JOHNS HOPKINS
CAREY BUSINESS SCHOOL

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

Elena Capatina
Australian National University

Michael Keane
Johns Hopkins University

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*

Elena Capatina and Michael Keane

June 9, 2024

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
JEL classification: D91, E21, I14, I31

*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 developed a life-cycle labor supply model that incorporates health and health shocks, along with with human capital, tied wage/hours/insurance offers, and medical treatment decisions. Our model includes both private and 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. We quantify 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. This amplifies the impact of health shocks 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).

Specifically, 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. 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.

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. We also present models calibrated to Black and Hispanic men with high school or less education, as small samples prevent us from modeling those with college education. The

[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.

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 that eliminating shocks would increase the expected present value of lifetime earnings (PVE) for White men by 11% on average, and reduce inequality in the PVE by 12% as measured by the coefficient of variation.

Our model allows us to distinguish four key channels through which health shocks affect earnings: (1) reduced labor supply directly attributable to health shocks; i.e., sick days and reduce tastes for work, (2) the knock-on effect of reduced human capital (work experience) that leads to worse job/wage offers, and (3) the effect of reduced health on productivity, which reduces wage offers. Fourth, there is the behavioral effect: The risk of health shocks influences agents' decision rules for labor supply, saving and treatment. In particular, 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.

For the typical White male, if health shocks are eliminated, the labor supply, human capital, health and behavioral effects lead to 5.7%, 2.7%, 1.4% and 0.8% increases in PVE, respectively. But for low skill workers effects are much greater: For example, for White high school men with low skill endowments, we have 10.7%, 14.8%, 1.3%, and 9.8%, respectively. Notice that the human capital effect is much greater for the low-skill high school workers (14.8% vs. 2.7%). This is because they are much more likely to exit employment following a major health shock, and they are slow to return. The behavioral effect is also much greater (9.8% vs. 0.8%) as eliminating health shocks reduces low skill workers' perverse incentive to rely on transfers. Health shocks generate inequality because the labor supply, human capital and behavioral effects on earnings are all much larger for low skill workers.

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, by reducing their incentive to rely on transfers, which reduces earnings inequality and increases 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.

The results for Blacks and Hispanics are similar to Whites. For example, our model implies that eliminating health shocks would cause the PVE for Whites, Blacks, and Hispanics with high school or less education to increase by 17.9%, 23.7% and 17.7%, respectively.

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 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 discusses the results for Blacks and Hispanics. Section 10 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,[2] incorporating endogenous human capital, including both ESHI and public insurance, as well as free care, and making treatment a choice.

Our paper is also related to reduced form work on effects of health shocks on employment and earnings. Health, human capital and employment/earnings are jointly determined over the life-cycle, so Smith (1999, 2004) argues one should identify effects of health on labor market outcomes by controlling for baseline health and human capital, and then estimate effects of specific health shocks. Adopting this approach, he finds a cumulative income loss of \$37k over ten years (1994-2003) following a major health shock for men in the HRS.

Our work is a structural extension of this type of analysis, where we build health shocks into a life-cycle labor supply model. 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 as major health shocks are more likely to afflict workers who avoid treatment, they tend to have low earnings to begin with.

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 health insurance on access to care, health care utilization and health outcomes. In the US the uninsured face not only cost barriers to treatment but direct access barriers as well; see Institute of Medicine (2001, 2002)

[2]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.

for surveys. Many studies document lower utilization 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. See also Marquis and Long (1994), Burstin et al. (1998), Schoen and DesRoches (2000), Hadley (2007) and Hoffman and Paradise (2008). We develop a model where insurance plays both cost-reducing and access-granting roles, and assess the importance of both for health and labor market outcomes.

Our paper is also related to work on how means-tested social insurance affects labor supply; see Moffitt 1992, Keane and Moffitt 1998. And we extend recent papers that study how health insurance affects labor supply: French and Jones (2011) study effects of transfers, ESHI, 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 Medicaid. 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 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.[3,4]

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.

We also contribute to the literature on racial health disparities – see, e.g., Cunningham and Kemper (1998), Nelson et al. (2002), Makridis and Eschbach (2011), Kang-Kim et al. (2008). Our results shed light on how the production process for health differs between Whites, Blacks and Hispanics, and why the three groups report different rates of health shocks and treatment. We calibrate access to care probabilities for each group. We also assess how health shocks differentially affect lifetime earnings for each of the three groups.

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

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

3 Model

Agents enter the model at age 25 and make annual decisions about labor supply, savings, treatment of health shocks, and payment of medical bills. They are characterized by three permanent state variables: education e, latent health ε^h, and latent skill ε^s. 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.[5] Within education groups, there are two latent health types, $\varepsilon^h \in \{Bad, Good\}$ and by 3 latent skill types $\varepsilon^s \in \{L, M, H\}$.

3.1 The Timing of Decisions and Shocks

Agents begin each annual period t with stocks of assets A_t, work experience X_t, functional health H_t, 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 men then receive an employment offer O_t^*. It may be full or part-time, and with or without insurance (ESHI), with probabilities that depend on O_{t-1}. Wage offers depend on human capital, functional health, and lagged employment. Agents then decide whether to accept or reject the tied wage, hours and insurance offer, and the result is O_t.

Next health shocks and sick days are revealed, and OOP treatment costs are drawn from a distribution that depends on insurance status. Agents then 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 may induce stigma. Agents who lack ESHI may lack access to care or may have access to free care. Their options are are drawn probabilistically.

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

From age 65 onward the problem simplifies, as retirement is mandatory and all agents are covered by the Medicare public insurance program. The maximum lifespan is 100 years.

[5]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%).

3.2 Health and Health Shocks

Our model includes 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). Functional health H measures aspects of health that affect productivity. It takes three values: poor, fair or good, $H_t \in \{P, F, G\}$. Health risk R captures risk factors that increase the probability of health shocks, but that do not affect current productivity, such as obesity, high cholesterol and hypertension. It takes two values: low and high ($R_t \in \{L, H\}$).

Our model also contains three types of health shocks: persistent and predictable (d_t^p), persistent and unpredictable (d_t^u), and unpredictable and transitory (s_t).[6] We define all three as "serious" shocks that affect productivity for at least two weeks, ignoring minor events like colds. Section 4 explains how we use the MEPS data to measure H, R and the three types of health shocks $\Upsilon_t = (d_t^p, d_t^u, s_t)$. Table 1 lists the state variables that enter the transition probabilities for H_t and R_t and the probabilities of health shocks:

Table 1: Health Transitions and Health Shocks

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

The transition probability of functional health H depends on current health, latent health, age, and the persistent (long-term) health shocks d^p and d^u. The transitory shocks s do not affect H transitions *per se*. But if a health shock of *any* type occurs ($I_\Upsilon = 1$), the health transition probability depends whether the shock is treated (I_{treat}).[7] Education does not enter explicitly, but, importantly, we allow it to be correlated with the latent health type.

Latent health type ε^h enters the H transition function Λ_H, which we specify as a logit, as a fixed effect. A person with good latent health is robust or resilient, as they have a high probability of remaining in good health as they age, even if they have adverse shocks.

The transition probability for R only depends on lagged R, H and age. Interestingly, we find 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 $\Gamma^H(H\vert e, \varepsilon^h)$.

Next consider the probabilities of health shocks: The d_t^p shocks are strongly predicted by education and risk factors R. We call the d_t^u and s shocks are "unpredictable" because they are not significantly predicted by education and they only weakly predicted by R. Thus "predictability" is not absolute but rather falls on a continuum. See Appendix B.3.2 for details. Note that R affects H transitions via its influence on the frequency of health shocks.

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

[6] Very few medical conditions are both predictable and transitory, so this category is excluded.

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

3.3 Health Insurance, and Medical Treatment Costs and Charges

Men aged 25 to 64 may or may not work for an employer who provides ESHI. We let ins be an indicator for ESHI coverage, and denote the (employer-subsidized) premium by $p^E I$.

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 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 $OOP(\cdot)$ no longer depends on ins. We denote the Medicare premium by p^{Med}.

3.4 Treatment/Payment Options

We generalize earlier work by modeling treatment/payment choices, and 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, a man aged 25-64 who lacks ESHI may be constrained in his options. There are three cases: (1) all treat/pay options available, (2) treat option not available, (3) default option not available. In the US, proof of insurance is often required for 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 serious contexts – motivating choice set (1). And there are contexts where treatment requires payment in advance – e.g., filling a prescription – motivating choice set (3).

Formally, 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 the three possible choice sets mentioned above:

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

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.[8]

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

[8] 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.

3.5 Marital Status

At the start 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. After age 65 there are no transitions into marriage.

For married men of working age, the spouse's employment status, $emp^w \in \{0, 1\}$, income, inc^w, and OOP medical costs, OOP^w, are all revealed at the start of the period. None of these are choices, as we do not model the spouse's labor supply decision. 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, to capture that spouse's labor supply may depend on husband's earning capacity. The spouse stops working when the husband reaches 65, and the household receives Social Security.

3.5.1 Spousal Health Insurance and Medical Costs

The spouse's ESHI status is given by the indicator ins^w. We assume the spouse is covered by ESHI if she is employed or if the husband is covered by ESHI.[9] For simplicity, we do not allow married men to be covered by their spouse's insurance, as only 1.3% of working age men in MEPS receive insurance through a working spouse.[10]

Spouse's OOP costs are given by $OOP^w(ins^w, t, e)$. Husband age and education enter this function as they are correlated with the wife's health and age. We abstract from modeling the spouse's decisions about medical treatment and payment of bills, as this vastly complicates the model. A 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}.

3.6 Employment and Wages

3.6.1 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. Let I^O be a 1/0 indicator for whether the offer is accepted. Once agents accept/reject their offer, employment status are given by $O = \{W, h, ins\}$.

It is useful to define the categorical variable $O^{**} = \{h^*, ins^*\}$ that summarizes the five possible combinations of hours and insurance.[11] The probabilities $\Pi(O^{**}|h^*_{t-1} \cdot I^O_{t-1}, ins_{t-1}, e, t)$ of receiving each type of offer depend on lagged employment and insurance status, as well as education and age. At age 25, the offer probabilities are given by $\Pi_{t=25}(O^{**}|e)$.

[9] 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.

[10] 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. As women tend to have frequent transitions in and out of employment, they may often lose ESHI, creating an extra incentive for married men to seek jobs with ESHI.

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

3.6.2 Hours Worked and Sick Days

When a worker accepts an employment offer, he commits to working h^* hours if healthy. Sick days are given by $sd(e, H_t, \Upsilon_t)$, which is a function of education, health and health shocks. Actual hours worked are then $h_t = h^* I^O - sd$.

Given the annual timing of our model, and our assumption that contractual hours are fixed annually, what we call "sick days" incorporates the entire short-run (intra-year) labor supply response to health shocks – i.e., the total reduction in annual work days due to health shocks. This is a different concept from the sick days that workers may be entitled to in an employment contract.[12] We let sick days vary by education 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. In Appendix D.16 we present descriptive evidence supporting this modeling assumption.

3.6.3 Human Capital Accumulation and the Wage Offer Function

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

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

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

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 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 offer distribution depend on $I_{h^*=PT}$, an indicator for part-time offers, to capture the fact 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 $\varepsilon \sim N(0, \sigma_\varepsilon^2)$.

3.6.4 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

[12] 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.

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.

As our model begins at age 25, the 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 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.

3.7 Social Security, Taxes and Social Insurance (Transfers)

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.

We describe the details of the tax system in Appendix D.15, including income, consumption and payroll taxes. Let Tax denote the tax bill defined there.

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:

$$Y^D{}_{t<65} = rA + W^{*} \cdot h + inc^w \cdot I_M - p^{EI}(ins, ins^w) - Tax \tag{3.5}$$
$$Y^D{}_{t\geq 65} = rA + SS - p^{Med} \cdot (1 + I_M) - Tax \tag{3.6}$$

Letting τ^c denote the consumption tax, so it costs $(1+\tau^c)\bar{c}$ to consume $\bar{c}$, the transfer is:

$$tr_{t<65} = max\{0, (1+\tau^c)\bar{c} + I_{pay}OOP + OOP^w - Y^D{}_{t<65} - A\} \tag{3.7}$$
$$tr_{t\geq 65} = max\{0, (1+\tau^c)\bar{c} + OOP + OOP^w - Y^D{}_{t\geq 65} - A\} \tag{3.8}$$

For households headed by working-age men, payment of the man's OOP costs is a choice, as reflected by the $I_{pay}OOP$ term in (3.7). If 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 (3.7).[13] As we see in (3.8), men who are 65+ always pay OOP costs.

3.8 Preferences

Agents derive utility from consumption (c) and leisure (l), and incur a stigma from 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 – see Section 5.4. Upon death agents obtain utility from bequests (U_{Beq}) and incur a death cost (ζ). The within-period utility function is given by:

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

We assume private consumption of married men equals household consumption C divided by the family size adjusted by the Oxford equivalence scale, $E(t,e)$.[14]

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:

$$l = 1 - h - sd(e, H, \Upsilon) - F(I^O, H) - hw(M, h^* \cdot I^O, emp^w). \tag{3.10}$$

where I^O is the employment indicator defined in Section 3.6.1. 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 3.6.2. 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.[15]

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 3.9 can be negative. This 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:

$$U_{Beq}(B) = \theta_{Beq} \frac{(B + k_{Beq})^{(1-\gamma)}}{1-\gamma} \tag{3.11}$$

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.[16]

[13] 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."

[14] 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.

[15] 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.

[16] The utility function in (3.9) 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.

3.9 Individual's Problem

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:

$$\Omega = ((e, \varepsilon^h, \varepsilon^s), t, X_t, h_{t-1}, H_t, R_t, A_t, O_t^* = (W_t^*, h_t^*, ins_t^*), (M_t, emp^w)) \tag{3.12}$$

Given Ω, an agent decides whether to accept/reject ($I^O = 1/0$) the employment offer O^*, so as to maximize the expected present value of lifetime utility. 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:

$$G(\Omega, I^o, I_{treat}, I_{pay}, \Upsilon, \varepsilon^C) = \max_c \{u(c, l) + \beta E_\Psi[\varphi V(\Omega') + (1-\varphi)(\zeta + U_{Beq})]\} \tag{3.13}$$

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 (3.11) and:

$$\begin{aligned} A' = (1+r)A + W^* \cdot h \cdot I^O - p^{EI}(ins^* \cdot I^O, ins^w) + inc^w \cdot I_M + tr - (1+\tau^c)C - Tax \\ -I_{pay} OOP(ins^* \cdot I^O, t, \Upsilon, H, \varepsilon^C) - OOP^w(ins^w(ins^* \cdot I^O), t, e) \cdot I_M \end{aligned} \tag{3.14}$$

$$\begin{aligned} C \leq \frac{1}{1+\tau^c}[(1+r)A + W^* \cdot h \cdot I^O - p^{EI}(ins^* \cdot I^O, ins^w) + inc^w \cdot I_M + tr - Tax \\ -I_{pay} OOP(ins^* \cdot I^O, t, \Upsilon, H, \varepsilon^C) - OOP^w(ins^w(ins^* \cdot I^O), t, e) \cdot I_M] \end{aligned} \tag{3.15}$$

where C is household consumption and private consumption is $c = C$ for single men and $c = C/E(t, e)$ for married men. Equation (3.15) 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 $(\Omega, I^O, \Upsilon, \varepsilon^C, J(ins))$:

$$B(\Omega, I^O, \Upsilon, \varepsilon^C, J(ins)) = \max_{I_{treat}, I_{pay} \in J(ins)} G(\Omega, I^O, I_{treat}, I_{pay}, \Upsilon, \varepsilon^C). \tag{3.16}$$

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

$$V(\Omega) = \max_{I^O} E_{(\Upsilon, \varepsilon^C, J(ins))} \left\{ B(\Omega, I^O, \Upsilon, \varepsilon^C, J(ins)) \right\}. \tag{3.17}$$

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

The problem for retired individuals is standard so we relegate it to Appendix H. The solution algorithm is also described in Appendix H.

4 Data and Variable Construction

Our main data source, MEPS, is 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. We also use the CPS, HRS and PSID to construct other statistics used in the analysis.

Our primary analysis sample consists of civilian, non-institutionalized White males aged 25+ and over who are not in school. We also present a more limited analysis of Black and Hispanic men with high school or less education, as limited sample size prevents us from considering those who attended college – see Appendix K.

4.1 Constructing Health Shocks (d^p, d^u, 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. This is converted by professional coders into three digit ICD-9 codes.[17] Based on medical expert advice, we classify the 989 ICD-9 codes into our d^p, d^u and s shocks.[18] The d shocks have a persistent impact on productivity that lasts for at least 2 weeks per year for two or more years, while s shocks have a short-term impact on productivity that lasts for at least 2 weeks in the year the shock occurs, but no effect in subsequent years. Minor shocks with a less than two-week impact are ignored altogether. The d shocks are further divided into those that are highly predictable based on past state variables (d^p) and those that are difficult to predict (d^s). We discuss these classifications in detail in Appendix A. We define d_t^p, d_t^u, and s_t as 1/0 indicators of whether a respondent has one or more conditions of each type. They are constructed at the annual level, based on the two years of interviews in each panel.

4.2 Constructing Health (H) and Asymptomatic Health Risk (R)

Our functional health measure, H, combines information from five types of variables: 1) self-reported health, 2) self-reported mental health, 3) activities of daily living (ADL) limitations, 4) instrumental activities of daily living (IADL) limitations, and 5) a set of eight physical functioning limitations. We combine these into a single continuos measure using factor analysis, as described in Appendix A.2.1, and then discretize it into Poor, Fair Good.

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%.

Our health risk measure R is based on conditions that do not effect current productivity but that predict future health conditions and/or long-term productivity (see Appendix A Table 6). Hypertension, high cholesterol and obesity are the most important factors. We discretize R into two categories corresponding to low and high risk.

[17]The International Statistical Classification of Diseases and Related Health Problems (abbreviated ICD) is published by the World Health Organization and is widely used in reimbursement systems.

[18]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.

4.3 Measurement Model

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.In contrast, functional health H is based on self-reported measures, so we assume it is not subject to *systematic* measurement error of that type.

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 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.

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 (e.g., persistent shocks may be reported more often).

Recall from Section 3.2 that the true shock probabilities are $\Gamma^{dp}(\cdot)$, $\Gamma^{du}(\cdot)$, and $\Gamma^{s}(\cdot)$. Letting $\tilde{\Gamma}^{dp}(\cdot)$, $\tilde{\Gamma}^{du}(\cdot)$, and $\tilde{\Gamma}^{s}(\cdot)$ denote observed 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 determined by model equation (3.16).

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 first calibrate the model to White males. Given the data limitations discussed in Appendix K, we can only extend the model to Black and Hispanics with high school or less education.

First, we estimate many parameters in a first stage outside the structural model. These are the stochastic processes for health shocks, health risk, sick days and medical treatment costs, as well as levels of disability benefits, social security and pension benefits, tax function parameters, ESHI premiums, survival probabilities, stochastic processes for marriage and family size, and processes for spousal employment, income and medical costs.

Second, we 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%).

We calibrate the remaining structural parameters internally, as we describe in Sections 5.1 to 5.9. Appendices B, C, D and E describe the calibration in great detail. Here we give a broad overview, aimed at giving intuition for how key model parameters are identified.

5.1 Probabilities of Health Shocks and R Transitions

We assume men covered by *ex ante* insurance (ESHI, DI or Medicare) almost always get treated for serious health shocks, so they do not under-report health conditions in MEPS. Later, we verify that our calibrated model does imply men with *ex ante* insurance (almost) always get treated, so our assumption is internally consistent.[19] 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.[20,21] We specify these functions as binary logits.

Our measurement model specifies that men who are not treated under-report medical conditions. Once the true frequencies of health shocks and high R are pinned down, the measurement model parameters $\eta(\Upsilon,H)$ and $\eta^R(ins)$ play an important role in matching the frequencies of observed health shocks and high R in MEPS for the uninsured. A key identifying assumption is that, conditional on H, R, t and 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.[22] Thus, we explain different rates of health shocks and high R between the insured and uninsured based on (i) sorting into insurance, and (ii) different rates of seeking treatment.

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 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.

To calibrate the parameters of the Λ_H function we run descriptive logits of health on lagged health, age, education and health shocks, for both MEPS and simulated data from the model. We find structural parameters such that these two logit models look similar. We also match H transition rates by age/education. See Appendix B.5 for details.

Two aspects of identification of the H function are worth noting: First, persistence in health can be generated by either latent health types or the lagged health status that enters the H transition function. If persistence in health status was due only to heterogeneity, and lagged health did not matter, d_t shocks would not affect health beyond period $t+1$. Then agents would have little incentive to treat shocks.[23] See Appendix B.5.2.3 for details.

Second, the frequency that uninsured go untreated is pinned down by differences in medical charges by insurance status (see section 5.4). Given that, the effect of non-treatment

[19] 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.

[20] This avoids the computational burden of estimating these functions inside the model. And it avoids concerns about identification that would arise if we treated the true frequency of health shocks as unobserved.

[21] Medicaid may provide insurance *ex post* if the cost of health shocks pushes a person below an income threshold. Thus, we exclude Medicaid recipients when estimating the probabilities of health shocks.

[22] Papers finding *ex ante* moral hazard is not important in the health insurance context include Newhouse and Group (1993), Khwaja (2001), Courbage and De Coulon (2004), and Fang et al. (2007).

[23] 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 $t+2$.

on health, captured by the coefficient on I_{treat}, is calibrated so the model can match the worse H transitions of the uninsured, as we discuss in Appendix B.5.2.4.

The uninsured *could* have worse H transitions because they are more likely to be the bad latent health type. But our model implies bad health types often end up on Medicaid. Hence, there is little difference in latent health between those with ESHI and those with no insurance, and non-treatment primarily drives the worse H transitions of the uninsured.

5.3 Medical Expenditures

Evidence suggests that men with ESHI get treated for serious shocks at a very high rate, and rarely default on medical bills.[24] Hence, 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 MEPS. Similarly, for men aged 65+, who are covered by Medicare, we estimate OOP treatment costs directly from OOP expenditures observed in MEPS.

For the uninsured rates of non-treatment and default are substantial (see Appendix C.8), so we need a different approach: Following Lockwood (2023) and Mahoney (2015), for men aged 25-64 without ESHI, we set OOP to a 40% discount on $Charges$ facing men with private insurance in MEPS. People with ESHI never pay these inflated charges, as insurers negotiate substantial discounts with providers (and their OOP costs are only a fraction of discounted charges). The uninsured can also negotiate discounts on charges, as we assume here.

5.4 Stigma and the Treatment and Payment Options

Men with ESHI always have all three treatment/payment options, but the data suggest they rarely default. Thus, we calibrate a high enough stigma κ so less than 3% default on bills, consistent with evidence from the MEPS that we discussed in Section 5.3.

In contrast, the data suggest that men without ESHI default at very a high rate – see Appendix C.8. 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. Thus, we decided to set the stigma cost κ of not paying medical bills to zero for the uninsured.

As noted in Section 3.4, if a health shock occurs, working-age men who lack ESHI face one of three possible choice sets: (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).

We can identify the choice set probabilities because medical charges are observed in MEPS for anyone who treats, *regardless* of whether they pay. The frequency that the uninsured have negligible charges conditional on a reported health shock allows us to construct a measure of how often they go untreated. And data on their OOP spending relative to their discounted charges allows us to measure how often they default and/or receive free care.

These two targets pin down the choice set probabilities $P(j), j = 1, 2, 3$ as follows: Let $P(T)$ denote probability of treatment, and let $P(Pay|T)$ denote probability of payment conditional on treatment. An uninsured man drawing choice set (1) will always treat and not pay, as stigma is zero (see Sect 3.4). 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.[25] So the

[24] In 2013-14, MEPS asked if the respondent or anyone in his family currently has any medical bills that the family was unable to pay. Among white men with ESHI, only 3% responded "Yes."

[25] 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.

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 also gives $P(2)$. We give details in Appendix C.8.

Overall, we estimate that uninsured men only treat 60% of the time, while our model generates a 62% rate, see Table 37. We also find that only 42% of completely uninsured men in MEPS 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.

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 probabilities of each of the 18 types. Within each education group, the three latent skill types have equal mass. We calibrate the conditional probability of being the good latent health type, $Prob(\varepsilon^h \mid \varepsilon^s, e)$, 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. See Appendix C.9 for details.

Three data patterns imply a strong positive correlation between latent health and skill: Employed men are much more likely to be in good health at all ages – see Appendix C Figures 14-16. Men in good health have significantly higher incomes, even conditional on full-time employment status, age and education – see Appendix C Table 47. And, at ages 56-60, within each education group, the bottom wealth terciles contain high fractions of individuals in poor/fair health – see Appendix C Table 48. Our model captures these patterns well.

5.6 Hours, Fixed Cost of Work and Hours of Homework

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.[26]

The time constraint (3.10) 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 employment. The probability a man works full-time is strongly increasing in health status – see Appendix C.10 Figure 20. Several factors help generate this pattern, including how wages and the consumption floor varies with health. But a fixed cost of work that increases with poor health is essential to obtain a good fit.

We calibrate homework hw to match the facts that married men work much more than single men, but men work similar hours regardless of spouse employment – see Appendix C Table 51. Our stochastic process for marriage implies men who have higher income and greater labor force attachment are more likely to become married in the first place. But our calibrated model implies the large employment gap between married and single men arises, in part, because married men lose less leisure than single men when they work full time.

5.7 Job and Insurance Offer Probabilities

Job offer probabilities depend on lagged employment and insurance status, education and age. In the data, full-time employment and ESHI coverage are highly persistent, while transition rates into full-time employment and ESHI coverage are low – see Appendix D.11.

[26] 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+.

Thus, in Appendix D Table 59, we calibrate that men who worked full-time with ESHI in the prior year are very likely to receive such an offer this year. Conversely, men who did not work full-time or have insurance in the prior year are unlikely to receive such offers.

5.8 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_t^w, 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 detailed in Appendix D.12, we target the following features of accepted wages: (1) average wages of full-time workers in good health in MEPS, conditional on age 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) variance of log wages for full-time workers in good health in the CPS.

We also target 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 to infer skill heterogeneity, as it is a long panel.

5.9 Consumption Floor and Disability Benefits

We calibrate the consumption floor $\bar{c}(educ, I_{H=Poor}, M, t)$ for men in poor health outside the model using data on disability benefits – see Appendix D.13. For men in fair and good health, we calibrate inside the model by targeting the fraction of men who receive government transfers in the CPS, by education, marital status and age. Here transfers include any public health insurance, as well as disability, welfare, or SSI benefits.

Our calibrated consumption floors for single men in fair/good health are quite low; only about one-third of the disability benefit levels for single men – see Appendix D Table 70. 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.

5.10 Bequest Function

Bequest utility (3.11) 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.10.4 for details.

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 discuss our fit to key statistics that were not targeted in the calibration.

6.1 Selection into Employer-Sponsored Insurance

Matching the selection of workers into ESHI by health status is crucial for counterfactuals that give insurance to the uninsured: The cost and health impacts of such a policy depend on the distribution of health status among the uninsured. In Appendix C.9, Figures 14 to 16, we see there is advantageous selection into ESHI. For example, among high school men, the share in fair/poor health is 15 to 20 percentage points higher among the uninsured, a gap that grows slowly with age. Our model provides an excellent fit to this selection pattern.

6.2 Health Transitions

Our structural model of health transitions is very simple: Health only depends on lagged health, health shocks, treatment, age, and latent type. But in the data, education, income and insurance are highly correlated with health transitions. Can we generate these patterns?

To address this question, Table 2 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 shows the results using MEPS data, while the second column shows results using simulated data from our 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. The simulated data regression implies positive "effects" of education, income and insurance on health that are very similar to those obtained from MEPS.

In Table 2 columns 3-5 we control for health type, treatment and true shocks in the simulated data regressions. Controlling for latent health type largely "knocks out" education, indicating the association between education and health is largely driven by the positive correlation between education and latent health types; see Appendix C.9 Table 45. And controlling for treatment and true shocks knocks-out insurance, indicating the association between insurance and health is driven by the fact that the insured are more likely to get treatment. Controlling for all three, as in column 5, also knocks out income.

Thus, 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 our model is silent on why latent health is correlated with education.

6.3 Earnings Inequality over the Life Cycle

Much of our analysis concerns how health shocks contribute to earnings inequality, so it is important to capture patterns of inequality in the data. Figure 1 plots the Gini coefficient for labor earnings by age in the CPS vs. model. The Gini increases very slowly from age 25 to 50, and then at an accelerating rate from 50 to 64. We fit this pattern quite well.

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 severe health shock on earnings. We define a shock as severe if it causes deterioration in health H. For men aged 50-60 the annual frequency of d^u shocks is 30%, of which 19% are severe.[27] We find on average a cumulative (non-discounted) earnings loss of \$42.8k over ten years after such a shock for men at age 50. For comparison, Smith (2004) estimates a cumulative income loss of \$37k over ten years (1994-2003) following severe health shocks for men in the HRS. His definition of a major shock is narrower than ours, but it is encouraging our estimates are in the same ballpark.

The chance a shock is severe 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. Hence, men with a severe d^u shock are a selected sample containing a high fraction of men who do not treat. They tend to have low-earnings even in the absence of shocks, so their earnings losses from health shocks are relatively small. 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 does, the loss is much higher (\$59.8k). We call this the average effect.

Table 3 reports average effects of severe d^u shocks for different types of workers at different ages. For example, for a college type man at age 40, the average effect is a reduction in the PV of remaining lifetime earnings by \$53.9k or 5.6%. A key result in Table 3 is that *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%, more than twice the drop for the college type.

7.2 How Human Capital Amplifies the Impact of Health Shocks

Table 3 also reports the share of the earnings decline after a health shock due to reduced human capital accumulation. In our model human capital depends on work experience and lagged employment status, which both affect multimensional job offers (wage, ESHI, hours). Thus, we run simulations where we hold human capital fixed as in the baseline path where no shock occurred. In these simulations, earnings only fall because the shock reduces labor supply, via sick days and reduced tastes for work, plus the direct effect of health on wages.

For example, for a typical college man, reduced human capital accounts for 34% of the decline in PVE following a major health shock at age 40. For a typical high school man we obtain 42%. So *the human capital mechanism is stronger for less educated men*. Note that lifetime work years decline by 1.89 for the high school man, compared to only 0.84 for the college man. The human capital channel accounts for about half of these declines.

Figure 2 examines the separate effects of health shocks on offer wages and employment rates. We again consider the impact of a severe d^u shock at age 40, and here we average over all education groups. The solid blue lines show a baseline simulation where no shock occurs, while the solid red lines show the impact of the shock.

We see that a major health shock leads to a sharp decline in wage offers in the year after the shock (about 10%). But 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. For employment the recovery is

[27] We obtain similar results for d^p shocks. See Appendix B Table 14 for shock frequencies by education/age.

much slower: Full-time employment drops by 12 percentage points one year after the shock, and even after 8 years employment is 7.8 pp below baseline.

Employment drops partly because reduced health reduces tastes for work, but as we see in the upper right panel of Figure 2 there is a persistent drop in the chance of getting a full-time job offer. There is a snowball effect: If a worker exits full-time employment after a shock it is difficult for him to return, as offer probabilities depend on lagged employment.

The dashed lines in Figure 2 show what happens if we hold human capital fixed along its baseline path – so job offer probabilities are identical to the baseline and offer wages only fall due to reduced health. Here the employment rate recovers much more quickly after the shock. It still falls as reduced health reduces taste for work and offer wages, but those effects vanish quickly as health recovers. Thus, *human capital amplifies the impact of health shocks mainly via offer rates and employment; i.e., slow return to full-time work after the shock.*

Figure 3 shows effects by education: The drop in employment after a severe health shock is larger and more protracted for low education men. For high school men the drop is 20 points in the first year post-shock, and after 8 years the drop is still 10 points. For college men these figures are only 7 and 3, respectively. But if we hold human capital fixed as in the baseline (dashed red line), so job/wage offers do not deteriorate due to lost work experience, employment recovers quite quickly to its baseline rate for workers of all skill levels.

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.

7.3 Effects of Health Shocks on Key Outcomes

In Table 4 we examine impacts of health shocks on key outcomes in our model. We compare simulated life-cycle histories from the baseline model with a counterfactual in which agents are "lucky" and do not experience health shocks, but we hold the perceived risk of shocks (and hence decision rules) unchanged. This gives the "direct" effects of health shocks.[28]

In the baseline, average annual sick days are 16.42. We define "sick days" as the total reduction in annual work days due to health shocks – as in Grossman (1972) – so it is a very different concept from sick days workers may be entitled to in an employment contract.[29] Given our assumption that contractual hours are fixed annually, what we call "sick days" incorporates the entire short-run (intra-year) labor supply response to health shocks.[30]

The second row of Table 4 compares the baseline to an experiment where men never experience serious health shocks (s, d^u or d^p) at working ages (25-64). We predict this would reduce total annual medical costs from \$4,618 to \$1,132, on average. Note this is total cost, not just OOP. It does not go to zero, as people still have minor illnesses, prescriptions,

[28] 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.

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

[30] 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.

preventive care, etc. We also predict the fraction of working age men in good health would increase from 60% to 75%, and the probability of survival to 65 increases from 82% to 87%.

Productivity effects of health shocks are substantial: If sick days of 16.4 per year are eliminated, we have a 6% increase in work days for employed workers. The employment rate increases from 88% to 91%. Combining the intensive and extensive margins, the increase in total hours is about 10%. The mean offer wage increases by 2.6% (from \$23.60 to \$24.22). Notice the impact on total hours is 4 times greater than that on offer wages: Most of the impact of health shocks on earnings operates through employment and hours.

The bottom panel of Table 4 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 increases their employment rate by 5 percentage points, compared to 3.2 points for all men. And their lifetime full-time equivalent work years 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.*

In the third row of Table 4 we assess the role of asymptomatic health risk R. We run an experiment where we give all agents low risk, $R = 0$, which lowers the probabilities of health shocks. Effects are in the same direction as eliminating health shocks, but much smaller in magnitude. Thus, there is a limited impact of policies aimed at reducing R on labor market outcomes for working age men. Of course, the potential benefits of reducing health risk are greater at ages over 65, when predictable shocks such as heart attack become more prevalent.

7.4 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 5 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).

To assess the contribution of health shocks to PVE inequality, we add a set of variables designed to capture impacts of health shocks during the working life. We include the number of times the agent experienced each of the eight combinations of the shocks (d^u, d^p, s), separately for if they are treated or untreated. We also enter counts of health shocks that occurred when the agent was in poor, fair, or good health, to capture 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, 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 5 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 about 8% to the variance of PVE.

Results in Table 5 that look *within* education groups reveal health shocks explain more of the variance of PVE within the high school group (15%) than for the college group (9.7%). The experiments in Section 7.5 provide an alternative way to evaluate the role of health shocks that sheds light on why they generate more inequality among less educated workers.

7.5 Effects of Health Shocks on Earnings and Earnings Inequality

The left-most column of Table 6 reports the PV of lifetime earnings (at age 25) for men of different types in the baseline model. The mean PVE across all men is $\$774k$. But great heterogeneity 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. Obviously, this is why initial conditions are so important in the regressions of Section 7.4.

The right-most column of Table 6 shows the change in the mean PVE when health shocks are eliminated at working ages.[31] Importantly, in contrast to experiments in earlier sections, we now allow agents' decision rules for labor supply and consumption to adapt to the new environment where health risk is eliminated. We call this the total effect.

For all men the PVE increases by 10.7%. But the impact on low-skill types is far greater. For the low-skill high school type, the PVE increases by 36.6% (or $116k). In contrast, for high-skill college men, eliminating health shocks only increases the PVE by 5.8% (or $88k).

Table 7 reports the coefficient of variation (CV) of the PVE in the baseline (left-most column), and how it changes when we eliminate health shocks (right-most column). The CV 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 that we capture here.

As our model is fit to pre-ACA data, one may wonder if enhanced insurance coverage has reduced inequality due to health shocks. In Section 8, we simulate providing public insurance to all men who lack ESHI. This only reduces the CV of PVE to .481, or 3.2%. So most of the impact of health shocks on inequality persists even in an environment where all are insured. Thus, it is unlikely that the impact of health shocks is much less in the post-ACA period.

Next, Table 8 reports effects on employment rates. The baseline rate of all men is 87.7%, and eliminating health shocks increases this to 92.4%. Baseline employment is much lower for low-skill men: Only 71.5% of low-skill HS types work in the baseline, but eliminating health shocks increases this to 92.3%. Notably, *removal of health shocks eliminates most of the differences in employment rates across education/skill groups.* Most of the increase in earnings for low-skill workers that we saw in Table 6, and hence most of the reduction in inequality we saw in Table 7, arises via this equalization in employment rates.

Returning to Table 7, it is notable that baseline inequality is much greater *within* lower-skill groups. For example, the CV is .454 for low-skill HS workers vs. only .350 for college

[31] 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.

workers. This is mainly because health shocks generate more earnings inequality *within* the low-skill group: When health shocks are eliminated, the CV for HS workers drops by 21.5%, to .356, while that for the college workers only drops by 4.7%, to .334. Health shocks generate more 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 health shocks affect earnings and 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.

We present this decomposition in Table 6, which reports the labor supply, human capital, productivity, behavioral and total effects in columns (1) to (5), respectively.[32] 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 only 0.8% to the behavioral effect. But there is a great deal of heterogeneity in the magnitudes of these effects across different types of workers:

If we focus on low-skill high school men, we see that health shocks reduce lifetime earnings by a substantial 10.7% via the labor supply channel alone. They lose an additional 14.8% due to the knock-on effects of reduced human capital accumulation. The behavioral effect is also substantial, as health risk creates an incentive for low skill men to curtail labor supply to maintain eligibility for means-tested transfers, reducing lifetime earnings by 9.8%. The direct impact of health on wages has a relatively minor effect of only 1.3%.

In contrast, among high-skill college men, health shocks only reduce lifetime earnings by 3.7% via the labor supply channel.[33] The knock-on effect of reduced human capital accumulation is only 0.75%, 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. Health risk causes college men to work slightly *more*, as they have more incentive to accumulate precautionary savings.

Table 7 shows how the four channels impact earnings inequality. For all workers, eliminating health shocks reduces the coefficient of variation in the PVE by 4.2% via the labor supply channel, 5.2% via the human capital channel, and 2.6% via the behavioral effect. The direct productivity effect on offer wages is similar for all types, so it contributes almost nothing to inequality. But the labor supply, human capital and behavioral effects are all much larger for low skill men, so they have large impacts on inequality.

[32] Appendix H.27 provides more details on the experiments we run to isolate the four channels.

[33] 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.

7.5.2 Mechanisms: How health shocks affect employment and transfers

Table 8 sheds more light on how the four channels operate by examining effects of health shocks on employment and social insurance. The four columns show: (1) the baseline, (2) the combined labor supply and health effects, (3) the additional effect of letting human capital adjust, and (4) the total effect that also lets decision rules adapt. We combine the labor supply and health productivity effects in (2) and call it the "labor supply" effect for convenience, as we find the health productivity effect on employment and transfer receipt is very small. Note that the human capital effect is (3)-(2) and the behavioral effect is (4)-(3).

For all workers, elimination of health shocks increases the employment rate (87.7%) by 0.9 points via the labor supply channel, 2.4 points via the human capital channel, and 1.4 points via the behavioral channel. The human capital effect is almost three times larger than the labor supply effect due to the mechanism we saw in Figure Figure 3: Health shocks generate very persistent drops in employment, but this persistence is mostly due to the knock-on effect of reduced human capital on the probability of full time job offers.

The elimination of health shocks reduces transfer receipt from 6.6% to 1.5% for all men. 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.

Again, there is substantial heterogeneity across types of workers: For low-skill high school men, eliminating health shocks increases the employment rate by 20.8 points (from 71.5% to 92.3%). 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.

In contrast, for high-skill college men, all effects on employment and transfers are minor, and the behavioral effect of eliminating health risk is a small *reduction* in employment.

For low-skill men, the behavioral effects of health risk on earnings and employment are important because, in the baseline model, they have an incentive to curtail their labor supply and human capital accumulation so as to maintain eligibility for social insurance. Health shocks reduce their incentive 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. 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).

This moral hazard effect is important for low-skill men in part because 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 compared to other groups. In Section 8 we explore how provision of public insurance for the uninsured reduces this moral hazard effect.

7.6 Health Types and the Effect of Health Shocks

Table 9 examines the role of latent health. Working age men of the poor health type are much less likely to be employed than the good type, 81.5% vs. 92.8%, and much more likely to receive transfers, 12.9% vs. 1.5%. They have lower PVE, $551k vs. $958k, and inequality is far higher within the poor health type, as the CV of PVE is .500 vs. .380. If we eliminate health shocks, the employment rate difference between the two groups is almost eliminated, as is the degree of inequality, and transfer receipt by the poor health type falls dramatically.

The vagaries of health shocks contribute much more to lifetime earnings inequality within the bad health type, accounting for their higher CV in the baseline. This is partly because the bad 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.

Elimination of health shocks increases the expected present value of lifetime earnings of the bad health type by 20.4%, compared to only 6% for the good type. But this only eliminates about 1/3 of the large PVE gap between groups. This is because the good health types still tend to have more education, and they are more likely to be the high skill type. According to the PVE regression from Table 5 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.

7.7 Health Shocks and the Present Value of Lifetime Consumption

Finally, we examine how health shocks affect consumption inequality. Table 10 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.[34]

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 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.[35] Earnings losses are personal, while consumption losses are shared within families, so they are mitigated relative to earnings losses. Furthermore, consumption 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 13.3% or $54k, while increasing that of college workers by only 5%, or $35k. 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.

[34] 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 6 and 10 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.

[35] This is perhaps surprising, as the reduction in earnings due to health shocks translates into reduced consumption, and, on top of that, health shocks generate OOP treatment costs that also reduce consumption.

8 Providing Public Health Insurance to the Uninsured

Here we use our model to simulate the provision of government funded health insurance to uninsured workers. In the baseline 39% of working age men lack ESHI.[36] Rates of coverage vary greatly by age, education and full/part-time employment status, and our model provides a good fit to these patterns (see Appendix D.11). The fractions of high school, some college and college types with ESHI are 54%, 60% and 69%, respectively.

In our experiment we leave the employer-sponsored system untouched, so probabilities jobs come with ESHI are unchanged. We require all men who end up uninsured to participate in a government-funded insurance program. Similarly, the ACA left the ESHI system in place while organizing the uninsured into a risk pool that could access a subsidized insurance plan, with mandated participation.[37,38] Of course the ACA had many other features we do not model. We seek to obtain generalizable knowledge about the effect of providing insurance to the uninsured, as opposed to analyzing a complex bundle of policies like the ACA.

Participants in our public plan pay an annual premium equal to employee's share of the ESHI 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, as well as the same stigma of default. 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.

Table 11 shows how the experiment affects medical spending and sources of payment for working-age men. Men with ESHI are little affected; in fact, they have a slight drop in healthcare costs as the population is healthier. Men without ESHI have treatment costs of $2,556 per person in the baseline, but they only pay $506 of this, the rest being covered by Medicaid or free care (unpaid bills). When the public plan is introduced, total spending on the uninsured increases by 54% to $3,966 per person, implying a very large "moral hazard" effect. This reflects an increase in the rate of treatment for men who lack ESHI from 55% in the baseline to 98% in the experiment, causing the latent cost of untreated shocks to drop

[36] This is close to the data: in the CPS, 37% of working age white men were not covered by a health plan provided by their own employer, and in 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.

[37] If we instead introduce a universal health insurance plan that *replaces* employer-provided 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. This is beyond the capacity of our partial equilibrium model.

[38] 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 makes jobs without ESHI more attractive, creating an incentive for the roughly 45% of small firms that do offer ESHI to drop it (Aizawa and Fang (2020)). But our experiment generates a tiny increase in the fraction of offers without ESHI accepted (from 81.1% in baseline to 83.9% in the experiment). We argue this creates little incentive for small firms to drop ESHI or offer lower wages.

from \$1624 to only \$52.[39] 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. We assume unpaid bills are ultimately paid by agents in some form (higher taxes, higher medical costs for the insured), so we will count the reduction in unpaid bills as a cost saving.

Table 12 shows how the public program affects aggregate outcomes. The top panel shows per capita 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).[40] A large part of the cost is covered by reduced spending on Medicaid/DI, which drops from \$372 per working age man to \$42 per capita, and on unpaid bills that drop from \$465 to \$48. Average OOP costs and ESHI-covered costs are almost unchanged in the experiment, as we saw in Table 11.

Summing up all cost components, total medical expenditures per capita increase \$528, from \$2,586 in the benchmark to \$3,114 in the experiment. This 20% increase reflects the "moral hazard" effect of providing insurance.[41] 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 \$662 to \$42. Interestingly, untreated costs drop more (\$601) than medical spending increases (\$528), as 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.

The "labor market outcomes" panel of Table 12 shows how the public program improves labor market outcomes. The mean offer wage increases by 0.9%, the employment rate increases by 1.1%, and the PV of lifetime earnings increases by 1.9% or \$15k.[42] The fraction of working-age men who rely on social insurance drops 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.[43] 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.

[39] Among those lacking ESHI, 65% experience a health shock annually. There is also an increase in spending on minor illness, etc., by formerly uninsured men with no shocks.

[40] 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.

[41] Most of this increase in medical expenditures (\$408) is due to an increase in the rate of treatment for health shocks. The rest (\$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.

[42] The increase in the employment rate is mostly due to a small increase in the fraction of job offers without ESHI accepted, from 81.1% to 83.9%. We argue this is a small enough change so 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).

[43] This figure includes individual consumption of single men, and household consumption for married men.

8.1 Budgetary Impacts

The "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.[44] 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.[45] 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+. The increase in Social Security and Medicare costs is \$204 per model household. Once we factor in these 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%.

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.[46] 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. 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 13 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

[44] 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.

[45] 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."

[46] 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.

are combined with an 0.8pp increase in the consumption tax. For high school men the employment rate increases by 1.7pp, and the PV of lifetime earnings increases by 3.6%. For more educated workers the increases in earnings are more modest. This is why provision of public insurance reduces earnings inequality, as the coefficient of variation in the PV of lifetime earnings falls from .497 in the baseline to .481 in the experiment, see Table 12.

The lower panels of Table 13 reveal that effects are much larger for men with low skill and bad latent health. For example, 32% of high school men are in this category. For 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 13 shows that introducing public insurance for the uninsured increases the present value of lifetime utility for all 18 types in the model, despite the tax increase, so *ex ante* we achieve a Pareto improvement. *Ex post*, some agents 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 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 Sensitivity to Price

Our analysis has taken into account the moral hazard effect of public insurance on total medical expenditures, as well as the costs generated by longer life expectancy. But there is one potential cost we have not considered: 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 95, 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,[47] 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.

8.4 Improving Medicaid Accessibility

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. Medicaid pays only the excess of treatment cost beyond what drives the person down to the consumption floor.[48] (In contrast to this experiment, the ACA Medicaid expansion did *two* things: It extended access to single men and women without children,[49] 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 is required to pay for this policy. 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%.

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

[48] This change only affects men who drew the "no access" choice set in the baseline.

[49] 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.

Table 14 reports results for all men and selected types (focusing on low skill/poor health types where effects are largest). 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.

The Medicaid access policy reduces 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 ESHI over a policy of improved access to Medicaid, where receipt is conditional on low income net of medical costs. The former policy encourages labor supply while the later 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. 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%.

8.5 Mechanisms: How Does Insurance Affect Health and Earnings?

Now we explore mechanisms thorough which public insurance affects health and earnings. The first two rows of Table 15 compare the baseline with the results from the public insurance experiment (where we do not change the consumption tax). We then present two experiments that elucidate the mechanisms through which public insurance affects behavior.

In the first experiment we eliminate the OOP cost of health shocks.[50] Notably, this only increases the rate of treatment from 80.1% to 81.7%. That is because it is lack of access, not cost *per se*, that mainly drives non-treatment by the uninsured (as they often have the option to default, obtain free care, or 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 for low-skill workers. As we see in the bottom panel of Table 15, 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.

The next row of Table 15 reports an experiment where we give all uninsured men access to treatment, by shifting the probability mass of the "cannot treat" choice set to the "can treat if pay" choice set.[51] This increases the treatment rate 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%.

[50] 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.

[51] 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.

9 Results for Blacks and Hispanics

Finally we use our model to explore the impact of health shocks on the earnings of Blacks and Hispanics. As we show in Appendix K Section 28.1, there are few Black and Hispanic men with any education past high school in the MEPS data. Hence, we lack adequate data to fit the model to these groups. So we focus on calibrating the model to the behavior and outcomes of Blacks and Hispanics with high school or less education.

Appendices K and L provide many descriptive statistics that illustrate the important differences between Whites, Blacks and Hispanics that we seek to match. Conditional on age, Blacks and Hispanics are less often in good health than Whites. If we also condition on ESHI status, Blacks and Whites have similar health. However, Hispanics with ESHI tend to have worse health than Whites, while those without ESHI have better health. In contrast to Blacks and Whites, there is much less advantageous selection into ESHI for Hispanics.

We also find that Blacks and Hispanics report substantially fewer d^u and s shocks than Whites, conditional on health, age and insurance status. The differences are much smaller for d^p shocks. We present evidence that Blacks and especially Hispanics get treated for health shocks at lower rates than Whites. Blacks tend to have larger Charges for health shocks than Whites and Hispanics, conditional on health, age and ESHI status. And Blacks pay for treated shocks at lower rates than Whites and Hispanics.

Of course, there are also important labor market differences. Blacks and Hispanics have substantially lower wages. Among men with HS or less education, Blacks have a 74.0% employment rate, compared to 84.8% for Whites and 84.9% for Hispanics. Their rate of transfer receipt is 16.0%, compared to 10.2% for Whites and 9.2% for Hispanics. Hispanics are also *much* less likely to have jobs with ESHI – see Appendix L, Figure 30.

9.1 Fitting the Model to Blacks and Hispanics

Appendix L describes how we calibrate the model to fit Blacks and Hispanics. The first step, as it was for Whites, is to estimate – outside the model – exogenous stochastic processes for survival, marriage, family size, spouse employment/income and spouse medical costs. Interestingly, mortality conditional on age and health is indistinguishable between Whites and Blacks, but mortality is lower for Hispanics, consistent with the well-known "Hispanic Paradox" in epidemiology (see Makridis and Eschbach (2011)).

For Blacks, we can then obtain a good fit by modifying a small set of internally calibrated parameters: (1) the distribution of initial employment at age 25, (2) the wage function intercepts (fixed effects), (3) the consumption floor, so as to match the fraction who receive government transfers, (4) the treatment/payment option probabilities, and (5) the probability of reporting s shocks if untreated. Remarkably, there was no need to change any of the parameters of the health production process.

The Hispanics are more challenging. They differ from Whites and Blacks in two major ways: They are much more likely to have jobs without ESHI, and their health transitions are surprisingly good given their state variables, again consistent with the "Hispanic Paradox," which states that health of Hispanics is surprisingly good given their relatively low SES.

So to fit Hispanics we also need to (1) change latent health type proportions at age 25, (2) change a few parameters of the H transition function to make Hispanics more resilient,

(3) change the probabilities of reporting d^p and d^u shocks if untreated, and (4) reduce the persistence of job offers with ESHI. We also needed to increase the probabilities that uninsured Hispanics lack access to care. And we introduce a probability that even insured Hispanics may lack access to care, which may reflect language barriers, lack of geographic proximity to providers, etc.[52] The finding that Hispanics have worse access to care is a key result of our analysis, and is consistent with results in, e.g., Cunningham and Kemper (1998), Nelson et al. (2002), Kang-Kim et al. (2008). Given these added features, our model provides a good fit to the data for Hispanics as well.

9.2 Counterfactuals for Blacks and Hispanics

Now we use the model to examine the impact of health shocks on the present value of lifetime earnings (PVE). As we see in Table 16, the expected PVE for Blacks with high school or less education is $422k compared to $483k for Hispanics and $562 for Whites (see Table 6). The PVE for the low-skill Blacks is particularly low ($167) compared to that for Hispanics ($245k) and for Whites ($318).

If we eliminate health shocks, we predict the PVE of HS Blacks would increase by 23.7%, compared to 17.9% for Whites and 17.7% for Hispanics. We again find much larger effects of health shocks on low-skill types. In Table 6 we saw that eliminating health shocks causes the PVE for low-skill HS Whites to increase by 36.6%, driven by a substantial increase in labor supply. Here, we see increases of 35.8% for low skill-Hispanics and a remarkable 77.3% for low skill Blacks, again driven by increased labor supply. As we see in Table 17, the fraction of low-skill HS Blacks who work increases from only 46% to 77% (a 67% increase). At the same time, the fraction who rely on transfers drops from 38% to 9%. So we again see the mechanism that health shocks tend to reduce labor supply of low-skill workers and induce them to become reliant on means tested transfers.

Magnitudes for Hispanics are more similar to Whites: The fraction of low-skill Hispanics who work in the baseline is similar to Whites (71% each), and the fraction who rely on transfers is slightly smaller (20.6% for Hispanics vs 25.5% for Whites). Eliminating health shocks causes the employment rate of low-skill Hispanics to increase by 27% and their reliance on transfers to drop by 17 pp, similar to effects for Whites. So it is unsurprising that the increase in PVE for low-skill HS Hispanics, 35.8%, is close to what we find for Whites, 36.6%.

Thus, health shocks have qualitatively similar effects on the PVE for Whites, Blacks and Hispanics. Quantitatively, effects on Hispanics are very similar to Whites. Effects on low-skill Blacks are much larger – as we would expect – because in the baseline they have particularly low earnings, low employment, and high reliance on transfers.

We also decompose the impact of health shocks into the labor supply, human capital, direct health and behavioral effects as we did in Section 7.5 Table 6. Qualitatively the results are similar. Quantitatively, what stands out is that the human capital channel for low-skill HS Blacks is very substantial. Elimination of health shocks increases their PVE by 36.7% via this channel (out of a total effect of 77.3%). This is because when low-skill Blacks exit the labor force after health shocks they are particularly unlikely to return, and very susceptible to becoming reliant on transfers, due to their very low wage rates and relatively poor health.

[52] The well-documented barriers to healthcare access for minorities are also discussed in Allen et al. (2017); Tarlov et al. (2010); Wang et al. (2008); Lurie and Dubowitz (2007); Bashshur et al. (1994), among others.

The behavioral channel is especially important for Blacks: For low-skill HS types, eliminating health shocks increases PVE by 24.4% for Blacks, 9.8% for Whites and 7.1% for Hispanics via the behavioral channel. As we have emphasized, health risk generates perverse incentives for low-skill workers to curtail labor supply and human capital accumulation, and to be more reliant on means-tested transfers (i.e., if health shocks are likely to push one unto the consumption floor anyway, there is little incentive to work). Here we see this perverse incentive is stronger for low-skill Blacks, which is not surprising as they have lower wages than low-skill Whites. The effect is weaker for Hispanics due to a lower consumption floor.

Finally, Appendix M reports results of giving public insurance to Blacks who lack ESHI, similar to the experiment in Section 8.[53] The per capita cost of the program (over all HS Black men) is $1,939, but 72% of this cost is offset by drops in Medicaid spending and unpaid bills. The net increase in medical expenditure per working age HS Black man is $596, close to what we see for HS Whites ($563). We also see an improvement in labor market outcomes, as lifetime work years increase 0.66, and the PVE increases from $422k to $433k, or 2.6%. There is also a substantial drop in social insurance payments, so the program almost pays for itself if we look only at spending and tax receipts for working age men. But, as with Whites, the increase in longevity leads to increased Social Security and Medicare spending, so in the end the program entails a small cost, close to what we found for Whites.

10 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, 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[54] – see Mahoney (2015), Lockwood (2023). In contrast, the access role of insurance is vital as non-emergency treatment generally requires proof of insurance. See Institute of Medicine (2001, 2002) for a general discussion.

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. Providing public insurance to men who lack ESHI plays both roles: For Whites, 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

[53] We did not implement the public insurance experiment for Hispanics as we do not know how to target the program. In ASEC data from 2001-13 on men with HS or less education, 49% of Hispanics in the US were not citizens. It would make sense to target the program at citizens and permanent residents, but we cannot see immigration citizenship status in MEPS, so we cannot calibrate the distribution of skill and health types conditional on immigration status.

[54] According to CMS, 55% of an emergency physician's time is spent providing uncompensated care. See Federal Register 67(251) Dec. 31, 2002.

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%).

Similarly, for working-age Blacks with high school or less education, our model implies the provision of public insurance for those who lack ESHI would cause the fraction in good health to increase by 7.6 points, full-time years of work to increase by .66 years or 2.7%, the employment rate to increase by 0.2 points, the offer wage rate to increase by 1.6%, and the present value of lifetime earnings to increase by 2.6%.

Second, comparing our results to an alternative simpler model where agents *always* treat and pay health shock costs, as in our earlier paper Capatina et al. (2020) and much prior literature, 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). Ignoring treatment decisions and free care causes one to exaggerate the incentives that health risk creates for workers to curtail labor supply to maintain eligibility for means-tested transfers. This incentive is important, but the simpler model over states 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 inequality in the present value of lifetime earnings in the aggregate is about 12% to 13% for White males. 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-education men, the contribution of health shocks to inequality is more substantial. Among White men with high school or less education, health shocks account for 21.5% of lifetime earnings inequality. The figures for Blacks and Hispanics with HS or less education are 26.4% and 18.4% respectively. 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 both overall and within the low-skill group. Provision of public insurance removes this perverse incentive, causing low-skill men to supply more labor and thus reducing earnings inequality.

Fourth, we show how universal insurance has important advantages over means-tested Medicaid in terms of labor supply incentives, health outcomes, and welfare. Institute of Medicine (2002) explains how Medicaid is inferior to ESHI because it does not provide continuity of access. 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.

Fifth, we find health shocks affect Whites, Blacks and Hispanics in similar ways. But Hispanics differ in two key respects: Their health production process implies they are more resilient, and we cannot explain their behavior unless they have worse access to care.

Finally, a key limitation of our paper is the focus on males. Extension to women is very difficult, as we must model fertility and costs of pregnancy. We pursue this in ongoing work.

Table 2: 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 3: 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		
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: 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 4: 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
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
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 5: 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	0.827	0.866	0.885	0.916

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 Row 2 "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.

Table 6: 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 7: 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

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. The experiments in columns (1)-(4) are explained in the note to Table 6.

Table 8: Effects of Health Shocks on Employment and Social Insurance

	Employment (%)				**Social Insurance (%)**			
	Baseline	**No Health Shocks**			**Baseline**	**No Health Shocks**		
		LS Effect	**LS+HC Effect**	**Total Effect**		**LS Effect**	**LS+HC Effect**	**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 column (1) shows the baseline simulation. The next three columns show counterfactuals where we eliminate health shocks at working ages: (2) holding human capital and decision rules fixed as in the baseline, to get the labor supply (LS) effect plus the health effect, (2) letting human capital also adjust, to get the LS+HC effect, and (3) letting decision rules also adjust, to get the total effect.

Table 9: Effects of Removing Health Shocks, by Latent Health Type

	PV Earnings		CV of PVE		Emp. Rate		SI Rate	
Latent Health	**Baseline**	**No HS**	**Base**	**No HS**	**Base**	**No HS**	**Base**	**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.

Table 10: 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

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.

Table 11: Mandatory Public Health Insurance, Impact on Health Spending/Sources of Payment

	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	32
All	2,586	515	1,234	372	465	0	662
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 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	662	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: Mandatory Public Health Insurance, by Latent Types, Balanced Budget

	EMP		SI		PV Earnings		% Good H		Δ PVU
Type	**Bench**	**Public**	**Bench**	**Public**	**Bench**	**Public**	**Bench**	**Public**	
	%	pp Δ	%	pp Δ		% Δ	%	pp 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 an experiment where we give public health insurance to men aged 25-64 who lack ESHI. The consumption tax increases to balance the government budget. PV Earnings are expressed in thousands of dollars. We report the percentage change in PV earnings and PV utility relative to the baseline. For employment, social insurance receipt and fraction in good health we show baseline levels and percentage point changes from the baseline.

Table 14: Medicaid Guaranteed Experiment, by Latent Types, Balanced Budget

	EMP		SI		PV Earnings		% Good H		Δ PVU
Type	**Bench**	**Public**	**Bench**	**Public**	**Bench**	**Public**	**Bench**	**Public**	
	%	pp Δ	%	pp Δ		% Δ	%	pp 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
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
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

Notes: The table presents statistics from an experiment where we allow all men aged 25-64 who qualify for the consumption floor to have access to treatment of health shocks using Medicaid. The consumption tax increases to balance the government budget. PV Earnings are expressed in thousands of dollars. We report the percentage change in PV earnings and PV utility from the baseline. For employment, social insurance receipt and fraction in good health we show baseline levels and percentage point changes from the baseline.

Table 15: 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
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

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.

Table 16: Effects of Health Shocks on Present Value of Lifetime Earnings (PVE), Racial Minorities

	Baseline PVE	Lab Sup Effect	Hum Cap Effect	Health Effect	Behavior Effect	Total Change
		(1)	(2)	(3)	(4)	(5)
Blacks ≤HS	421,798	9.24	8.10	1.57	4.80	23.71
Low Productivity	167,139	14.73	36.71	1.50	24.35	77.29
Med Productivity	412,442	9.80	7.16	1.49	3.92	22.37
High Productivity	685,875	7.57	1.70	1.63	0.57	11.46
Hispanics ≤HS	482,608	8.70	4.98	1.77	2.28	17.73
Low Productivity	244,637	10.58	16.44	1.70	7.11	35.83
Med Productivity	496,821	8.42	3.88	1.72	1.76	15.77
High Productivity	706,425	8.23	1.79	1.84	0.97	12.83

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 17: Effects of Health Shocks on Employment and Social Insurance, Racial Minorities

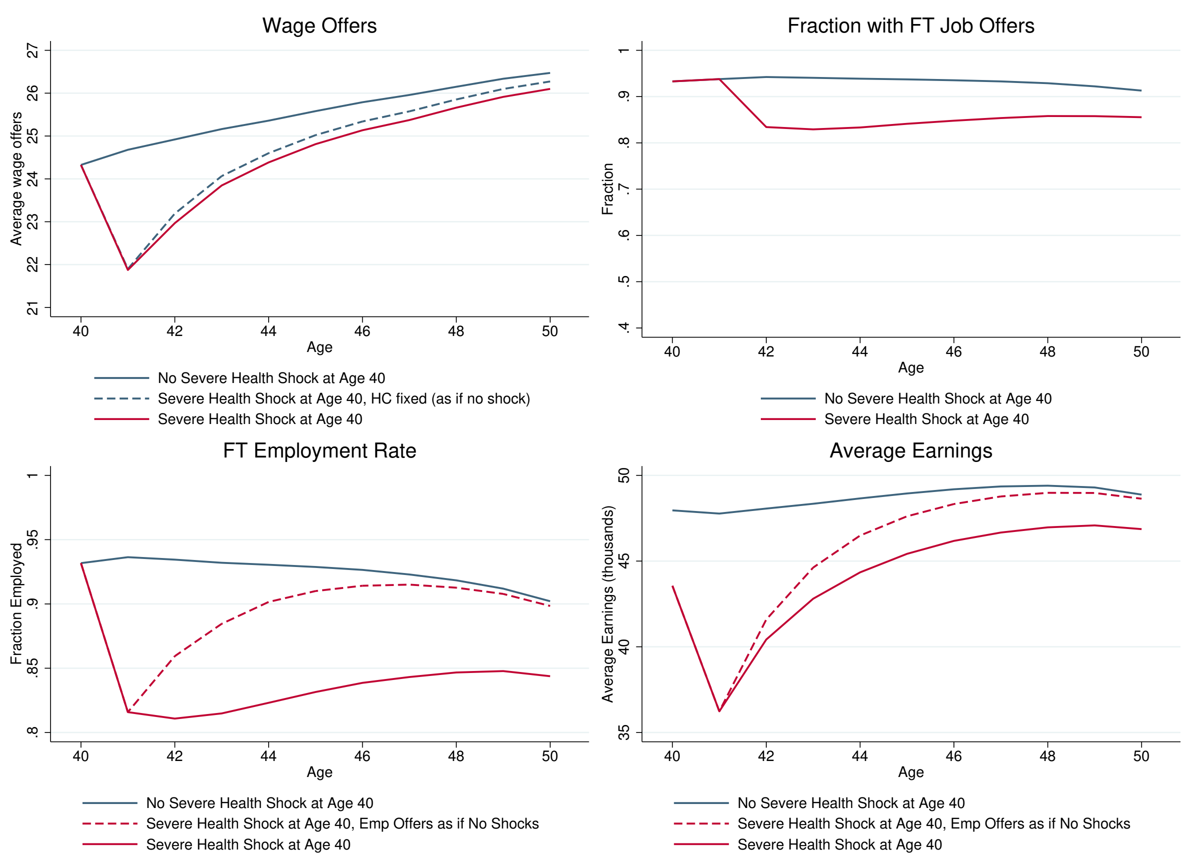
	Employment (%)				Social Insurance (%)			
	Baseline	No Health Shocks			Baseline	No Health Shocks		
		LS Effect	LS+HC Effect	Total Effect		LS Effect	LS+HC Effect	Total Effect
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Blacks ≤ HS	74.0	76.2	82.5	86.9	16.0	12.4	7.0	3.6
Low Skill	46.2	49.0	66.5	77.3	38.4	33.2	18.3	8.8
Med Skill	83.0	86.5	88.9	90.4	8.4	3.6	2.1	1.3
High Skill	92.1	92.5	92.1	92.8	1.8	0.8	0.7	0.8
Hispanics ≤ HS	84.9	85.4	89.9	93.1	9.2	6.8	3.6	1.7
Low Skill	70.7	72.2	84.1	89.5	20.6	16.1	8.0	3.8
Med Skill	89.5	89.9	91.7	94.3	5.4	3.5	2.1	0.9
High Skill	94.2	94.1	94.0	95.6	1.7	0.9	0.8	0.6

Notes: The table presents the full-time employment rate and rate of government transfer receipt for working age men. The column (1) shows the baseline simulation. The next three columns show counterfactuals where we eliminate health shocks at working ages: (2) holding human capital and decision rules fixed as in the baseline, to get the labor supply (LS) effect plus the health effect, (2) letting human capital also adjust, to get the LS+HC effect, and (3) letting decision rules also adjust, to get the total effect.

Figure 1: Earnings Inequality over the Life-cycle, Model and Data (CPS)

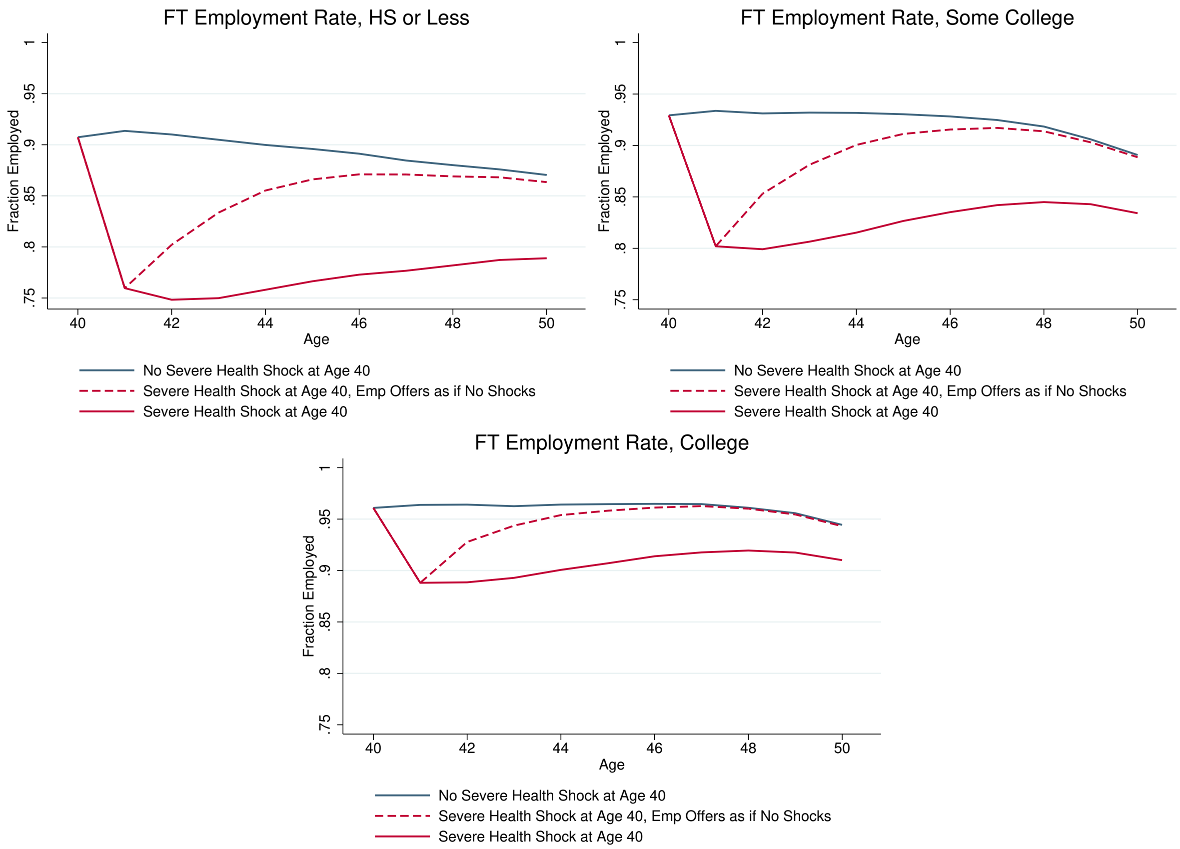
Note: Earnings are pre-tax. In the CPS, earnings inequality is calculated using data on white men. To reduce sensitivity to outliers, we drop the top 2% of earnings observations at each age, as well as observations on employed men with wage rates below the minimum wage and or above $81.45. In the model,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

Figure 2: Effects of a Severe Health Shock at Age 40



Note: Severe health shocks defined in Section 7.1. Figures based on men in good or fair health at age 40. We compare four counterfactuals: (1) no one has a d^u shock at age 40 (solid blue lines), (2) all men 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 3: Effects of a Severe Health Shock at Age 40 on FT Employment, by Education



References

Aaronson, D. and E. French (2004). The effect of part-time work on wages: Evidence from the social security rules. *Journal of Labor Economics 22*(2), 329–252. 9

Adams, P., M. D. Hurd, D. McFadden, A. Merrill, and T. Ribeiro (2003, January). Healthy, wealthy, and wise? Tests for direct causal paths between health and socioeconomic status. *Journal of Econometrics 112*(1), 3–56. 4

Aizawa, N. and H. Fang (2020). Equilibrium labor market search and health insurance reform. *Journal of Political Economy 128*(11), 4258–4336. 27

Allen, E., K. Call, T. Beebe, D. McAlpine, and P. Johnson (2017). Barriers to care and healthcare utilization among the publicly insured. *Medical Care 55*(3), 207–214. 33

Attanasio, O., S. Kitao, and G. L. Violante (2010). Financing Medicare: A general equilibrium analysis. In *Demography and the Economy*, NBER Chapters, pp. 333–366. NBER, Inc. 3

Baker, D. W., M. F. Shapiro, and C. L. Schur (2000). Health insurance and access to care for symptomatic conditions. *Archives of Internal Medicine 160*(9), 1269–1274. 4

Bashshur, R., R. Homan, and D. Smith (1994). Beyond the uninsured: Access to care. *Medical Care 32*(5), 409–419. 33

Benítez-Silva, H., M. Buchinsky, H. M. Chan, J. Rust, and S. Sheidvasser (1999). An empirical analysis of the Social Security disability application, appeal, and award process. *Labour Economics 6*(2), 147 – 178. 10

Benıtez-Silva, H., M. Buchinsky, and J. Rust (2010). Induced entry effects of a $1 for $2 offset in SSDI benefits. 4

Bureau of Labor Statistics (2023). Paid leave benefits: Average number of sick and vacation days by length of service requirement. `https://www.bls.gov/charts/employee-benefits/paid-leave-sick-vacation-days-by-service-requirement.htm`. Accessed: 2023-07-08. 9

Burstin, H., K. Swartz, A. OâNeill, E. Orav, and T. Brennan (1998). The effect of change of health insurance on access to care. *Inquiry 35*(4), 389–397. 4

Capatina, E. (2015). Life-cycle effects of health risk. *Journal of Monetary Economics 74*, 67–88. 3

Capatina, E., M. P. Keane, and S. Maruyama (2020). Health shocks and the evolution of earnings over the life-cycle. *UNSW Business School Research Paper*. 35

Cole, H. L., S. Kim, and D. Krueger (2018). Analyzing the effects of insuring health risks. *Review of Economic Studies*. 3

Conti, G., J. Heckman, and S. Urzua (2010a). The early origins of the education-health gradient. under revision. *Perspectives on Psychological Science*. 4

Conti, G., J. Heckman, and S. Urzua (2010b). The education-health gradient. *American Economic Review 100*(2), 234–38. 4

Courbage, C. and A. De Coulon (2004). Prevention and private health insurance in the uk. *The Geneva papers on risk and insurance issues and practice 29*(4), 719–727. 15

Cunningham, P. and P. Kemper (1998). Ability to obtain medical care for the uninsured: How much does it vary across communities? *Journal of the American Medical Assoc. 280*(10), 921–927. 4, 33

De Moor, M. H., G. Willemsen, I. Rebollo-Mesa, J. H. Stubbe, E. J. De Geus, and D. I. Boomsma (2011). Exercise participation in adolescents and their parents: evidence for genetic and generation specific environmental effects. *Behavior genetics 41*, 211–222. 10

De Nardi, M. (2004). Wealth inequality and intergenerational links. *The Review of Economic Studies 71*(3), 743–768. 11

De Nardi, M., E. French, and J. B. Jones (2010). Why do the elderly save? The role of medical expenses. *Journal of Political Economy 118*(1), pp. 39–75. 1, 3

De Nardi, M., S. Pashchenko, and P. Porapakkarm (2022, October). The lifetime costs of bad health. Working Paper 23963, National Bureau of Economic Research. 3, 10

Degenhardt, L., C. O'Loughlin, W. Swift, H. Romaniuk, J. Carlin, C. Coffey, W. Hall, and G. Patton (2013). The persistence of adolescent binge drinking into adulthood: findings from a 15-year prospective cohort study. *BMJ open 3*(8), e003015. 10

Eckstein, Z. and K. I. Wolpin (1989). Dynamic labour force participation of married women and endogenous work experience. *The Review of Economic Studies 56*(3), pp. 375–390. 3

Fang, H., M. Keane, A. Khwaja, M. Salm, and D. Silverman (2007). Testing mechanisms of structural models: The case of the mickey mantle effect. *American Economic Review 97*(2), 53–59. 15

Finkelstein, A., N. Hendren, and E. F. Luttmer (2019). The value of medicaid: Interpreting results from the oregon health insurance experiment. *Journal of Political Economy 127*(6), 2836–2874. 29

Finkelstein, A., N. Mahoney, and M. J. Notowidigdo (2018). What does (formal) health insurance do, and for whom? *Annual Review of Economics 10*, 261–286. 1

French, E. (2005). The effects of health, wealth, and wages on labour supply and retirement behaviour. *Review of Economic Studies 72*(2), 395–427. 3

French, E. and J. B. Jones (2011). The effects of health insurance and self-insurance on retirement behavior. *Econometrica 79*(3), 693–732. 1, 3, 4

García, J. L. and J. J. Heckman (2021). Early childhood education and life-cycle health. *Health Economics 30*, 119–141. 4

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy 80*(2), 223–55. 1, 21

Hadley, J. (2007). Insurance coverage, medical care use, and short-term heath changes following and unintentional injury or the onset of a chronic condition. *Journal of the American Medical Association 297*(16), 1073–1774. 4

Hai, R. and J. J. Heckman (2019). A dynamic model of health, addiction, education, and wealth. *Becker Friedman Institute for Research in Economics Working Paper* (2688384). 4

Heckman, J. (1974). Shadow prices, market wages, and labor supply. *Econometrica: journal of the econometric society*, 679–694. 18

Heckman, J., J. Humphries, and G. Veramendi (2018). Returns to education: The causal effects of education on earnings, health, and smoking. *Journal of Political Economy 126*(S1), S197–S246. 4

Heckman, J. J. and T. E. MaCurdy (1980). A life cycle model of female labour supply. *The Review of Economic Studies 47*(1), 47–74. 3

Hoffman, C. and J. Paradise (2008). Health insurance and access to health care in the united states. *Annals of the NY Academy of Sciences 1136*, 149–160. 4

Hokayem, C. and J. P. Ziliak (2014). Health, human capital, and life cycle labor supply. *American Economic Review 104*(5), 127–31. 3

Hosseini, R., K. A. Kopecky, and K. Zhao (2021). How important is health inequality for lifetime earnings inequality? 3

Hubbard, R. G., J. Skinner, and S. P. Zeldes (1995). Precautionary saving and social insurance. *Journal of Political Economy 103*(2), 360–399. 1, 10

Huurre, T., T. Lintonen, J. Kaprio, M. Pelkonen, M. Marttunen, and H. Aro (2010). Adolescent risk factors for excessive alcohol use at age 32 years. a 16-year prospective follow-up study. *Social psychiatry and psychiatric epidemiology 45*, 125–134. 10

Imai, S. and M. P. Keane (2004, 05). Intertemporal labor supply and human capital accumulation. *International Economic Review 45*(2), 601–641. 3, 9

Institute of Medicine (2001). *Coverage Matters: Insurance and Health Care*. Committee on the Consequences of Uninsurance: Washington (DC): National Academies Press (US). 3, 34

Institute of Medicine (2002). *Care Without Coverage: Too Little, Too Late*. Committee on the Consequences of Uninsurance: Washington (DC): National Academies Press (US). 3, 34, 35

Janicki, H. (2013). Employment-based health insurance: 2010. 27

Jeske, K. and S. Kitao (2009). U.S. tax policy and health insurance demand: Can a regressive policy improve welfare? *Journal of Monetary Economics 56*(2), 210 – 221. 3

Jung, J. and C. Tran (2016). Market inefficiency, insurance mandate and welfare: U.S. health care reform 2010. *Review of Economic Dynamics 20*, 132 – 159. 3

Kang-Kim, M., J. Betancourt, J. Ayanian, A. Zaslavsky, R. Yucel, and J. Weissman (2008). Access to care and use of preventive services by hispanics. *Medical Care 46*(5), 507–515. 4, 33

Keane, M. and R. Moffitt (1998). A structural model of multiple welfare program participation and labor supply. *International Economic Review 39*(3), 553–589. 4

Keane, M. P. and K. I. Wolpin (1997). The career decisions of young men. *Journal of Political Economy 105*(3), 473–522. 3, 9, 22

Keane, M. P. and K. I. Wolpin (2001). The Effect of Parental Transfers and Borrowing Constraints on Educational Attainment. *International Economic Review 42*(4), 1051–1103. 3

Khwaja, A. (2010). Estimating willingness to pay for Medicare using a dynamic life-cycle model of demand for health insurance. *Journal of Econometrics 156*(1), 130–147. 3

Khwaja, A. W. (2001). Health insurance, habits and health outcomes: A dynamic stochastic model of investment in health. Computing in Economics and Finance 2001 166, Society for Computational Economics. 15

Kitao, S. (2014). A life-cycle model of unemployment and disability insurance. *Journal of Monetary Economics 68*, 1–18. 3, 4

Lochner, L. (2011). Nonproduction benefits of education: Crime, health, and good citizenship. *Handbook of the Economics of Education 4*, 183–282. 4

Lockwood, L. M. (2023). Health insurance and consumption risk. 3, 16, 34

Low, H. and L. Pistaferri (2015). Disability insurance and the dynamics of the incentive insurance trade-off. *American Economic Review 105*(10), 2986–3029. 4, 10

Lundberg, S. (1985). The added worker effect. *Journal of Labor Economics 3*(1), 11–37. 9

Lurie, N. and T. Dubowitz (2007). Health disparities and access to health. *Journal of the American Medical Association 297*(10), 1118–1121. 33

Lushniak, B. D., J. M. Samet, T. F. Pechacek, L. A. Norman, and P. A. Taylor (2014). The health consequences of smokingâ50 years of progress: A report of the surgeon general. 10

MaCurdy, T. E. (1981). An empirical model of labor supply in a life-cycle setting. *Journal of political Economy 89*(6), 1059–1085. 3

Mahoney, N. (2015). Bankruptcy as implicit health insurance. *American Economic Review 105*(2), 710–46. 3, 16, 34

Makridis, K. and K. Eschbach (2011). Hispanic paradox in adult mortality in the united states. In R. Rogers and E. Crimmins (Eds.), *International Handbook of Adult Mortality*, Volume 2, Part II, Chapter 11, pp. 227–240. 4, 32

Marquis, S. M. and S. H. Long (1994). The uninsured access gap: Narrowing the estimates. *Inquiry 31*(4), 405–414. 4

Moffitt, R. (1984). The estimation of a joint wage-hours labor supply model. *Journal of Labor Economics 2*(4), 550–66. 9

Moffitt, R. (1992). Incentive effects of the us welfare system: A review. *Journal of Economic Literature 30*(1), 1–61. 4

Moffitt, R. and B. Wolfe (1992). The effect of the medicaid program on welfare participation and labor supply. *The Review of Economics and Statistics*, 615–626. 4

Nelson, A. R., A. Y. Stith, B. D. Smedley, et al. (2002). *Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care*. National Academies Press. 4, 33

Newhouse, J. P. and R. C. I. E. Group (1993). *Free for all?: lessons from the RAND health insurance experiment*. Harvard University Press. 15

Oreopoulos, P. and K. G. Salvanes (2011). Priceless: The nonpecuniary benefits of schooling. *Journal of Economic perspectives 25*(1), 159–84. 4

Palumbo, M. G. (1999). Uncertain medical expenses and precautionary saving near the end of the life cycle. *The Review of Economic Studies 66*(2), 395–421. 3

Pashchenko, S. and P. Porapakkarm (2017). Work incentives of medicaid beneficiaries and the role of asset testing. *International Economic Review 58*(4), 1117–1154. 3, 4

Reilly, J. J. and J. Kelly (2011). Long-term impact of overweight and obesity in childhood and adolescence on morbidity and premature mortality in adulthood: systematic review. *International journal of obesity 35*(7), 891–898. 10

Rose, E. K. and Y. Shem-Tov (2023, July). How replaceable is a low-wage job? Working Paper 31447, National Bureau of Economic Research. 21

Sawyer, S. M., R. A. Afifi, L. H. Bearinger, S.-J. Blakemore, B. Dick, A. C. Ezeh, and G. C. Patton (2012). Adolescence: a foundation for future health. *The lancet 379*(9826), 1630–1640. 10

Schoen, C. and C. DesRoches (2000). Uninsured and unstably insured: The importance of continuous insurance coverage. *Health Services Research 35*(1), 187–206. 4

Shaw, K. L. (1989). Life-cycle labor supply with human capital accumulation. *International Economic Review 30*(2), 431–56. 3

Singh, A. S., C. Mulder, J. W. Twisk, W. Van Mechelen, and M. J. Chinapaw (2008). Tracking of childhood overweight into adulthood: a systematic review of the literature. *Obesity reviews 9*(5), 474–488. 10

Smith, J. P. (1999). Healthy bodies and thick wallets: The dual relation between health and economic status. *Journal of Economic Perspectives 13*(2), 145–166. 3

Smith, J. P. (2004). Unraveling the ses: Health connection. *Population and Development Review 30*, 108–132. 3, 20

Stowasser, T., F. Heiss, D. McFadden, and J. Winter (2011). Healthy, Wealthy and Wise? revisited: An analysis of the causal pathways from socioeconomic status to health. In *Investigations in the Economics of Aging*, NBER Chapters, pp. 267–317. National Bureau of Economic Research, Inc. 4

Tarlov, E., S. Zenk, R. Campbell, R. Warnecke, and R. Block (2010). Characteristics of mammography facility locations and stage of breast cancer at diagnosis in chicago. *Journal of Urban Health 86*(2), 196–213. 33

Van Der Zee, M. D., D. Van Der Mee, M. Bartels, and E. J. De Geus (2019). Tracking of voluntary exercise behaviour over the lifespan. *International Journal of Behavioral Nutrition and Physical Activity 16*(1), 1–11. 10

Wang, F., S. McLafferty, V. Escamilla, and L. Luo (2008). Late-stage breast cancer diagnosis and health care access in illinois. *Professional Geographer 60*(1), 54–69. 33