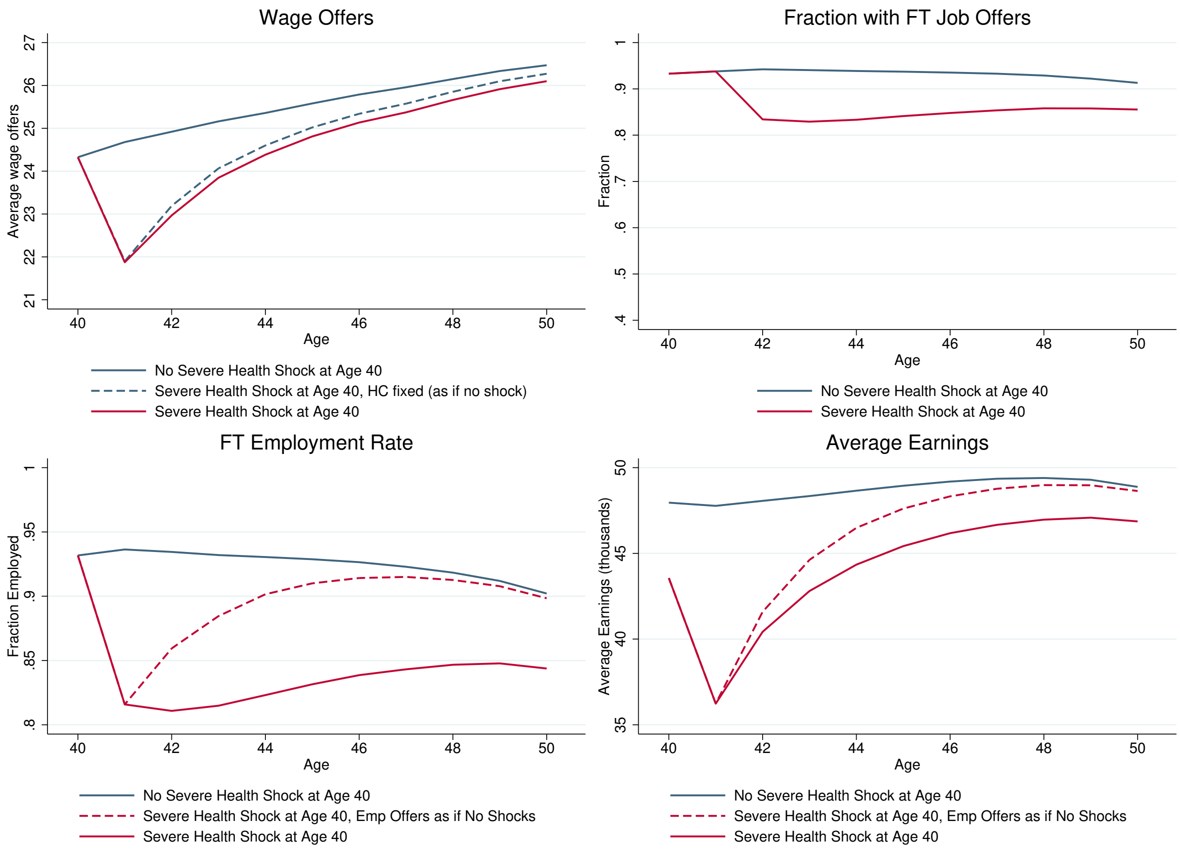


Figure 2: Earnings Inequality over the Life-cycle, Model and Data (CPS)

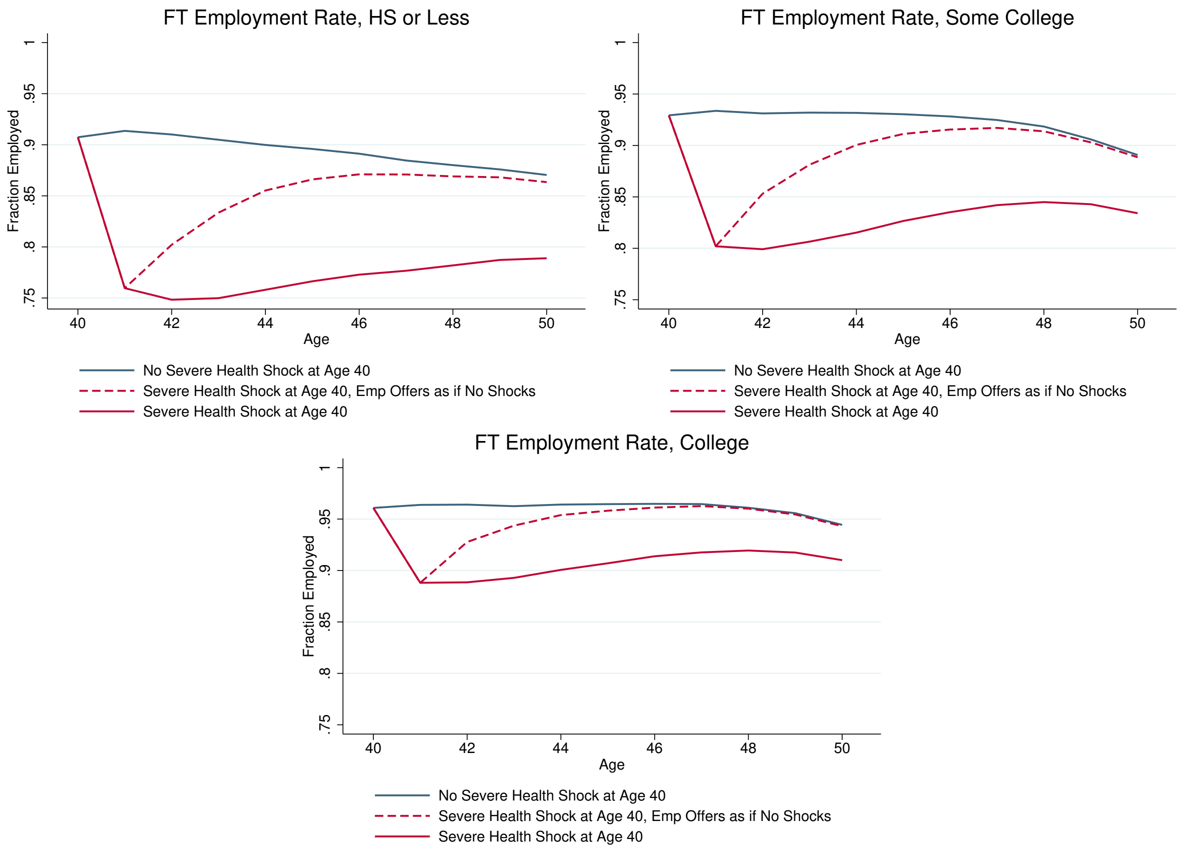
Note: Earnings are pre-tax. In the CPS, earnings inequality is calculated using data on white men. To reduce sensitivity of the Gini to outliers, we drop the top 2% of earnings observations at each age, as well as observations on employed workers with reported wage rates below the minimum wage and those with wages above \$81.45. In the model, earnings include simulated measurement error.

Figure 3: Effects of a Severe Health Shock at Age 40



Note: Severe health shocks are defined as in Section 7.1. Figures constructed for those in good or fair health at ages 40. We compare several counterfactuals: (1) no individual has a d^u shock at age 40 and hence no health deterioration resulting from these shocks (solid blue lines), (2) all individuals experience a d^u shock followed by health deterioration from age 40 to 41 (solid red lines), (3) same experiment as (2) but giving everyone the same work experience and lagged employment as in experiment (1) for the purpose of calculating wages (dotted blue line), and (4) same experiment as (2) but giving everyone the same employment offers as in experiment (1) (dotted red lines).

Figure 4: Effects of a Severe Health Shock at Age 40 on FT Employment, by Education



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