How Important Is Health Inequality for Lifetime Earnings Inequality?*

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Abstract

Using a dynamic panel approach, we provide empirical evidence that negative health shocks significantly reduce earnings. The effect is primarily driven by the participation margin and is concentrated among the less educated and those in poor health. Next, we develop a life cycle model of labor supply featuring risky and heterogeneous frailty profiles that affect individuals' productivity, likelihood of access to social insurance, disutility from work, mortality, and medical expenses. Individuals can either work or not work and apply for social security disability insurance (SSDI/SSI). Eliminating health inequality in our model reduces the variance of log lifetime (accumulated) earnings by 28 percent at age 55. About 60 percent of this effect is due to the impact of poor health on the probability of obtaining SSDI/SSI benefits. Despite this, we show that eliminating the SSDI/SSI program reduces *ex ante* welfare.

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1 Introduction

Poor health affects individuals in multiple ways. It reduces their potential earning ability. It increases their cost of working, their mortality, and their medical expenses. It also increases their likelihood of accessing social insurance programs such as Social Security Disability Insurance (SSDI) and Supplemental Security Income (SSI). In this paper we assess how much of the variation in lifetime earnings among older individuals in the United States is due to the fact that they have faced heterogeneous and risky health events over their life cycles. We also assess the relative contributions of the various channels through which health impacts individuals. We focus on lifetime earnings because it is a measure of resources that incorporates the transitory and persistent impacts of past health events including those that lead to permanent exits from the labor force.

Our analysis employs an objective measure of health status, called the *frailty index*. The frailty index is simply the accumulated sum of all adverse health events that an individual has incurred. Each health problem is referred to as a *deficit*. An important feature of the frailty index is that it measures health and its variation on a fine scale.

We start by showing empirically that frailty shocks have a large impact on current labor earnings. The effects operate primarily through participation and wages and are concentrated among less educated and poor health individuals. Given these findings, we develop and calibrate a life cycle model of labor supply. Individuals in the model have risky heterogeneous frailty profiles that impact their productivity, disutility from work, medical expenses, mortality, and likelihood of successfully becoming SSDI or SSI (DI) recipients. They decide whether or not to work, and also choose whether or not to apply for DI benefits. Frailty heterogeneity in the model arises due to a frailty process that features fixed heterogeneity, a highly persistent AR(1) shock, and a transitory shock. In Hosseini et al. (2022) we show that this process generates health and mortality dynamics over the lifecycle that match those in the underlying data extremely well.

To measure the impact of health inequality on lifetime earnings inequality we use the calibrated model to conduct the following exercise. We collapse all heterogeneity in frailty by giving every agent in the economy the average frailty age profile. In this counterfactual economy, by age 55, the variance of log lifetime earnings (measured as the sum of all past earnings) is 28 percent lower relative to benchmark. A decomposition exercise reveals that nearly 60 percent of this decline is due to the effect of poor health on the likelihood of receiving DI benefits. The effect of poor health on labor productivity also plays an important role. Other factors, such as the impact of health on the disutility from working, medical expenses and mortality matter less. Crucial for our findings is the use of frailty to measure health. We demonstrate that a similar exercise using self-reported health status (SRHS), a coarser and less persistent measure of health, understates the importance of health inequality for lifetime earnings inequality because it is unable to fully capture the impacts of health that operate through the DI program.

Given our finding that the DI program is the primary channel through which health inequality generates lifetime earnings inequality, we ask whether individuals in our model economy would be better off without it. We find that, even though the DI program increases lifetime earnings inequality, it is welfare improving. Together with the tax implications of rebalancing the government budget, long-run *ex ante* welfare falls by 0.28 percent if the program is removed.

The fact that we can measure frailty on a fine scale means that we can treat it as a continuous variable. In our empirical analysis, we use the Panel Study of Income Dynamics (PSID) and a dynamic panel data approach (Blundell and Bond, 1998) to estimate the marginal effects of changes in frailty on employment, earnings, hours worked, and wages. We find that incurring one additional deficit reduces workers' wages by 2 percent and the probability of employment by 1.6 percentage points, with no statistically significant effect on hours conditional on working. Combining these effects indicates that an additional deficit reduces earnings by 3.9 percent on average. About half of this effect is due to the increase in the probability of non-employment and half to the decline in wages.

Our empirical findings contribute to the literature that estimates the impacts of declines in health on employment and earnings. While previous papers have focused on the impact of health deterioration on the employment of older workers (see O'Donnell et al. (2015) for a survey), we show that declines in health also reduce employment of younger workers, under the age of 45. Moreover, most earlier work does not decompose the effects of health on employed workers into effects on hours versus effects on wages. Those that do focus on the impacts of self-reports of health-driven work limitations. One concern with self-reports of work limitations is justification bias, evidence of which has been documented in the literature.[1] We contribute to this literature by showing, using an objective measure of health, that the effects of health on employed workers' earnings operate primarily through wages as opposed to hours.

We also use our dynamic panel estimator to estimate the causal effect of changes in earnings on frailty. Controlling for age and fixed effects, we fail to find statistically significant effects both overall and, on average, within the education and health groups we consider. As Cutler et al. (2011) discuss in a survey of the literature on health and socioeconomic status, there is little evidence that, after controlling for education, income and wealth have substantial causal effects on adult health in developed countries including the United States. Our results are consistent with these findings.

We use these empirical results to guide the development of our structural model which focuses on men for simplicity. Since we do not find statistically significant effects of earnings on frailty, we do not allow for such feedback effects in the model. However, we do allow life-cycle frailty dynamics to differ by education which is important because, as we document in Hosseini et al. (2022), these differences are substantial. In addition to frailty risk, individuals in the model face both productivity and employment risk. They jointly make consumption, savings, and labor supply decisions in each period over their life cycle. Given that we do not find effects of declines in health on hours, we assume that individuals in the model only adjust labor supply on the extensive margin. Working-age individuals can choose to work or exit the labor force. If not working, they can choose whether or not to apply for disability insurance. Retirement-age individuals can choose to work or retire. Markets are incomplete, but there exists a government that collects taxes to finance the DI program, as well as, a social security program and a means-tested transfer program.

An individual's frailty affects their behavior through five different channels: mortality rates, out-of-pocket medical expenditures, labor productivity, probability of successful DI

[1] See Blundell et al. (2020) for examples and further discussion.

application, and disutility from working. We estimate the effect of frailty on the first three channels directly from the data. In particular, we estimate the effect of frailty on mortality using the Health and Retirement Study (HRS) and the effect of frailty on out-of-pocket medical expenditures using the Medical Expenditures Panel Survey (MEPS). When estimating the effect of frailty on productivity it is important to control for selection due to non-participation. Thus, we use PSID and our dynamic panel data estimator together with a selection correction procedure proposed by Al-Sadoon et al. (2019).

The effects of frailty on the probability of successfully obtaining DI and the disutility from work are estimated using the model and a simulated method of moments procedure. Targeted moments include DI recipiency rates by age and frailty, and DI application success rates by the number of tries. The set of targeted moments also contains employment rates by age and frailty for both younger workers and workers over the age of 65. Targeting the variation in older workers' employment with frailty is key to distinguishing the effects of frailty operating through the disutility channel from those that operate through DI. While both channels impact the decision to work for individuals under 65, those aged 65 and older are not eligible for DI. Consequently, for these older individuals, the variation in employment with frailty must be driven by variation with frailty in their disutility from working.

The calibrated model generates a similar degree of lifetime earnings inequality as in the data. Since we do not have long earnings histories for respondents in our PSID sample, this is demonstrated by comparing earnings inequality in the model to that in a sample constructed using the National Longitudinal Survey of Youth 1979 (NLSY79). The calibrated model also reproduces several other non-targeted moments. For instance, approximately one-third of individuals are employed three years after initial DI benefit denial in the model. This rate is in line with estimates from the empirical literature. At 11 percent, the two-year transition rate from non-employment to DI beneficiary in the model replicates that in our PSID sample. The model also generates variation in this rate by frailty that is consistent with the data. Finally, the model replicates the empirical patterns of employment and DI recipiency by frailty and age within education groups.

Removing all heterogeneity in health by giving every agent in the baseline economy the average frailty profile lowers the variance of log lifetime earnings for each age group 35 and older. The difference peaks at age 55 when the decline is 28 percent, with the impacts on lifetime earnings inequality sizable at all ages after age 35. For instance, lifetime earnings inequality declines by 22 percent at age 45 and 26 percent at age 65. Inspection of the ratios of lifetime earnings at the 5th and 95th percentiles relative to the median reveals that the effects of frailty on earnings are heavily concentrated in the bottom of the earnings distribution.

To decompose the effect of health inequality into the various channels through which frailty operates in the model we conduct a series of counterfactual exercises. In each experiment we turn off the effect of frailty only in one channel. For example, in our first counterfactual exercise, we assume that the probability of DI award does not depend on an agent's individual frailty, but rather depends on the average frailty profile. We find that, at younger ages, the decline in lifetime earnings inequality when we remove health inequality is primarily due to the labor productivity channel. However, at older ages, it is primarily due to the impact of frailty on the probability of DI receipt. Thus, the DI channel the most important channel through which health inequality increases lifetime earnings inequality from age 55 onward. Relative to the labor productivity and DI channels, the other three channels have a relatively small impact. In particular, the effect of frailty on disutility of work does not seem to be an important determinant of how health affects labor supply and earnings inequality.

Despite decreasing aggregate output and consumption and increasing earnings inequality, we find that the DI program is welfare improving. The *ex ante* welfare loss from removing it is due to frail less educated workers who have low labor productivity and high disutility from work. Without the DI program, they choose between increased dependence on means-tested transfers or working more despite the high utility costs and relatively low returns. College graduates welfare increases because their tax contributions to the program primarily subsidize less educated individuals and the welfare costs of this redistribution outweigh the program's insurance value for them. Given these findings, we ask whether agents in our model would prefer a DI program that does not allow for redistribution across education groups. College graduates value such a program because it shifts the overall tax burden of insurance provision towards less educated individuals. However, for those without a college degree, welfare losses are even larger than when the DI program is removed completely. These individuals prefer having only the less generous means-tested transfer program since it is mostly financed by college graduates. These results indicate that the gains from the DI program come primarily from redistribution, and not insurance.

Our findings highlight the importance of the SSDI and SSI programs for the relationship between health and earnings inequality over the lifecycle. To show that our rich measure of health, frailty, plays a key role in obtaining these results, we recalibrate the model using SRHS collapsed (in two different ways) into a binary measure. We find that these calibrations understate the impact of health inequality on lifetime earnings inequality by 62 to 84 percent compared to the benchmark. SRHS is a coarser and less persistent measure of health than frailty. Moreover, unlike our frailty process, which features fixed heterogeneity and a highly persistent shock, our SRHS process follows a first-order Markov process, consistent with the most common way of capturing SRHS dynamics in previous literature. For both these reasons, many individuals experience the bad SRHS state during the working period, which reduces the correlation between poor health and DI recipiency relative to that in the benchmark, as well as the cumulative impacts of bad health on wages and earnings.

These findings shed light on previous results in the literature. French (2005) shows that a model of health and employment over the lifecycle which abstracts from DI is unable to replicate the relatively sharper decline in employment with age for individuals in bad health.[2] One solution is to assume that the time costs of bad health (or similarly the disutility costs of working when in bad health) increase with age as in Pashchenko and Porapakkarm (2013) Our findings illustrate that this issue can also be resolved by modeling the relationship between declines in health and DI application and entry.

It is common in the literature that builds structural models of DI (see Kitao (2014), Low and Pistaferri (2015) and Pashchenko and Porapakkarm (2017) for examples) to augment SRHS with an additional 'disabled' health state. This state is typically based on self-reported disability or work limitations and sometimes DI recipiency. While this approach addresses

[2]Difficulty replicating the differential rates of employment decline with health can also be observed in the calibrated model of Jung and Tran (2023).

SRHS's limitations in capturing the variation in DI recipiency rates, it relies on outcome-based measures prone to justification bias (Benítez-Silva et al., 2004). Our analysis shows that adding a separate disability state is unnecessary; a single health measure suffices if it measures health on a fine enough scale especially when health is relatively poor.

Our paper contributes to recent advances in the macro health literature aimed at better modeling health dynamics and their economic and welfare implications. De Nardi et al. (2023) enhance SRHS by incorporating history dependence and fixed heterogeneity. They use the improved measure to quantify the welfare cost of bad health in a dynamic life cycle model. Assuming current health transitions depend on health type and the previous sequence of health states allows them to capture severity and persistence of bad health on a finer scale. Our approach to measuring health using frailty also accounts for fixed heterogeneity. In addition, it captures the severity and persistence of bad health by allowing frailty to vary on a fine scale, especially at the right tail of the distribution. The main advantage of our approach is that, unlike SRHS, frailty is cardinal and can be treated as a continuous variable, which increases its flexibility and ease of adaptability to various problems and contexts. Another approach, by Capatina and Keane (2023), codes MEPS respondents' medical conditions, classifying them by predictability and duration with medical experts' guidance. They combine these classifications into a single continuous measure of health using factor analysis, to study the effects of health shocks and health insurance on human capital investment over the life cycle. While our frailty measure shares some similarities, it is simpler and less resource-intensive to construct.

The remainder of the paper is organized as follows. In Section 2 we document empirical facts on the relationship between health status and earnings. These facts are used to guide the development of the model we present in Section 3. The calibration of the model is outlined in Section 4. In Section 5 we assess the model's ability to replicate non-targeted moments. Section 6 reports the results of our quantitative exercises and Section 7 concludes.

2 Empirical Facts on Health and Earnings

We start by documenting some empirical facts on the relationship between *health status* and earnings that guide the development of our structural model. First, we introduce our measure of health: the *frailty index*. As people age, they accumulate various health issues, from mild (e.g., reduced vision) to serious (e.g., heart disease). As the number of conditions rises, the person's body becomes more frail and vulnerable to adverse outcomes. Each condition is termed a *deficit*. The frailty index is calculated as the ratio of accumulated deficits to the total number of deficits considered. Mitnitski et al. (2001, 2002) establish that a person's health can be quantified using the frailty index and we show in Hosseini et al. (2022) that it predicts health outcomes better than self-reported health.[3]

We use three datasets—PSID, HRS, and MEPS—to quantify the impact of health inequality on lifetime earnings inequality. To construct frailty indices, we use health deficit

[3]In Online Appendix Section 2.6.3, we demonstrate that the frailty index, while equally weighting health deficits, effectively captures the effects of both major and minor health events on earnings. This is due to the correlation between deficit severity and the number of deficits. Thus, while each deficit has the same weight, more severe events tend to increase frailty more, leading to greater impacts on earnings and employment.

variables from three broad categories: difficulties in Activities of Daily Living (ADLs) and Instrumental ADLs (IADLs); mental and cognitive impairments; and medical diagnosis. Examples include challenges with eating or dressing (ADLs), memory test scores (mental impairments), and diagnoses like high blood pressure or diabetes (medical conditions). A complete list of deficits used to construct the frailty index is available in the Online Appendix.

Our PSID sample includes household heads and spouses in waves 1999–2017, aged 25 to 94. We restrict the sample to ages 25 to 64 for the empirical analysis below. Information on medical conditions, ADLs, and IADLs were collected starting in wave 2003, so our frailty measure covers waves 2003–2017. The frailty index is constructed using 28 deficit variables, meaning each additional deficit raises the index by 1/28, or 3.6 percent. Summary statistics in Online Appendix Table 2 show that mean frailty rises with age and falls with education. The frailty distribution is right-skewed, indicating significant variation in health severity among the unhealthy. On average, 39 percent of the sample experiences wave-to-wave changes in frailty, with two-thirds of these being increases.

Frailty and earnings are negatively correlated at all ages in our PSID sample (Online Appendix Figure 1). This correlation is due to frailty's negative correlation with each component of earnings (employment, hours worked, and wages). The correlation with employment is the largest. Earnings includes income from wages, salaries, commissions, bonuses, overtime and self-employment. In each year, a person is employed if they worked at least 520 hours and earned at least \$4 an hour. Non-workers' earnings set to zero. Annual hours worked are calculated as weekly hours times weeks worked. Wages are constructed by PSID using annual labor earnings and hours worked. Additional summary statistics and sample selection details are in the Online Appendix.

2.1 The impact of health on earnings

Even though there is a strong correlation between frailty and all four measures of economic activity (earnings, employment, hours worked, and hourly wages) at all ages, these correlations may misrepresent the impact of health on earnings for three reasons. First, the correlations may be driven by composition effects. For example, higher-educated individuals tend to be healthier, with lower frailty, higher employment, and higher wages. Second, frailty may be endogenous to earnings. For instance, lower past earnings (or loss of employment) may negatively impact current frailty through its impact on mental health, access to insurance, or medical care choices. Lastly, frailty and earnings are highly persistent variables. Past earnings are correlated with current earnings but may also be correlated with both past and current frailty.

To address these challenges, we use a dynamic panel approach to estimate the effect of frailty on employment, hours worked, and wages.[4] We then use our estimates to quantify the overall effect of frailty on earnings and the relative contribution of each component.

[4]In earlier work, Smith (1999, 2004) addresses these challenges by estimating the impacts of serious health events (such as cancer and heart disease) on employment and earnings controlling for prior health. Our dynamic panel approach allows us to extend his work to a more general measure of health. We are not the first to use a dynamic panel estimator to study impacts of declines in health. Michaud and Van Soest (2008) find evidence, using this approach, that declines in health reduce wealth but there is no causal effect going from wealth to health.

Dynamic panel estimation. Consider the following statistical model

$$y_{i,t} = \alpha_1 y_{i,t-1} + \alpha_2 y_{i,t-2} + \gamma f_{i,t} + \delta \boldsymbol{Z}_{i,t} + b_i + \varepsilon_{i,t}, \tag{1}$$

in which $y_{i,t}$ is either a 0/1 indicator of employment at time t (equal to 1 if employed) or the logarithm of earnings, hours worked, or hourly wages for individual i at time t. The frailty of individual i at time t is denoted by $f_{i,t}$ and $\boldsymbol{Z}_{i,t}$ is a vector of exogenous controls that includes marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, year dummies, and a fourth-degree polynomial in age. b_i is an individual fixed effect and $\varepsilon_{i,t}$ is the error term which we assume satisfies $E[b_i] = E[\varepsilon_{i,t}] = E[b_i\varepsilon_{i,t}] = 0$ and $E[\varepsilon_{i,t}\varepsilon_{i,t'}] = 0$ for $t \neq t'$. Our goal is to estimate the parameter γ which measures the impact of frailty on the dependent variable.

Estimating equation (1) is complicated for the same reasons that the negative raw correlations between earnings and frailty may be misleading. First, individuals vary in unobservable ways (such as innate ability) which may be correlated with both their earnings and their frailty. The inclusion of the fixed effect, b_i, in equation (1) allows us to control for this type of heterogeneity assuming it is non-time-varying. However, it also implies that we cannot estimate this equation using simple OLS (see Wooldridge (2010)).

The second complication arises from the dynamic nature of the panel. Earnings, employment, hours, wages and frailty are highly persistent variables. Past earnings (or employment/hours/wages) is correlated with current earnings but may also be correlated with both past and current frailty. This concern is the motivation behind including lagged values of earnings in equation (1). But, the presence of these lagged values means that the standard within groups (fixed effect) estimator is also not an appropriate choice. To calculate the within groups estimator, equation (1) is first transformed by demeaning each individual's earnings and frailty using their average values over time. This process removes the individual fixed effect, b_i, but also creates a correlation between the resulting lagged regressors and error terms. This correlation means estimates of α_1 and α_2 will be biased and the bias may be large when, as is the case here, the number of time periods is small (see Nickell (1981) and Arellano and Honoré (2001) for details). Estimates of γ will also be biased due to the persistence and potential endogeneity of frailty.

To obtain a consistent and unbiased estimate of the effect of frailty on earnings we use a dynamic GMM panel estimator. This class of estimators was introduced by Holtz-Eakin et al. (1988) and Arellano and Bond (1991), and further developed by Blundell and Bond (1998) and others. We employ the System GMM estimator, which jointly estimates equations (1) and equation (1) in first differences using lagged first differences as 'internal' instruments for levels and lagged levels as 'internal' instruments for first differences. A detailed description of the dynamic panel estimation procedure can be found in Section 2 of the Online Appendix.

In the following tables, we report p-values from two sets of test statistics. First, we test for first and second-order serial correlation in the residuals of the difference equation. In dynamic panel estimation, we expect first-order but not second-order serial correlation. Tables (1) and (2) show that in all specifications the null hypothesis of no second-order serial correlation cannot be rejected. Second, we report instrument validity tests, including the Hansen J-statistic, which follows a χ^2 distribution under the null hypothesis of no correlation between the error terms and the instruments. We also report the Difference Hansen-Sargan test statistic to check if our lagged first-difference instruments are uncorrelated with the fixed effects. With a few exceptions in Panel C of Table 2 (the effect on hourly wage), we cannot reject the null hypotheses of no second-order correlation and instrument validity at conventional significance levels.

The Hansen-Sargan and Difference Hansen-Sargan tests assess instrument validity but not their power. To assess power, we follow Wintoki et al. (2012) and examine F-statistics from OLS regressions of the endogenous variables on their appropriate instrument sets. Results reported in Online Appendix Tables 16 and 17 show that lagged differences of frailty, employment and log earnings are strong instruments for current levels, while lagged levels of employment are sufficient for current differences. However, lagged levels of frailty and log earnings are weak instruments for differences, likely due to their high persistence. This is why we use the system GMM estimator instead of relying solely on the difference equation.

Our approach performs well in various additional tests and robustness checks reported in the Online Appendix. There, we compare our dynamic panel GMM estimates with those from OLS, fixed effects, and a logit estimator for employment. We also assess the robustness of our results to different instruments and present Difference Hansen-Sargan test results separately for the lagged left-hand-side variables and frailty in the levels equation. Finally, to further support the use of lagged changes in frailty as instruments, we visually show that changes in frailty are independent of various measures of permanent income.[5]

Impact of frailty on employment. To estimate the impact of frailty on employment, we use equation (1) with an employment indicator as the left-hand-side variable $y_{i,t}$.[6] Results are shown in Table 1, where all effects of frailty are reported as the impact of accumulating one additional deficit. With 28 potential deficits in our PSID sample, each additional deficit increases the frailty index by 1/28, so the numbers reported in Table 1 represent $\frac{\gamma}{28}$ (and standard errors are scaled accordingly).

Table 1 shows that incurring one additional health deficit significantly reduces employment, particularly for less-educated workers, older individuals, and those in poor health. The first column indicates that one additional deficit reduces the probability of employment by an average of 1.6 percentage points. For high school dropouts, the reduction is 2.5 percentage points, while for college graduates, it is only 0.8 percentage points (insignificant).

The third column shows that for individuals in 'Poor Health' (frailty above the 85th percentile), one additional deficit lowers employment probability by 1.8 percentage points. The effect for those in 'Good Health' (frailty below the 85th percentile) is similar, but not significant. Yet, the relatively large standard error on this estimate suggests that there may be a significant and sizable effect of incurring additional deficits even when in good health for some individuals. Finally, the fourth column shows that for those over 45, one additional deficit decreases the probability of employment by 1.9 percentage points. For younger individuals the effect is smaller and less significant.

[5] We thank an anonymous referee for suggesting this robustness check.

[6] While a nonlinear probability model would be ideal, estimating nonlinear dynamic panels with unobserved fixed effects is complex (see Arellano and Honoré (2001)). Therefore, we follow Carrasco (2001) and Arellano and Honoré (2001) and use a linear probability model. Marginal effects from a logit model without fixed effects, reported in the Online Appendix, closely match the results here.

Table 1: Effect of frailty on employment

	(1)	(2)	(3)	(4)
frailty_t	-0.016**			
	(0.006)			
$\text{frailty}_t \times$ HSD		-0.025***		
		(0.007)		
$\text{frailty}_t \times$ HS		-0.020***		
		(0.007)		
$\text{frailty}_t \times$ CL		-0.008		
		(0.005)		
$\text{frailty}_t \times$ Good Health			-0.015	
			(0.011)	
$\text{frailty}_t \times$ Poor Health			-0.018***	
			(0.005)	
$\text{frailty}_t \times$ Young				-0.014*
				(0.007)
$\text{frailty}_t \times$ Old				-0.019***
				(0.006)
employed_{t-1}	0.520	0.327	0.255	0.451
	(0.403)	(0.447)	(0.363)	(0.380)
employed_{t-2}	0.172	0.314	0.382	0.224
	(0.317)	(0.352)	(0.284)	(0.299)
Controls	YES	YES	YES	YES
Observations	66,576	66,576	66,576	66,576
AR(1) test (p-value)	0.289	0.478	0.441	0.311
AR(2) test (p-value)	0.890	0.598	0.379	0.751
Hansen-Sargan test (p-value)	0.201	0.158	0.148	0.332
Diff. Hansen-Sargan test (p-value)	0.125	0.087	0.074	0.163

Note: Frailty effects are the effect of incurring one additional deficit. Controls are marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, year dummies, and a fourth degree polynomial in age. 'HSD' is high school dropout, 'HS' is high school graduate, and 'CL' is college graduate. 'Good/Poor Health' is frailty below/above the 85th percentile. 'Young/Old' are individuals younger/older than 45 years of age. Standard errors are in parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Impact of frailty on earnings of workers. We now present the results from our dynamic panel estimation on a subsample of workers. Panel A in Table 2 reports estimation results with log earnings of workers as the dependent variable $y_{i,t}$ in equation (1). Panels B and C report results for log hours worked and log hourly wages.

The first row in Table 2 shows that frailty significantly affects earnings and hourly wages but has no impact on hours worked. Adding one additional deficit reduces earnings by about 3 percent and hourly wages by about 2 percent, while the effect on hours worked is small, positive, and not statistically significant. The second, third, and fourth rows illustrate how frailty's effects differ by education. In Panel A, frailty significantly impacts earnings for high school dropouts and graduates, with reductions of 6.3 percent and 3.8 percent, respectively, while the effect for college graduates is only 1.5 percent and not significant. Panel C shows similar effects on hourly wages, while Panel B indicates insignificant effects on hours worked.

The fifth and sixth rows present results by health status. In Panel A, frailty significantly affects earnings for individuals with bad health (frailty above the 85th percentile). Among these individuals, one more deficit leads to a 2.6 percent drop in earnings. For those in good health (frailty below the 85th percentile), the effect is also large but is imprecisely

Table 2: Effect of frailty on earnings, hours and wages of workers

	Panel A. Earnings regression				**Panel B.** Hours regression				**Panel C.** Wage regression			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
frailty$_t$	-0.029**				0.005				-0.020**			
	(0.014)				(0.009)				(0.009)			
frailty$_t$ × HSD		-0.063**				-0.020*				-0.065***		
		(0.028)				(0.012)				(0.021)		
frailty$_t$ × HS		-0.038***				0.001				-0.029***		
		(0.015)				(0.010)				(0.010)		
frailty$_t$ × CL		-0.015				0.011				-0.005		
		(0.016)				(0.009)				(0.010)		
frailty$_t$ × Good Health			-0.032				0.013				-0.009	
			(0.033)				(0.017)				(0.023)	
frailty$_t$ × Poor Health			-0.027**				0.000				-0.021**	
			(0.012)				(0.008)				(0.008)	
frailty$_t$ × Young				-0.035				0.014				-0.015
				(0.026)				(0.016)				(0.020)
frailty$_t$ × Old				-0.016				-0.003				-0.022*
				(0.013)				(0.009)				(0.012)
log(earnings$_{t-1}$)	1.259***	1.197***	1.215***	1.050***								
	(0.455)	(0.358)	(0.400)	(0.307)								
log(earnings$_{t-2}$)	-0.427	-0.394	-0.392	-0.250								
	(0.411)	(0.323)	(0.362)	(0.282)								
log(hours$_{t-1}$)					-0.086	0.013	0.097	0.181				
					(0.366)	(0.326)	(0.361)	(0.342)				
log(hours$_{t-2}$)					0.336	0.191	0.248	0.244				
					(0.229)	(0.227)	(0.215)	(0.239)				
log(wage$_{t-1}$)									0.205	0.160	0.381	0.399
									(0.505)	(0.344)	(0.411)	(0.390)
log(wage$_{t-2}$)									0.543	0.570*	0.380	0.365
									(0.454)	(0.307)	(0.368)	(0.351)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	34,505	34,505	34,505	34,505	34,505	34,505	34,505	34,505	34,401	34,401	34,401	34,401
AR(1) test (p-value)	0.048	0.016	0.030	0.016	0.495	0.354	0.353	0.300	0.629	0.486	0.463	0.429
AR(2) test (p-value)	0.230	0.154	0.202	0.243	0.218	0.489	0.429	0.531	0.408	0.190	0.543	0.549
Hansen-Sargan test (p-value)	0.396	0.770	0.604	0.358	0.206	0.375	0.325	0.163	0.079	0.292	0.140	0.106
Diff. Hansen-Sargan test (p-value)	0.227	0.411	0.366	0.140	0.404	0.333	0.380	0.391	0.046	0.160	0.156	0.257

Note: Frailty effects are the effect of incurring one additional deficit. Controls are marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, year dummies, and a fourth degree polynomial in age. 'HSD' is high school dropout, 'HS' is high school graduate, and 'CL' is college graduate. 'Good/Poor Health' is frailty below/above the 85th percentile. 'Young/Old' are individuals younger/older than 45 years of age. Standard errors are in parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

estimated and statistically insignificant. Like with employment, this result suggests that, for some individuals in relatively good health, incurring an additional deficit leads to a significant reduction in earnings. Panel C shows similar effects on hourly wages, while Panel B indicates no significant effects on hours worked.

Finally, the seventh and eight rows show the effects by age groups. Surprisingly, frailtyâs effects on earnings are smaller for those over 45 than for younger individuals (column (4) in Panel A), though both estimates are imprecise and not significant. Panel C shows a significant 2.2 percent drop in hourly wages of older workers, but this effect is also imprecisely estimated. No significant effects on hours worked are observed.

The results in Table 2 tell us that increases in frailty reduce earnings and wages of workers and that the effects are concentrated in low-educated workers and those with bad health. At the same time, there is no evidence of effects of frailty on hours worked for workers.

Overall impact of frailty on earnings. We now combine our empirical results to estimate the overall effect of frailty on earnings and assess each margin's contribution. Since there is no significant effect of frailty on hours worked, the impact on earnings must come from two sources: the probability of employment and hourly wages.

Let $p(f)$, $w(f)$ and $h(f)$ denote the probability of employment, hourly wages, and hours as a function of frailty, respectively. Then the marginal effect of one additional deficit on the logarithm of expected earnings is

$$\frac{d\log\left(p\left(f\right)\cdot w\left(f\right)\cdot h(f)\right)}{df} = \frac{1}{p}\times \overbrace{\frac{dp(f)}{df}}^{\substack{\text{marginal effect on}\\ \text{prob. employed}}} + \underbrace{\frac{d\log\left(w\left(f\right)\right)}{df}}_{\substack{\text{marginal effect}\\ \text{on log wages}}} + \underbrace{\frac{d\log\left(h\left(f\right)\right)}{df}}_{\substack{\text{marginal effect}\\ \text{on log hours}}}. \tag{2}$$

The first term in equation (2) is the contribution of changes in the probability of employment to changes in expected log earnings. This is equal to the marginal effect of frailty on the probability of being employed divided by the average employment rate. The second term is the contribution of changes in log hourly wages to changes in expected log earnings. Finally, the last term is the contribution of changes in log hours worked to changes in expected log earnings. Since we did not find any significant effects of frailty on hours worked for workers (Panel B in Table 2) we set this term to zero.

The first column in Table 3 reports percent changes in the probability of employment. These are calculated as the marginal effects we estimated and reported in Table 1 divided by average employment rates by education groups, health groups, and age groups which are reported in Online Appendix Table 5. The second column reports the percent changes in hourly wages of workers due to one additional deficit taken from Panel C of Table 2. The third column provides the overall effect which is the sum of the employment and hourly wage effects and the last column shows the contribution of the employment margin (the first term in equation (2)) to the total effect.

Table 3 shows that one additional deficit reduces average earnings by 3.9 percent, with about half of this reduction coming from reduced employment and half from lower wages for those still employed. While the overall effect decreases with education, the employment

Table 3: Overall effect of frailty on average earnings

	Changes in average earnings due to one additional deficit			
	Employment (%)	Workers' hourly wages (%)	Total (%)	Share due to employment (%)
frailty_t	-1.89**	-1.99**	-3.87***	49
	(0.87)	(0.89)	(1.27)	
$\text{frailty}_t \times$ HSD	-3.65***	-6.53***	-10.18***	36
	(1.05)	(2.06)	(2.32)	
$\text{frailty}_t \times$ HS	-2.48***	-2.88***	-5.36***	46
	(0.84)	(1.03)	(1.36)	
$\text{frailty}_t \times$ CL	-0.90	-0.52	-1.42	64
	(0.62)	(1.02)	(1.21)	
$\text{frailty}_t \times$ Good Health	-1.76	-0.92	-2.68	66
	(1.41)	(2.28)	(2.94)	
$\text{frailty}_t \times$ Poor Health	-3.38***	-2.06**	-5.44***	62
	(1.12)	(0.85)	(1.50)	
$\text{frailty}_t \times$ Young	-1.62*	-1.54	-3.16	51
	(0.87)	(1.96)	(2.27)	
$\text{frailty}_t \times$ Old	-2.39***	-2.19*	-4.59***	52
	(0.82)	(1.18)	(1.39)	

Note: 'HSD' is high school dropout, 'HS' is high school graduate, and 'CL' is college graduate. 'Good/Poor Health' is frailty below/above the 85th percentile. 'Young/Old' are individuals younger/older than 45 years of age. Bootstrapped standard errors clustered at the individual level with 1,000 replications are in parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

margin's relative importance increases. For high school dropouts, the earnings reduction is 10.2 percent, but only about a third is due to reduced employment. For high school graduates, the effects are split roughly evenly between employment and wage declines. For college graduates, the impacts are small and not statistically significant, with declines in employment being the main driver of reduced earnings.

Finally, Table 3 shows that the impact of health declines on earnings is greater for older individuals and those in poor health. For individuals in poor health, one additional deficit reduces earnings by 5.4 percent, with 62 percent of this effect attributed to the employment margin. In contrast, for those in good health, an additional deficit reduces earnings by 2.7 percent and the effect is not statistically significant. For older individuals, an additional deficit decreases earnings by 4.6 percent, with just over half of the effect due to reduced employment probability, while the effect on younger individuals is again not statistically significant.

To summarize, these finding indicate that health deterioration has a significant impact on earnings especially among less educated individuals, those already in poor health, and older individuals. The effect is driven by a combination of declines in the probability of employment and declines in wages with both margins playing an important role.

2.2 The impact of earnings on health

The empirical analysis above focuses on the effect of frailty on earnings, hours worked, and hourly wages. However, it is also possible that earnings affects frailty. To examine this possibility we estimate the following regression:

$$f_{i,t} = \alpha_1 f_{i,t-1} + \alpha_2 f_{i,t-2} + \gamma y_{i,t} + \beta \boldsymbol{Z}_{i,t} + (b_i + \varepsilon_{i,t}), \tag{3}$$

Table 4: Effect of employment and earnings on frailty

	Panel A. Everyone (x_t = employed$_t$)				**Panel B.** Workers (x_t = log(earnings$_t$))			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
x_t	1.018				-0.001			
	(0.786)				(0.130)			
x_t × HSD		0.626				-0.049		
		(0.806)				(0.168)		
x_t × HS		0.143				-0.058		
		(0.831)				(0.152)		
x_t × CL		1.087				-0.050		
		(0.965)				(0.140)		
x_t × Good Health			-0.388				-0.039	
			(1.012)				(0.098)	
x_t × Poor Health			0.457				0.035	
			(0.796)				(0.108)	
x_t × Young				0.246				-0.031
				(0.490)				(0.126)
x_t × Old				-0.386				-0.072
				(0.473)				(0.126)
frailty$_{t-1}$	0.674	0.353	0.182	0.156	1.134**	0.944***	0.717**	1.194***
	(0.447)	(0.366)	(0.331)	(0.365)	(0.470)	(0.337)	(0.334)	(0.428)
frailty$_{t-2}$	0.355	0.653*	0.745****	0.809**	-0.156	0.024	0.164	-0.217
	(0.418)	(0.341)	(0.267)	(0.356)	(0.451)	(0.327)	(0.322)	(0.413)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	51,775	51,775	51,775	51,775	27,636	27,636	27,636	27,636
AR(1) test (p-value)	0.360	0.486	0.508	0.562	0.124	0.085	0.189	0.071
AR(2) test (p-value)	0.637	0.163	0.137	0.076	0.537	0.754	0.898	0.416
Hansen-Sargan test (p-value)	0.475	0.728	0.514	0.065	0.182	0.370	0.259	0.279
Diff. Hansen-Sargan test (p-value)	0.572	0.697	0.618	0.063	0.181	0.539	0.128	0.306

Note: Frailty effects are the effect of incurring one additional deficit. Panel A shows regression results for the entire sample. Panel B shows results conditional on continued employment. Controls are marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, year dummies, and a fourth degree polynomial in age. 'HSD' is high school dropout, 'HS' is high school graduate, and 'CL' is college graduate. 'Good/Poor Health' is frailty below/above the 85th percentile. 'Young/Old' are individuals younger/older than 45 years of age. Standard errors are in parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

using the same System GMM estimator. Note that this is simply the reverse of equation (1). Here, $f_{i,t}$ is the level of frailty of individual i at date t and $y_{i,t}$ is their date-t log earnings (for workers) or an employment indicator. The set of controls $\boldsymbol{Z}_{i,t}$ is the same as those in Section 2.1.

We conduct two sets of estimations. In the first set, we estimate the effect of employment on frailty for the full sample of individuals. These results are reported in Panel A of Table 4. In the second set, we estimate the effect of log earnings on frailty for the worker subsample. These results are reported in Panel B. To ease comparison with Tables 1 and 2, the results are reported as the impact of employment and earnings on the total number of deficits an individual has at date t. In other words, the estimated effects in Table 4 are in fact $\gamma \times 28$.

Table 4 shows no significant effects of employment or earnings on frailty.[7] All effects

[7] Although summing the coefficients on the first and second frailty lags indicate that frailty is highly persistent, their significance is limited due to high correlation between lags, which reduces estimation precision. Small F-statistics from regressing first differences of frailty on lagged levels further indicate this persistence (see Online Appendix Tables 16 and 17).

remain small and insignificant at conventional levels, and diagnostic tests fail to reject that there is no second-order serial correlation in error terms. Additionally, the Hansen-Sargan tests do not reject the null hypothesis of valid instruments.

It is important to note that these findings do not imply that better access to healthcare does not improve health outcomes. In fact there is evidence to the contrary. See for example Gruber and Sommers (2019), Miller et al. (2021), Ghosh et al. (2019), and Eguia et al. (2018) who find that states that expanded Medicaid under the Affordable Care Act saw an improvement in mortality, better treatment of chronic conditions, earlier detection and treatment of cancers, and increases in the use of preventative care. It is also important to note that the fact that we do not find shorter-term effects of earnings or employment on health does not rule out the possibility that effects may occur over longer horizons.

2.3 Implications of empirical findings

Our empirical analysis yields the following five findings. One, declines in health reduce employment and the effect is concentrated in lower-educated individuals, those already in poor health, and older individuals. Two, declines in health reduce hourly wages and earnings of workers, and these effects are also larger for the lower-educated and those in poor health. Three, there is no effect of declines in health on hours worked of workers. Four, there is no reverse effect of changes in earnings or employment on health. Five, declines in health lead to a sizable loss in expected earnings with about half of the decline due to loss of employment and half due to declines in wages.

For simplicity, we focus on men in the quantitative analysis that follows.[8] The left panel of Figure 1 shows employment rates by age and age-specific frailty percentile groups for men in our PSID sample. Consistent with the results of our dynamic panel estimations, the figure shows that most of the variation in men's employment with frailty is concentrated in the poor health tail of the distribution. Employment shows little variation for frailty below the 70th percentile, but men in the top 5 percent of frailty have significantly lower employment rates than those in the 90 to 95th percentiles, who in turn have lower rates than those in the 70 to 90th percentiles. The overall dispersion in employment rates with frailty is most pronounced for men in their fifties. In particular, only 20 percent of men aged 55–59 in the top 5 percent of frailty are employed, compared to over 90 percent of those in the 0 to 70th percentiles.

The fact that roughly half of the impact of frailty on earnings works through the employment margin suggests that the SSDI and SSI programs may be an important driver of the relationship between health and earnings inequality. DI application and recipiency generates strong work disincentives for frail individuals. Those who apply for SSDI must be non-employed or have earnings below the substantial gainful activity (SGA) threshold for at least 5 months before benefit receipt can occur.[9] Once on SSDI, recipients risk losing benefits if their earnings exceed the SGA threshold. Similarly, SSI beneficiaries must not only meet disability requirements, but also have limited income and assets. As a result, most

[8]Our main empirical findings are similar for subsamples of men only and women only (see Online Appendix Section 2.6.1).

[9]For example, in 2019 the SGA threshold was $1,220 per month.

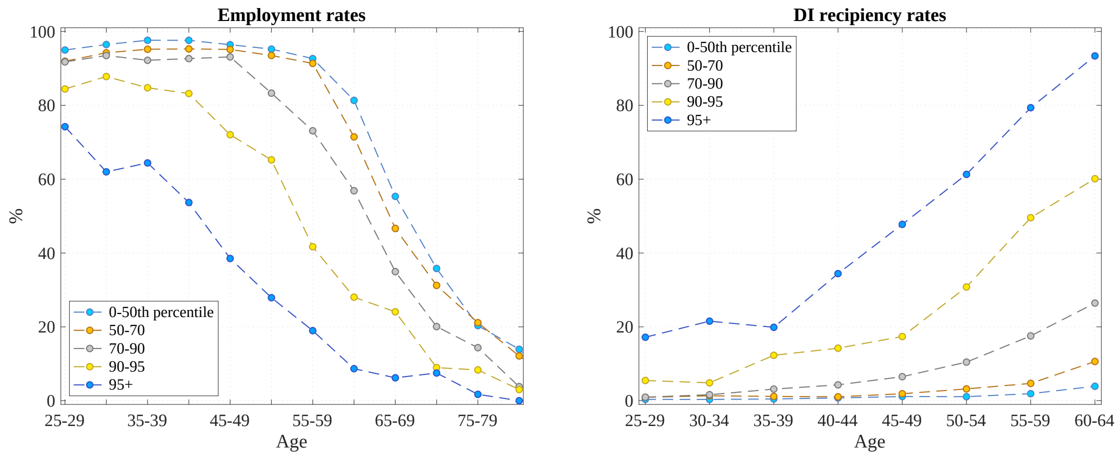

Figure 1: Employment rates (left) and DI recipiency rates (right) by age-specific frailty percentiles groups and age for men. Source: Authors' calculations using PSID data (left) and MEPS and Social Security Administration data (right).

DI beneficiaries do not work.[10]

The right panel of Figure 1 shows the fraction of 25- to 64-year-old men who are on SSDI or SSI by age and the same frailty percentile groups as in Figure 1.[11] The pattern of DI recipiency by frailty and age is very similar to that by employment. There is little variation until frailty is above the 70th percentile of the distribution and then the variation is substantial. Eighty percent of 55- to 59-year-olds in the top 5 percent of the frailty distribution are on DI while the fraction is nearly zero for those with frailty below the 70th percentile.

The SSDI and SSI programs are not the only mechanism through which health may impact earnings. Our empirical findings indicate that increases in health inequality can also lead to increases in productivity or wage inequality. Moreover, while poor health can impact labor supply through its impact on SSDI, SSI or other means-tested transfer program eligibility, it can also impact labor supply purely through an impact on preference for leisure. Finally, health inequality contributes to inequality in mortality and out-of-pocket medical expenditures. To quantify the impact of each of these mechanisms on lifetime earnings inequality we need a structural model.

3 The Model

Building off the findings in Section 2, we build a structural model that features individuals with risky and heterogeneous frailty profiles. Given that we did not find any statistically significant effects of frailty on hours conditional on working, we focus the model on the participation margin: individuals chose to participate in the labor market or exit and apply for disability insurance. We allow for poor health to impact individuals' labor productivity

[10] Maestas et al. (2013) document that, in 2008, 4.3% of beneficiaries who started receiving benefits in 2005 were working and earning more than the SGA threshold.

[11] The figure is constructed using MEPS data. See Online Appendix Section 4.

and for this effect to be stronger for those with low education. Frailty profiles are exogenous in the model, since we did not find a statistically significant feedback effect from earnings to health.

3.1 Demographics

Time is discrete and one period is one year. The economy is populated by a continuum of individuals in J overlapping generations. The population grows at rate ν. Each period an age $j = 1$ cohort is born and lives up to the maximum age $j = J$. Individuals' health status is summarized by their frailty index, f, which evolves stochastically as we describe below. Frailty affects labor productivity, disutility from working, out-of-pocket medical expenditures and mortality risk. It also affects the chance of becoming a DI beneficiary. At each age j, the probability of surviving one more year depends on frailty, f, and education level, s, and is denoted by $p(j, f, s)$. Individuals are *ex ante* heterogeneous with respect to their education level, and they face a labor productivity process that is uncertain due to its dependence on both their frailty and direct labor productivity shocks.

We follow Braun et al. (2017) and adopt the following timing regarding the realization of mortality shocks. Every period, before individuals make consumption and asset allocation decisions, they learn whether this is their last period of life or they will survive another period. With this assumption there are no accidental bequests in the model. Instead, individuals consume all their resources once they learn that they are in the final period of life.[12]

3.2 Endowments and assets

Before retirement each individual is either employed, non-employed or enrolled in DI. An employed individual works a fixed (exogenously given) fraction of time and earns wage $w \cdot \eta(j, f, s, \epsilon)$ which is the product of two terms. The first term is the wage per efficiency unit of labor services, w. The second term is the efficiency unit of labor services per hour worked, $\eta(j, f, s, \epsilon)$. This term depends on the worker's age j, frailty f, education s, and a stochastic component ϵ. The stochastic component, ϵ, consists of both a fixed effect and a persistent shock.[13] It evolves according to transition probability $\pi^e(\epsilon'|j, \epsilon, s)$, which depends on age j and education s. Employed workers may choose to quit and become non-employed. They can also become exogenously separated from their job with probability $\sigma(s)$, which depends on their education level, s. Exogenously separated workers can go back to work immediately by paying fraction χ of their hourly wage as a penalty. This penalty captures the cost of job

[12] There is ample evidence that bequests and inheritances are low at the end of life, especially for low income individuals who are the focus of this analysis. For example, using HRS data, Poterba et al. (2011) find that 46.1% of individuals have less than \$10,000 in financial assets in the last year observed before death and 50% have zero home equity. Also, Hendricks (2001) finds that most households in the Survey of Consumer Finances receive very small or no inheritances. Fewer than 10% of households receive an inheritance larger than twice average annual earnings and the top 2% account for 70% of all inheritances.

[13] We do not include a transitory shock directly in the productivity process. However, the fact that individuals in the model face a positive probability of an exogenous job separation means that there is a transitory component to earnings risk.

search as well as the lost earnings during unemployment.[14]

A non-employed individual can choose to apply for DI, go back to work or remain non-employed. If he applies for DI, he is awarded benefits with probability $\theta\left(j, f, n_a\right)$ in the next period.[15] Here, n_a indicates the number of consecutive previous applications. Individuals who are awarded DI benefits remain on DI until age $R < J$. After that they transition to receiving social security retirement benefits. If DI application is unsuccessful, the individual can choose to remain in non-employment, reapply or go back to work. Those who choose to go back to work find a job with probability $\varphi < 1$. This probability captures the low job finding rate in the data for those who have been out of the labor force for more than one year. Upon finding employment, these workers also incur a temporary reduction in their wage by fraction χ.

Those who are older than retirement age R receive social security retirement benefits but can choose to work or retire. Once an individual chooses to retire he remains retired until death. Both social security retirement and disability benefits (including SSI payments), are given by $SS(\bar{e})$, which is a function of the beneficiary's earning history, $\bar{e}$.[16]

Finally, everyone has access to a risk-free asset a that pays return r. There are no other financial assets in the economy.

3.3 Frailty and medical expenditures

An individual's frailty is given by $f \equiv \psi(j, s, \epsilon_f)$. It depends on his age, j, education level, s, and a stochastic component, ϵ_f. The stochastic component consists of a fixed effect, a persistent shock, and a transitory shock. It evolves according to transition probability $\pi^f\left(\epsilon_f' | j, \epsilon_f, s\right)$, which depends on age j and education s.

Out-of-pocket medical expenditures are a deterministic function of age, education, frailty, and employment status. An individual of age j and education s who has frailty f incurs out-of-pocket medical expenditures $m^i\left(j, f, s\right)$ where $i = E, N, D, R$ depending on whether he is employed (E), non-employed (N), a DI beneficiary (D) or retired (R).[17]

3.4 Government

The government runs a social security retirement and disability program which provides benefit $SS\left(\bar{e}\right)$ to individuals who are older than age R, as well as individuals under age R who successfully enroll in DI. These benefits depend on individuals past earnings and include both social security (retirement and/or disability) benefits and SSI. The government also runs a means-tested transfer program that guarantees individuals a minimum level of consumption, $\underline{c}$. Transfers, $Tr\left(a, y\right)$, depend on individuals assets, a, and after-tax income net of medical

[14]We only include the monetary/income costs of short-term joblessness and abstract from the details of unemployment and job search because the average duration of unemployment in the US during the non-recession-period 2000 to 2007 was 18 weeks which is shorter than a period in our model.

[15]Dependence on age allows us to capture the fact that the criteria for DI acceptance becomes less stringent at age 55 resulting in a jump in the acceptance rate. See footnote 30.

[16]The U.S. Social Security administration uses the same benefit formula to calculate both retirement and disability benefits. The SSI benefit formula also does not depend on retirement status.

[17]All workers who are older than age R are Medicare beneficiaries and face the same process for out-of-pocket medical expenditures as retirees.

expenditures and job search costs, y. The transfer is zero if $a + y \geq \underline{c}$. Otherwise, it is just enough to provide consumption level $\underline{c}$. The government also has exogenous expenditures G. It raises revenue by levying a nonlinear tax on labor income, $T(w\eta)$, and a proportional tax on capital income, τ_K (paid by the firm). Taxes $T(w\eta)$ consist of income taxes, a proportional and capped social security tax, and a Medicare earnings tax.

3.5 Individual decision problems

To economize on notation we denote a subset of the state space as $x \equiv (j, a, f, s, \epsilon, \bar{e})$. We use x as the argument of functions with the understanding that not all functions depend on all elements of x. Let $V^E(x, i_s)$ be the value function of an employed individual, $V^N(x, n_a)$ be the value function of a non-employed individual, $V^D(x, n_d)$ be the value function of a DI beneficiary, and $V^R(x)$ be the value function of a retiree. The variable i_s is an indicator that an employed worker is returning from an exogenous separation or non-employment spell. Variable n_a tracks the number of consecutive periods a non-employed individual has applied for DI. Recall that non-employed individuals can choose to apply for DI. Motivated by evidence provided in French and Song (2014) we allow the likelihood of successful DI application to depend on the number of previous consecutive attempts. Variable n_d represents the number of periods an individual has been on DI. We use this variable to determine Medicare eligibility for DI beneficiaries.[18] Period utility, $u(c, l, f)$, depends on consumption c, employment status $l \in \{0, 1\}$ where 1 denotes working and 0 denotes not working, and frailty f. Individuals discount the future at rate β. We now describe the problems facing each type of individual.

As we mentioned earlier, at the beginning of each period before any decisions have been made, with probability $p(x)$ an individual learns that he will die at the end of the period. Individuals who learn that the current period is the terminal period consume all their resources. We denote this terminal consumption by c_{T} and set it equal to the sum of resources (right side of the respective budget constraints) net of out-of-pocket medical expenditures. In the interest of brevity we do not write this equation explicitly in what follows.

The employed worker's problem: employed workers face the risk of exogenously separating from their employer with probability $\sigma(x)$ at the beginning of the next period. If separated, they can choose to go back to work immediately or go to non-employment. If they survive the separation shock, they can choose to quit the job voluntarily. After reaching age R, employed workers choose between working and retirement which, unlike non-employment, is a permanent exit from the labor force. However, they are eligible to claim social security retirement benefits regardless of whether they work or not.[19] They are also eligible for

[18]SSDI beneficiaries are eligible for Medicare after two years. For those on SSI only, eligibility depends on the nature of their disability.

[19]We make this assumption for simplicity. Aside from the tax implications, which Jones and Li (2018) find to have a relatively small effect on the labor supply of older workers, there is no cost of working past full retirement age while also claiming benefits.

Medicare, which affects their out-of-pocket medical expenditures. Let

$$W^E(x,i_s) \equiv \begin{cases} \max\left\{V^E(x,i_s), V^N(x,0)\right\}, & \text{if } j < R, \\ \max\left\{V^E(x,i_s), V^R(x)\right\}, & \text{if } j \geq R, \end{cases}$$

be the value function of an employed worker after the separation shock is realized. The employed worker faces the following maximization problem

$$\begin{aligned} V^E(x,i_s) = \max_{c,a' \geq 0} & (1-p(x))\, u(c_{\mathrm{T}},1,f) + \\ & p(x)\left(u(c,1,f) + \beta\left\{\sigma(x) E\left[W^E(x',1)\right] + (1-\sigma(x)) E\left[W^E(x',0)\right]\right\}\right), \end{aligned}$$

subject to

$$\frac{a'}{1+r} + c = \begin{cases} a + (1-i_s\chi)\, w\eta(x) - T(w\eta(x)) + Tr^E(x,i_s) - m^E(x), & \text{if } j < R, \\ a + SS(\bar{e}) + (1-i_s\chi)\, w\eta(x) - T(w\eta(x)) + Tr^{OE}(x,i_s) - m^R(x), & \text{if } j \geq R, \end{cases}$$

where

$$\bar{e}' = \begin{cases} [(j-1)\,\bar{e} + w\eta(x)]/j, & \text{if } j < R, \\ \bar{e}, & \text{if } j \geq R, \end{cases}$$

and $Tr^E(x,i_s) \equiv \max\left\{0, \underline{c} + m^E(x) + T(w\eta(x)) - (1-i_s\chi)\, w\eta(x) - a\right\}$ are means-tested transfers before age R while $Tr^{OE}(x,i_s) \equiv \max\left\{0, \underline{c} + m^R(x) + T(w\eta(x)) - (1-i_s\chi)\, w\eta(x) - a - S(\bar{e})\right\}$ are means-tested transfer after age R. As explained above, when workers return from a separation ($i_s = 1$), they pay fraction χ of their wages as penalty.

The non-employed worker's problem: non-employed individuals choose whether to apply for DI or not. This decision is denoted by $i_D \in \{0,1\}$. If they apply, they qualify for benefits with probability $\theta(x)$. Variable n_a tracks the cumulative number of times that a worker has consecutively applied during the current non-employment spell. First-time applicants ($n_a = 0$) pay a non-pecuniary cost of application ξ. If awarded DI, they start receiving benefits in the following period and remain on DI until they reach retirement age R.[20] At that time, they start receiving social security retirement benefits.

If they do not apply for DI or apply but their application is not successful, they can go back to work or remain non-employed. If they choose to go back to work, they find employment with probability φ and, once employed, pay χ of their wages as penalty. When

[20] We do not model exits from DI due to reasons other than transition to old-age social security or death because they are rare. According to the Social Security Administration, in 2018, the fraction who exited SSDI due to the next two most common reasons were 0.6 percent (who exited because they earned more than the maximum allowed level) and 0.5 percent (who exited because they were deemed medically able to work during a medical review). The annual exit rate from SSDI/SSI for reasons other than retirement or death for men in our PSID sample is higher but still small (5%).

$j < R-1$, the non-employed individual's problem can be specified as follows

$$V^N(x, n_a) = \max_{c,a' \geq 0, i_D} (1 - p(x)) u(c_\mathrm{T}, 0, f) +$$
$$p(x) \left(u(c, 0, f) - i_D \mathbf{1}_{n_a=0} \xi + \beta \left\{ \begin{array}{l} i_D \theta(x) E\left[V^D(x', 0)\right] + \\ i_D (1 - \theta(x)) \varphi E\left[\max\left\{V^E(x', 1), V^N(x', n_a + i_D)\right\}\right] + \\ i_D (1 - \theta(x))(1 - \varphi) E\left[V^N(x', n_a + i_D)\right] + \\ (1 - i_D) \varphi E\left[\max\left\{V^E(x', 1), V^N(x', 0)\right\}\right] + \\ (1 - i_D)(1 - \varphi) E\left[V^N(x', 0)\right] \end{array} \right\} \right),$$

subject to

$$\frac{a'}{1+r} + c + m^N(x) = a + Tr^N(x), \tag{4}$$

where $Tr^N(x) \equiv \max\left\{0, \underline{c} + m^N(x) - a\right\}$ and $\bar{e}' = [(j-1)\bar{e}]/j$.

When $j = R-1$, non-employed individuals cannot apply for DI anymore as they will reach the retirement age next period. The problem facing them becomes

$$V^N(x, n_a) = \max_{c,a' \geq 0} (1 - p(x)) u(c_\mathrm{T}, 0, f) +$$
$$p(x) \left(u(c, 0, f) + \beta \left\{ \begin{array}{l} \varphi E\left[\max\left\{V^E(x', 1), V^R(x')\right\}\right] + \\ (1 - \varphi) E\left[V^R(x')\right] \end{array} \right\} \right),$$

subject to equation (4).

The DI beneficiary's problem: DI benefit recipients only make consumption and saving decisions. It is important to note that DI recipients can also get access to Medicare benefits after being enrolled in the program for two years. In the model, this eligibility is determined by the state variable n_d, which tracks the number of periods the individual has been on DI. Let

$$W^D(x, n_d) \equiv \begin{cases} V^D(x, n_d), & \text{if } j < R, \\ V^R(x), & \text{if } j = R. \end{cases}$$

Then, DI benefit recipients face the following problem

$$V^D(x, n_d) = \max_{c,a' \geq 0} (1 - p(x)) u(c_\mathrm{T}, 0, f) + p(x) \left(u(c, 0, f) + \beta E\left[W^D(x', n_d + 1)\right] \right),$$

subject to

$$\frac{a'}{1+r} + c + m^D(x, n_d) = a + SS(\bar{e}) + Tr^D(x, n_d),$$

where $Tr^D(x, n_d) \equiv \max\left\{0, \underline{c} + m^D(x, n_d) - a - SS(\bar{e})\right\}$ and $\bar{e}' = \bar{e}$.

The retiree's problem: retirees remain retired until they die. They receive social security benefits and only make consumption and saving decisions. Their problem is given by

$$V^R(x) = \max_{c,a' \geq 0} (1 - p(x)) u(c_\mathrm{T}, 0, f) + p(x) \left(u(c, 0, f) + \beta E\left[V^R(x')\right] \right),$$

subject to

$$\frac{a'}{1+r} + c + m^R(x) = a + SS(\bar{e}) + Tr^R(x),$$

where $Tr^R(x) \equiv \max\left\{0, \underline{c} + m^R(x) - a - SS(\bar{e})\right\}$ and $\bar{e}' = \bar{e}$.

3.6 Technology and Equilibrium

There is a representative firm that produces a single consumption good using a Cobb-Douglas production function $Y = AK^{\alpha}N^{1-\alpha}$ where α is the output share of capital, K and L are the aggregate capital and aggregate labor input, and A is the total factor productivity. Capital depreciates at a constant rate $\delta \in (0, 1)$. The firm pays a proportional tax on capital income τ_k. We assume a small open economy such that the after-tax return on assets, r, is exogenous. The definition of the stationary competitive equilibrium is provided in Section 3 of the Online Appendix.

4 Calibration

Our calibration strategy consists of two stages. In the first stage, we set the values of some parameters that can be determined based on independent estimates from the data or the existing literature. In the second stage, we calibrate the rest of the parameters by minimizing the distance between data targets and their model counterparts. The parameters set directly using data are summarized in Online Appendix Table 35 and the parameters calibrated by targeting data moments are summarized in Online Appendix Table 36 .

Our goal is to quantify the impact of health inequality on lifetime earnings inequality. To do so we must first pin down the magnitudes of the various channels through which frailty impacts earnings and employment in the model. Recall that the five channels through which frailty operates are: 1) mortality rates, 2) out of pocket medical expenditures, 3) labor productivity, 4) probability of successful DI application, and 5) disutility from working. The effect of frailty on the first three channels can be estimated directly from the data without using the model. As we describe in more detail below, we estimate these effects in the first stage of the calibration.

The effects of frailty on the probability of successful DI application and the disutility from working cannot be discerned directly from the data.[21] These effects are, instead, determined in the second stage of the calibration by minimizing the distance between model and data moments. Specifically, the parameters governing DI eligibility and disutility from work are chosen by targeting the employment rates and DI recipiency rates of men by age and frailty percentile groups shown in Figure 1. The moments are concentrated in the unhealthy tail of the frailty distribution since this is where the effects of frailty on labor supply and DI recipiency are most pronounced.

[21] We cannot directly estimate the probabilities of successful DI application because none of the datasets we use provide information on whether or not a respondent has applied. We only see whether or not respondents are currently receiving DI benefits.

The idea behind identification is the following. The set of targeted moments includes employment rates by frailty for both younger workers and workers over the age of 65. This is intentional. Those who are older than 65 qualify for social security retirement benefits only. The effect of frailty on the probability of successful DI application does not have a direct impact on their labor supply choices. Therefore, the variation in their labor supply with frailty must be driven by variation with frailty in their disutility from working. In other words, the variation in these older workers' employment rates identifies the disutility parameters (and their dependence on frailty). Given these disutility parameters, the variation in DI recipiency by frailty and age identifies the parameters that determine the probability of successful application.

Demographics and initial distributions. Model age $j = 1$ corresponds to age 25 and retirement age $R = 41$ corresponds to age 65. The maximum age in the model, $J = 70$, corresponds to age 94. Conditional survival probabilities at each age are estimated using HRS data and a probit regression. Mortality depends on a quadratic in frailty, a quadratic in age, and education. See Section 4 of the Online Appendix. The population growth rate is set to $\nu = 0.02$ so that the ratio of old (over 65) to young (65 and younger) is equal to 0.2 (this is consistent with the year 2000 U.S. Census).

The population is divided into three education groups: high school dropouts, high school graduates, and college graduates. The initial distribution of agents across the three groups is 12 percent high school dropouts, 52 percent high school graduates, and 36 percent college graduates based on the education distribution of 25- to 26-year-old males in our PSID sample.

Even though the fraction of men non-employed and on DI is only 2.0 percent at ages 24–26, it varies substantially across frailty and education. For this reason, we set the initial distributions of individuals across employment states (employed, non-employed, and DI beneficiary) by education and frailty percentile group to be consistent with their counterparts in the data. Section 4 of the Online Appendix provides the numbers.

Preferences. Individuals have utility over consumption, c, and suffer disutility from working which depends on their frailty, f. Period utility of workers is given by,

$$u(c, l, f) = \frac{\left(c^{\mu}\left(1 - \left[\phi_0 + \phi_1 f^{\phi_2}\right] l\right)^{1-\mu}\right)^{1-\gamma}}{1-\gamma},$$

where $l \in \{0, 1\}$ is equal to 1 if the individual is working and 0 otherwise.[22]

The parameters ϕ_0, ϕ_1, and ϕ_2 determine how frailty affects the disutility of work. We assume $\phi_0 \geq 0$, $\phi_1 \geq 0$, and $\phi_2 \geq 0$ so that the disutility of work is increasing in frailty. It also implies that the marginal utility of consumption declines as health deteriorates. This is consistent with empirical findings in Finkelstein et al. (2013). Moreover, in our benchmark calibration ϕ_2 is larger than one, which implies that the marginal effect of increasing frailty

[22]This utility function is very common in the literature. See, for example, Capatina (2015), De Nardi et al. (2023), French (2005), Pashchenko and Porapakkarm (2017) and Pashchenko and Porapakkarm (2019). The only difference is that in our model health enters the utility function via a smooth nonlinear function as a opposed to a jump variable.

Table 5: Estimated effect (%) of one additional frailty deficit on log productivity (wage)

	HSD	HS	CL (frailty $<$ 76th prctile)	CL (frailty = 95th prctile)
No bias correction	-4.4	-2.6	0.0	-2.9
Bias correction	-4.8	-2.9	0.0	-2.9

is higher for more frail individuals. As we explained above, the parameters ϕ_0, ϕ_1, and ϕ_2 are determined in the second-stage minimization. They are pinned down by the level and variation by age and frailty in the employment rates of men aged 25 to 74. However, as we mentioned above, what identifies them separately from the parameters that determine the probability of successful DI application is the variation in employment rates among men aged 65 to 74.

The rest of the preference parameters are standard. For the benchmark calibration, we set $\gamma = 2$ and $\mu = 0.5$, which implies a coefficient of relative risk aversion of $1 - (1 - \gamma)\,\mu = 1.5$. This is in the middle of the range of values used in the literature.[23]

Labor productivity, job separation, and job finding. We estimate the labor productivity process, $\eta\,(j, f, s, \epsilon)$, separately for each education group using PSID and HRS data on men only. For each group, labor productivity is the sum of a deterministic component and a stochastic component. The deterministic component consists of age and frailty effects. The stochastic component contains a fixed effect, a transitory shock, and an AR(1) shock.

One concern when estimating the labor productivity process is selection bias. We do not observe hourly wages (our proxy for labor productivity) of those who do not work. If men whose frailty more negatively impacts their labor productivity are less likely to work, not controlling for selection will lead us to underestimate the impact of frailty on productivity. To correct for potential selection bias, we estimate the labor productivity process in three steps. First, we use the system GMM dynamic panel estimator outlined in Section 2.1 and a selection correction procedure to estimate the effect of frailty on productivity. Second, removing the frailty effects from our productivity observations, we estimate the age effects via OLS. Third, using variance-covariance moments constructed with the final frailty residuals, we estimate the stochastic component via GMM.

Table 5 reports the estimated effects of accumulating one additional deficit on log wages for each education group with and without controlling for selection.[24] Consistent with our findings in Section 2.1, the negative effects of frailty on men's wages are decreasing with education and only present for college graduates who are already in poor health. One additional deficit reduces wages by 4.8 percent for high school dropouts and 2.9 percent for high school graduates.[25] The estimated effect for college graduates with frailty below the

[23]See Attanasio (1999) and Blundell and MaCurdy (1999) for surveys.

[24]There are two important differences between theses estimations and those in Section 2.1. First, the estimation in this section is done only on a sample of men. Second, we treat frailty as exogenous in these regressions given our earlier finding on the absence of reverse causality. In the Online Appendix Section 4 we show that the estimated effects of frailty are robust to making frailty endogenous.

[25]Using a different measure of health, Low and Pistaferri (2015) also estimate the effect of poor health on labor productivity for non-college men. In a rough comparison, we find that our effects are similar in

76th percentile is zero. Starting at the 76th percentile, the effect increases at an increasing rate. As the right column of the table reports, accumulating one additional deficit when at the 95th percentile of the frailty distribution reduces wages by 2.9 percent for college graduates. Notice that, consistent with our concerns, the effect of frailty on wages is slightly smaller when not controlling for selection bias. For additional details and the full set of estimation results see Section 4 of the Online Appendix.

Our productivity process estimation strategy doesn't capture the effects of severe lifelong disability on productivity. To capture these effects we assume that a small fraction of individuals, those who are already DI beneficiaries at age 25, have permanent zero productivity. As we stated above, the fraction of such individuals varies by education and initial frailty percentile group. Overall, 2.0 percent of 25-year-olds are assigned to this group. These individuals are primarily high school dropouts and are concentrated in the top percentiles of the frailty distribution.

The job separation rate, $\sigma(s)$, is set to 27, 15, and 6 percent for high school dropouts, high school graduates, and college graduates, respectively. These are averages of (annualized) monthly rates in the Current Population Survey (CPS) from 2000 to 2019. The job finding rate after a non-employment spell is set to $\varphi = 52\%$, which is the average (annualized) monthly rate of transition from out of the labor force to employment between 2000 and 2019 in the CPS.[26] In the model, employed workers who just came back from separation or non-employment suffer a wage penalty, χ, which mimics the share of earnings that is lost during job search within the period. According to the U.S. Bureau of Labor Statistics, the average duration of unemployment in the U.S. was approximately 18 weeks over the period 1970 to 2019. Therefore, we set the wage penalty to be 34.6 percent of one year's earnings.

Frailty and medical expenditures. Our specification and estimation of the frailty process, $\psi(j, s, \varepsilon_f)$, follows closely that in Hosseini et al. (2022). For the estimation, we use the full PSID sample that includes both men and women to increase the sample sizes. Hosseini et al. (2022) show that there is little difference in lifecycle frailty dynamics by gender. We assume that there is a positive mass of individuals with zero frailty at age 25. Each period, these individuals move to a positive frailty value with a probability that depends on their education and a quadratic in age. Once positive, an individual's frailty never goes back to zero.[27] We use a probit regression to estimate the conditional probabilities of positive frailty by age and education.

For individuals with positive frailty, log frailty is given by the sum of a quartic age polynomial and a stochastic component. The stochastic component consists of an AR(1) shock, a transitory shock, and a fixed effect. The AR(1) shock captures persistent health events such as developing diabetes, while the transitory shock captures acute ones such as a temporary inability to walk due to a broken leg. We find that there are large differences in frailty dynamics by education. For this reason, we estimate the log frailty process separately for each education group.

Frailty and mortality are highly correlated. Thus, when estimating the nonzero frailty

magnitude, albeit slightly larger, as compared to theirs. See Section 4 of the Online Appendix.

[26]There is very little variation in job finding rates by education in the CPS.

[27]Less than 1 percent of individuals in our PSID sample with positive frailty have zero frailty next period.

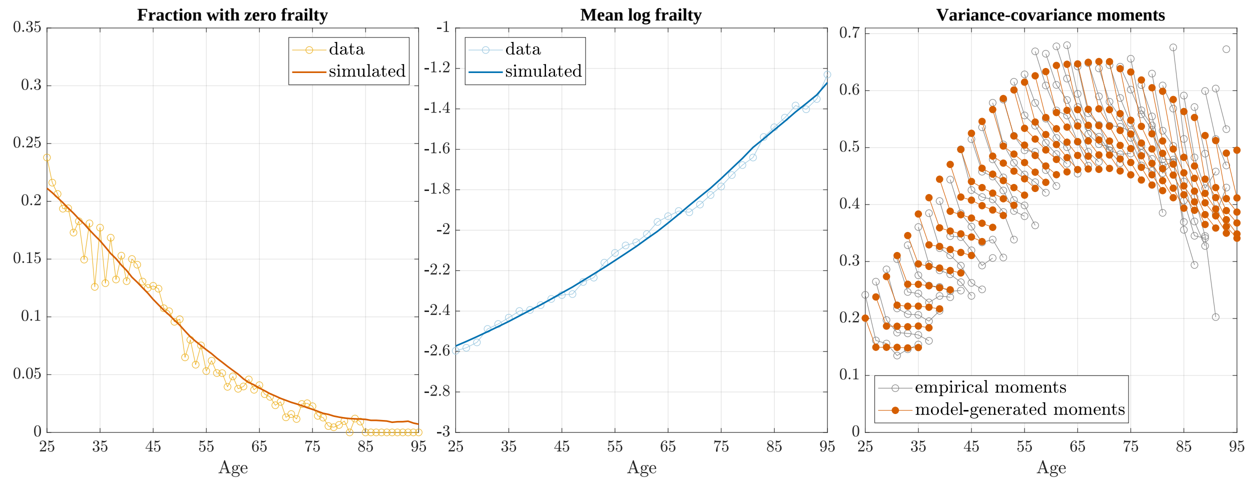

Figure 2: Estimation targets: auxiliary simulation model vs PSID data for high school graduates (other education groups are in the Online Appendix). Left panel is the fraction with zero frailty by age, middle panel is mean log frailty by age for those with nonzero frailty, and right panel is the age-profile of the variance and covariances of log frailty residuals (the stochastic component of log frailty).

process, it is important to control for selection bias due to mortality. To this end, we estimate the frailty processes using an auxiliary simulation model and the method of simulated moments (MSM). The auxiliary simulation model simulates the frailty dynamics described above together with the mortality rates by age and education given by the specification described above. For each education group, the coefficients of the age polynomial are determined by targeting the age profile of log frailty for 25- to 95-year-old PSID respondents. The variance and persistence of the AR(1) shock, variance of the transitory shock, and variance of the fixed effect are determined by targeting variance-covariance moments by age of the log frailty residuals.

Figure 2 shows the estimation results for high school graduates (the largest education group in our sample).[28] The left panel shows the fraction of high school graduates with zero frailty by age in the data and in the simulation of the model. The middle figure shows the age profile of mean log frailty targeted in the data and the model counterpart. The right panel shows the age profile of the variance-covariance moments in the model and the data. Notice that our estimated frailty process is able to generate autocovariance patterns that are very similar to those in the data.

We estimate out-of-pocket medical expenditures for men separately by education and labor market status: employed, non-employed, and on Medicare (which includes both retirees and those who are on DI). To capture the nonlinear effect of frailty on medical spending, we assume that log out-of-pocket medical expenditures are determined by a cubic in age and a cubic in frailty. We estimate the coefficients of these functions using male-only sample from MEPS. Note that although we do not include any randomness directly in this formulation,

[28]All parameter estimates as well as the estimation results for the other two education groups are in Section 4 of the Online Appendix.

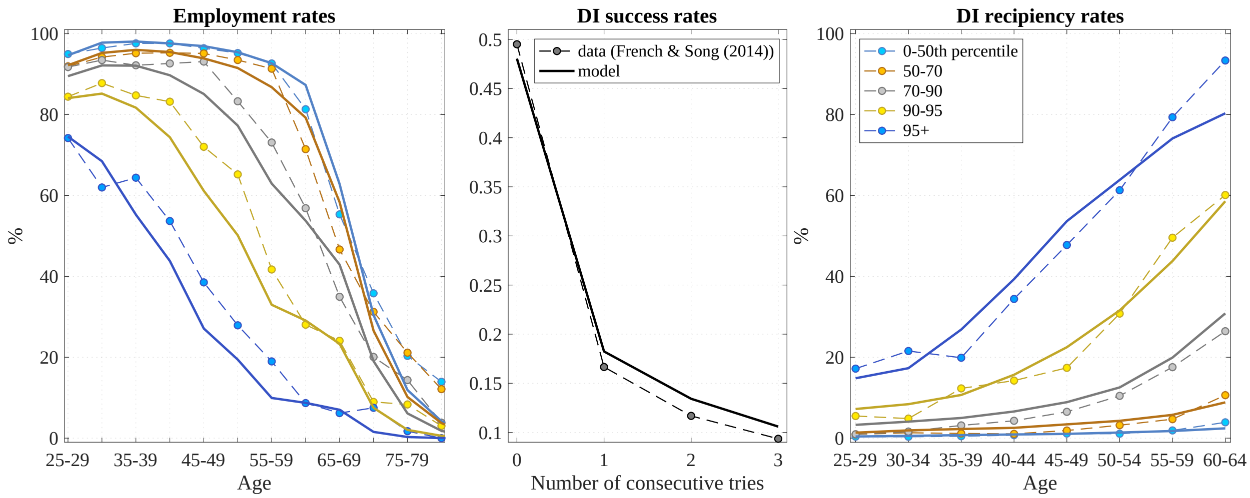

Figure 3: Calibration targets: solid (dashed) lines are the model (data). The left panel shows male employment rates (PSID), the right panel shows male DI recipiency rates (MEPS and Social Security Administration), and the middle panel shows DI application success rates by number of consecutive tries (French and Song, 2014).

out-of-pocket medical expenditures are random through their dependence on frailty. The results of these estimations are presented in Section 4 of the Online Appendix.

DI application. The DI application process is complex and lengthy. Moreover, even though the probability of successfully obtaining benefits is generally higher for individuals in worse health, the outcome is uncertain.[29] The process starts with a 5 month waiting period during which applicants are not allowed to be gainfully employed. After this initial period, applicants' cases are reviewed by the Disability Determination Service (DDS) review board. The most definite cases are approved for benefits at this point. For instance, individuals with one of 100 specifically listed and verifiable medical conditions are usually given benefits at this stage. Less definite cases are usually denied. However, denied applicants can request reconsideration by the DDS office. After a 60 day waiting period, further denials can be again appealed. Such appeals are assessed by an administrative law judge (ALJ) after a period of roughly one year. Judges have considerable latitude in assessing appeals. Applicants whose appeals are denied, can continue to appeal for multiple rounds with approximately a one year turnaround time between appeal and decision each round. Alternatively, denied applicants can end the appeals process and start over applying for benefits by submitting a new application.

French and Song (2014) document that by one year after initial application, about 50 percent of applicants will usually have been awarded benefits. After this point, the probability of obtaining benefits continually declines in the number of years since initial application (see the middle panel of Figure 3). After 10 years, only 70 percent of applicants who continually appeal or reapply are approved. Thus, individuals can spend years trying to successfully get on DI.

[29] See French and Song (2014) and the references therein for a detailed overview of the program.

Motivated by the description above, the probability of successful DI application in the model depends on an individual's frailty, f, and the cumulative number of times that he has consecutively applied for DI during the current non-employment spell, n_a. We assume that applications by individuals with frailty below a certain threshold, $\underline{f}$, will never be approved. This captures the fact that one has to be relatively unhealthy to have a chance at successfully getting on DI. We also assume that, all else equal, applications of individuals who are 55 years of age or older have a higher chance of being accepted. This captures, in a parsimonious way, the relaxation of DI eligibility criteria at ages 50 and 55.[30] Specifically, we set

$$\theta\left(j, f, n_a\right)=\begin{cases}\min\left\{1,\left(1+\mathbf{1}_{\{j\geq 55\}}\left(\varrho-1\right)\right)\vartheta\left(n_a\right)f^{\kappa}\right\}, & \text{if } f>\underline{f},\\ 0, & \text{otherwise.}\end{cases}$$

As described in Section 3.5, individuals incur a one time non-pecuniary cost of applying for DI, which we denote by ξ. This parameter captures the stigma associated with applying for DI, as well as, other hassles and inconveniences involved in submitting to medical exams and preparing scores of medical and legal documents.[31]

The utility cost, ξ, as well as the parameters ϱ, $\vartheta(n_a)$ (for $n_a = 0, 1, 2, 3$), κ, and $\underline{f}$, are determined in the second stage of the calibration by targeting three sets of moments. The first set of moments is the DI recipiency rates by 5-year age groups and frailty percentile groups in Panel (b) of Figure 1. These comprise 40 moments. The second set includes the average DI success rate at the initial try, as well as success rates after one, two, and three tries. We obtain these data moments from French and Song (2014). Finally, we target the share of DI applicants as a percentage of the 25- to 64-year-old population. We use the average of this ratio between 2000 and 2019, which is 2 percent.[32]

Even though all of these parameters are calibrated jointly, each set can be associated with a specific set of moments. Conditional on an applicant's frailty, the success rates of each subsequent DI application, $\vartheta(n_a)$ (for $n_a = 0, 1, 2, 3$), are determined by the average DI success rates in the data. The parameter κ is determined by the overall level of dispersion in DI recipiency rates with frailty. The age loading factor ϱ is determined by the age pattern in the recipiency rates, particularly the higher recipiency rates among those 55 and older relative to those younger than 55. The cutoff for DI eligibility $\bar{f}$ is determined by the increasing dispersion in DI recipiency rates with frailty as individuals age. This parameter also helps us match the low DI recipiency rates in the youngest age groups. Finally, the utility cost of application, ξ, is determined by the overall fraction of 25- to 64-year-olds who apply for DI. The values of calibrated parameters, as well as respective targets, are reported in Figure 3 and Online Appendix Table 36. See Section 4.2 of the Online Appendix for an extended discussion of parameter identification.

[30] Work capacity requirements for DI eligibility become less stringent at age 50 and again at age 55. Carey et al. (2021) find that these features of the DI application process lead to a discontinuous increase in the DI acceptance rate at these ages.

[31] See Currie (2004) for an overview of the literature on the take up of social programs in the U.S. and U.K. and the "stigma hypothesis". See Hoynes et al. (2022) for a discussion of the extent of legal and medical documentation that is required in order to apply for DI.

[32] This calculation uses the 2019 Annual Statistical Supplement to The Social Security Bulletin (Table 6.C7).

Policy and technology parameters. Old-age social security and SSDI benefits are determined using the Social Security Administration's formula for calculating the primary insurance amount:

$$\widetilde{SS}\left(\bar{e}\right)=\begin{cases}0.9\bar{e}, & \text{if } \bar{e}\leq 0.2\bar{e}_a,\\ 0.18\bar{e}_a+0.33\left(\bar{e}-0.2\bar{e}_a\right), & \text{if } 0.2\bar{e}_a<\bar{e}\leq 1.25\bar{e}_a,\\ 0.5265\bar{e}_a+0.12\left(\bar{e}-1.25\bar{e}_a\right), & \text{if } 1.25\bar{e}_a<\bar{e},\end{cases}$$

where $\bar{e}_a$ is the average earnings in the economy. The SSI program provides an income floor to individuals eligible for either social security retirement or DI benefits. To capture SSI we assume that

$$SS\left(\bar{e}\right)=\max\{\widetilde{SS}\left(\bar{e}\right),\underline{b}\},$$

where $\underline{b}$ is 13 percent of average earnings which is the ratio of the maximum annual Federal SSI payment in 2000 ($6,156) to male average earnings in 2000 ($47,552).

The tax function $T\left(\cdot\right)$ has three components. One is a nonlinear component mimicking the U.S. income tax/transfer system. One is a social security payroll tax component consisting of a proportional tax that is subject to a maximum taxable earnings cap. And, one is a proportional Medicare payroll tax. We model the nonlinear component in the fashion of Benabou (2002) and Heathcote et al. (2017). Specifically, the tax function is

$$T(e)=e-\lambda e^{1-\tau}+\tau_{ss}\min\{e,2.47\bar{e}_a\}+\tau_{med}e.$$

Here, τ controls the progressivity of the tax function and is set to 0.036 based on the estimates in Guner et al. (2014). The value of λ is determined in the second stage of the calibration by targeting total U.S. federal income tax receipts as a share of GDP of 8 percent.

The social security payroll tax rate is set to $\tau_{ss}=0.124$ and the Medicare tax rate is set to $\tau_{med}=0.029$. The capital tax, $\tau_K=0.3$, is paid by the firm and set based on Gomme and Rupert (2007). The minimum consumption level, $\underline{c}$, is set to 9.2 percent of average earnings, equivalently, $4,375. This is the average maximum combined benefits from the Temporary Assistance for Needy Families (TANF) program and food stamp program for a single individual in 2003 based on the 2003 U.S. *Green Book* (Committee on Ways and Means, 2003). Exogenous government purchases, G, are set to 12.8 percent of GDP to clear the government budget constraint. We hold this share fixed in all counterfactual experiments.

We assume a small open economy and set $r=0.04$. The capital share α is set to 0.36. We normalize aggregate TFP, given by A, to 1, and choose β in the second stage such that the model generates a wealth-to-earnings ratio of 3.2.[33] The depreciation rate is set to $\delta=0.07$ based on calculations in Gomme and Rupert (2007).

5 Assessment

Figure 3 provides a comparison of the employment rates, DI recipiency rates, and DI success rates targeted in the data with the model counterparts. All these targeted moments are

[33] We follow Hong and Ríos-Rull (2012) and target the wealth-to-earnings ratio of the bottom 95 percent.

Table 6: Employment and DI recipiency rates by education

	HSD		HS		CL	
	Data	Model	Data	Model	Data	Model
LFPR (% of 25–74 yo)	73.5	73.0	83.2	82.2	89.8	89.3
DI recipiency rates (% of 25–64 yo)	14.3	13.7	7.3	7.4	1.7	1.6

reasonably matched. Notice that although the model slightly understates the employment rates of men ages 75–84, it matches well the level and dispersion in employment rates of men aged 65–74. This is important as it is these rates relative to the rates of those under 65 that determine the disutility from work parameters.

To assess the model's performance with regards to non-targeted moments, we first look at employment and DI recipiency rates of men across the different education groups. Table 6 shows that the model does reasonably well in matching overall employment rates, as well as, DI recipiency rates by education. To inspect the fit further, we report employment and DI recipiency rates by age and frailty percentile groups for each education group. The employment rates are presented in Figure 8 and the DI recipiency rates are presented in Figure 9 in the Online Appendix. From these figures we see that the model performs reasonably well in capturing the patterns in the data. In particular, it captures well the reduced dispersion in both employment rates and DI recipiency rates with frailty as education increases.

Next, we look at the impact of DI benefit denial on employment. The first row of Table 7 reports the fraction employed three years after they are denied benefits. In the model, 37 percent of those between ages 25 and 64 who are denied benefits on their first application are employed three years after denial. This fraction falls to 34 percent for those 35 to 64 years old, and to 30 percent for those 45 to 64 years old. These numbers are broadly consistent with estimates of the impact of benefit denial on employment in the empirical literature. For instance, Maestas et al. (2013) find that in the early 2000s benefit denial at the DDS review board stage (about 1 year after application) increased the employment rates of 18- to 64-year-olds three years later by 33 to 36 percent. French and Song (2014) find that in the 1990s benefit denial at the ALJ stage (about 2 years after application) increased the employment rates of 35- to 64-year-old males three years later by 27 percent. Similarly, Von Wachter et al. (2011) show that the employment rates of 45- to 64-year-old males were between 30 to 33 percent higher three years after benefit denial. Finally, in earlier work, Bound (1989) looks at the impact of benefit denial on 45- to 64-year-old males in 1972 and 1977 and finds that it increased the fraction working full-time by 26 to 29 percent.[34]

As a further assessment of the model, we look at transition rates from non-employment to DI. Figure 4 shows the fraction of men not employed and not on DI who are on DI two years later in the model and in our PSID sample. The fraction is reported by frailty percentile group and overall. Ninety-five percent confidence intervals for the data estimates can also be seen in the figure. We chose to use these empirical moments for assessment rather than calibration because they are imprecisely estimated in the tail of the frailty distribution due to small sample sizes. Despite not targeting these rates, the model delivers the same overall

[34]The reason French and Song (2014) find lower employment rates than others in the literature is because they focus on denials at the ALJ stage as opposed to the initial stage.

Age range	25–64	35–64	45–64
Model	37	34	30
Maestas et al. (2013)[a]	33–36		
French and Song (2014)[b]		27	
Von Wachter et al. (2011)[c]			30–33
Bound (1989)[c]			26–29

[a] Rejection is at the DDS review board stage (18–64 yr olds).
[b] Rejection is at the ALJ stage (males only).
[c] Rejection is at the DDS review board stage (males only).

Table 7: Probability of employment 3 years after initial DI application rejection (%).

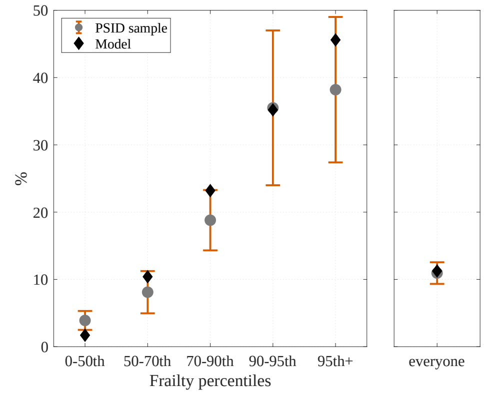

Figure 4: Transition rates from non-employment to DI for men by frailty in our model (diamonds) and PSID sample (circles). Bars are 95% confidence intervals on the data estimates.

transition rate as in the data (11%). Moreover, the model transition rates are in the 95 percent confidence intervals of their data counterparts for all the frailty percentile groups except one. The transition rate in the model for the healthiest frailty percentile group is slightly outside of this range.

Finally, we assess the model's performance in capturing the degree of inequality in lifetime earnings over the lifecycle. We define lifetime earnings at age j as the sum of all earnings from age 25 up to age j.[35] Although computing lifetime earnings at each age in the model is straightforward, it is not possible to compute it in our PSID sample because we do not have long enough earnings histories. Instead, we construct a sample in NLSY79 that mimics our sample selection in PSID.[36] The variance of log current earnings over the lifecycle in the model, the PSID sample, and the NLSY79 sample are very similar (see Figure 16 in the Online Appendix). This is not surprising. The model is calibrated to match the wage and employment dynamics in the PSID sample. Panel (a) of Figure 5 shows the variance of log lifetime earnings in the benchmark calibration and the NLSY79 sample, and Panel (b) shows the fraction of men with zero lifetime earnings. The model also captures the inequality in lifetime earnings well including the fraction of men with zero earnings.[37][38]

In summary, the model is able to replicate the empirical patterns of employment and

[35] Several other papers in the literature studying lifetime earnings inequality use a similar definition including Haan et al. (2017). Guvenen et al. (2017) and Kopczuk et al. (2010).

[36] Recall that our model does not allow for an intensive margin of labor supply. To construct a measure of earnings variation in the data that is comparable to the model we use variation in hourly wages conditional on employment. See Section 7 of the Online Appendix for additional details about the NLSY79 sample.

[37] The variance of log lifetime earnings is slightly higher in the model than in the NLSY79 sample at younger ages and the fraction of individuals with zero earnings is slightly lower. This is partly due to differences between the PSID and NLSY samples. As Online Appendix Figure 16 shows, the variance of log current earnings is also slightly higher in the PSID as compared to the NLSY sample at younger ages.

[38] Additional comparisons of inequality in the model and the NLSY79 sample are provided in Online Appendix Section 7.

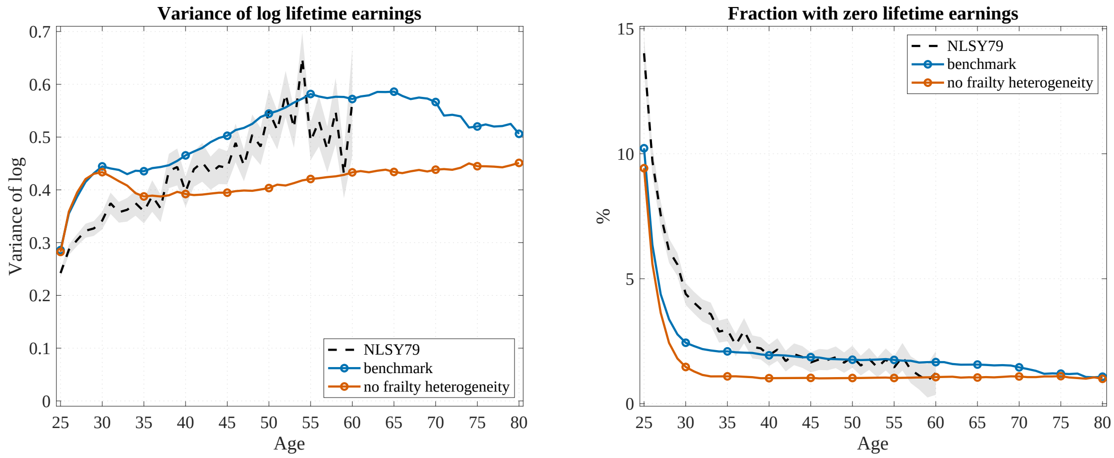

Figure 5: The variance of log lifetime earnings (left) and the fraction of men with zero lifetime earnings (right) in the NLSY79 (grey), the benchmark economy (blue) and the no-frailty-heterogeneity economy (red).

DI recipiency by age, education, and frailty. It also generates employment rates after DI benefit denial and transition rates from non-employment to DI recipiency that are inline with counterparts estimated from data. Finally, the model is able to generate similar degrees of current and lifetime earnings inequality as observed in the data.

6 Quantitative Exercise

We now consider a counterfactual economy in which everyone has the average frailty profile. Giving all individuals in the economy the average frailty profile removes all cross-sectional variation in frailty conditional on age. In particular, it removes heterogeneity in frailty due to education and individuals' fixed frailty types. It also removes the heterogeneity in frailty due to the persistent and transitory frailty shocks. We refer to the counterfactual economy as the no-frailty-heterogeneity (NFH) economy. We compare the inequality in lifetime earnings at different ages in the NFH economy and the benchmark.

Removing health inequality significantly reduces inequality in lifetime earnings at older ages. The left panel of Figure 5 shows the age-profile of the variance of log lifetime earnings in the benchmark economy and the NFH economy. The variation in lifetime earnings is similar in the two economies at younger ages. However, the variance of log lifetime earnings increases more rapidly with age in the benchmark economy. As a result, there is significantly less variation in lifetime earnings in the NFH economy starting around age 35. As reported in Table 8, the variance of log lifetime earnings is 11 percent lower at age 35 and 21.5 percent lower at age 45 in the NFH economy relative to the benchmark. The relative difference peaks at age 55 when the variance of log lifetime earnings is 27.7 percent lower.[39] However,

[39]Intuitively, removing health inequality has a smaller impact on lifetime disposable income inequality. However, this smaller impact does not translate into a smaller impact of health inequality on consumption inequality. The variance of log consumption at age 65 is 18.2 percent lower in the NFH economy due to the effect of removing health inequality on wealth accumulation. See Section 6.2 of the Online Appendix.

Table 8: Effect of frailty heterogeneity on the variance of log lifetime earnings

	age 35	age 45	age 55	age 65	age 75
Benchmark	0.435	0.502	0.582	0.586	0.520
No frailty heterogeneity (NFH)	0.388	0.395	0.421	0.434	0.445
	% Δ relative to benchmark				
NFH	-11.0	-21.5	-27.7	-26.0	-14.5
NFH in DI	8.9	-4.3	-16.2	-20.8	-17.6
NFH in Labor Prod.	-8.8	-11.9	-13.0	-10.2	-5.7
NFH in Disutility	-0.2	-1.1	-1.7	-1.4	-1.8
NFH in Med. Exp.	-1.7	-1.4	-1.4	-0.2	1.2
NFH in Mortality	-2.6	-1.3	-0.9	5.5	9.9

Note: In the "No frailty heterogeneity" counterfactual all individuals have the average frailty age profile. Each additional counterfactual is identical to the benchmark expect that there is no frailty heterogeneity in the listed channel. Instead, the impact of frailty via that channel is determined by the average frailty age profile.

beyond age 55 the gap closes. This is due to the effect of mortality in the benchmark model. Those with very low lifetime earnings are also those with high frailty and therefore high mortality. This selection effect leads to a fall in the variance of log lifetime earnings in the benchmark at older ages. In the NFH economy, since everyone has the same frailty, there is much less variation in mortality conditional on age.[40] The impacts of health inequality on lifetime earnings inequality are due to both initial fixed frailty heterogeneity and frailty shocks. Both play an important role. At age 55, removing only heterogeneity due to shocks reduces lifetime earnings by 23 percent whereas removing only fixed effect heterogeneity reduces lifetime earnings by 16 percent (see Online Appendix Section 6 for details).

Removing health inequality, not only reduces the variance of log lifetime earnings, it also leads to a smaller fraction of individuals with zero lifetime earnings. As the right panel of Figure 5 shows, the fraction of these individuals in the benchmark and NFH economy declines rapidly between ages 25 and 30 after which it remains low. While small in both, the fraction of individuals with zero lifetime earnings is considerably less in the NFH economy, especially between ages 30 and 55.

Almost all of the difference between the variance of log lifetime earnings in the benchmark and the NFH economy is due to higher earnings at the bottom of the distribution in the NFH economy. Figure 6 displays the ratios of lifetime earnings at the 5th and 95th percentile relative to the median by age in the two economies.[41] Notice that, after age 30, there is a large difference across the two economies between the ratio of the 5th percentile relative to the median. In contrast, there is no difference in the ratio of the 95th. Individuals in the bottom of the lifetime earnings distribution in the benchmark economy are more likely to be in poor health. They are also more likely to be less educated which means they face larger negative effects of poor health on their labor productivity and larger replacement rates of their earnings if they become a DI beneficiary. Giving these individuals the average frailty profile increases both their wages and their labor supply. In contrast, individuals at the top

[40] Some variation in mortality conditional on age still remains due to the effect of education.

[41] The ratios of lifetime earnings at the 10th and 90th percentiles relative to the median are available in Section 6 of the Online Appendix.

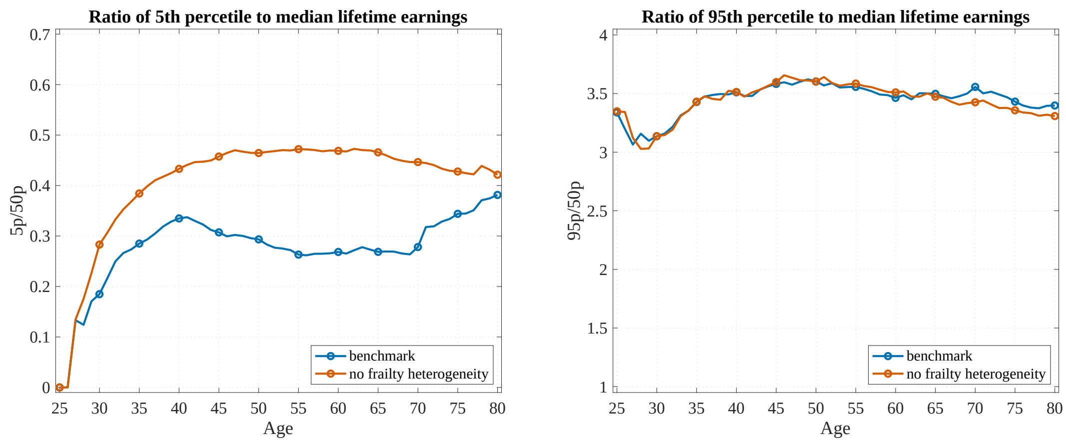

Figure 6: Inequality in lifetime earnings in the benchmark economy (blue) and the no-frailty-heterogeneity economy (red).

of the lifetime earnings distribution in the benchmark economy are mostly college-educated and healthy. As a result, giving these individuals the average frailty profile has little effect on their earnings.

6.1 Breaking down the effect of health inequality

Recall that there are five channels through which frailty can affect earnings inequality in the model: DI acceptance probabilities, labor productivity, disutility of work, amount of out-of-pocket medical expenditures, and mortality risk. How important is each of these channels for generating the differences in the variance of log lifetime earnings profiles between the benchmark and NFH economies?

To assess the relative importance of each channel, we consider five additional counterfactual economies. Each economy is identical to the benchmark except that, for one of the five channels, the impact of frailty is determined by the average frailty profile instead of a person's individual profile. Specifically, in counterfactual economy 1, labelled "NFH in DI", individuals' probability of successful DI application is determined by the average frailty profile. In counterfactual economy 2, labelled "NFH in Labor Productivity", individuals' labor productivity is determined by the average frailty profile. In counterfactual economy 3, "NFH in Disutility", disutility from working is determined by the average frailty profile. In counterfactual economy 4, "NFH in Medical Expenditure", out-of-pocket medical expenditures are determined by the average frailty profile. Finally, in counterfactual economy 5, "NFH in Mortality", mortality rates are determined by the average frailty profile.

The results of this decomposition exercise show that, according to the model, the DI program (SSDI and SSI) is the most important channel through which health inequality generates lifetime earnings inequality. Table 8 presents the differences in the variances of log lifetime earnings between the benchmark and each counterfactual economy at five ages. Notice that the labor productivity channel has the largest impact on lifetime earnings inequality at younger ages. Shutting down this channel reduces lifetime earnings inequality at age 35 by 8.8 percent and at age 45 by 11.9 percent, whereas, shutting down the DI channel *increases* lifetime earnings inequality at age 35 by 8.9 and decreases it at age 45 by only 4.3 percent. However, by age 55, the DI channel is the primary channel through which health inequality generates lifetime earnings inequality. Shutting down the DI channel reduces lifetime earnings inequality at this age by 16.2 percent. In contrast, shutting down the labor productivity channel, the second most important channel, reduces it by only 13.0 percent. At age 65, removing the DI channel reduces lifetime earnings inequality by 20.8 percent, more than double the effect of removing the labor productivity channel.

Why does shutting down the DI channel increase lifetime earnings inequality at age 35 but decrease it at later ages? In the benchmark economy, at older ages the DI program creates strong work disincentives for frail individuals. However, it has the opposite effect on very young frail people. Young frail individuals have a high probability of getting DI transfers in the future. Thus, they want to accumulate earnings credits to raise their benefit in anticipation. Using the average frailty profile to determine DI eligibility substantially weakens this incentive, as now, the likelihood of a frail individual getting on DI is much lower. However, these individuals still suffer high disutility of work and have relatively low wages. These effects push some young frail workers in the "NFH in DI" economy out of the labor force and onto means-tested programs.

Figure 7 presents the average employment, DI recipiency, and means-tested transfer recipiency rates of individuals in the top five percentiles of the frailty distribution in the benchmark and several of the counterfactual economies. Consistent with the intuition above, the left panel of the figure shows that highly frail 25- to 29-year-olds in the "NFH in DI" economy are less likely to be in the labor force than those in the benchmark, while the right panel shows that they are more likely to be on means-tested transfers. Thus, by reducing the incentives for young frail individuals to work, shutting down the DI channel reduces their employment rates and increases earnings inequality. The impact of this effect on lifetime earnings inequality quickly declines with age. This is because shutting down the DI channel increases employment rates of frail individuals ages 30 to 65 as the first panel of Figure 7 shows. Compared to young highly frail individuals, these older highly frail individuals are more likely to have worked and accumulated wealth. As a result, many are not eligible for means-tested programs. In the "NFH in DI" economy, given that they have a low probability of getting on DI, they continue to work. This impact of removing the DI channel on the labor supply of frail individuals ages 30 to 65 is the primary reason for the large decline in the variance of log lifetime earnings at ages 55, 65 and 75 in the"NFH in DI" counterfactual relative to the benchmark.[42]

The labor productivity channel is the second most important channel through which health inequality impacts lifetime earnings inequality in the model. Shutting down this channel reduces lifetime earnings inequality at all ages. Using the average frailty profile to determine labor productivity reduces the variation in wages conditional on age. This has two effects. First, it leads directly to a reduction in earnings, and hence, lifetime earnings inequality. Second, it increases the returns from working for less educated individuals and

[42]The effects of the DI channel on the employment, DI recipiency, and mean-tested transfer recipiency rates of the other frailty groups can be seen in Section 6 of the Online Appendix. The figures show that there is little impact of removing health inequality for individuals with frailty below the 70th percentile. For those in the 70th–95th percentiles, the effects of removing the DI channel are similar to those in Figure 7 except that employment rates decrease more at younger ages.

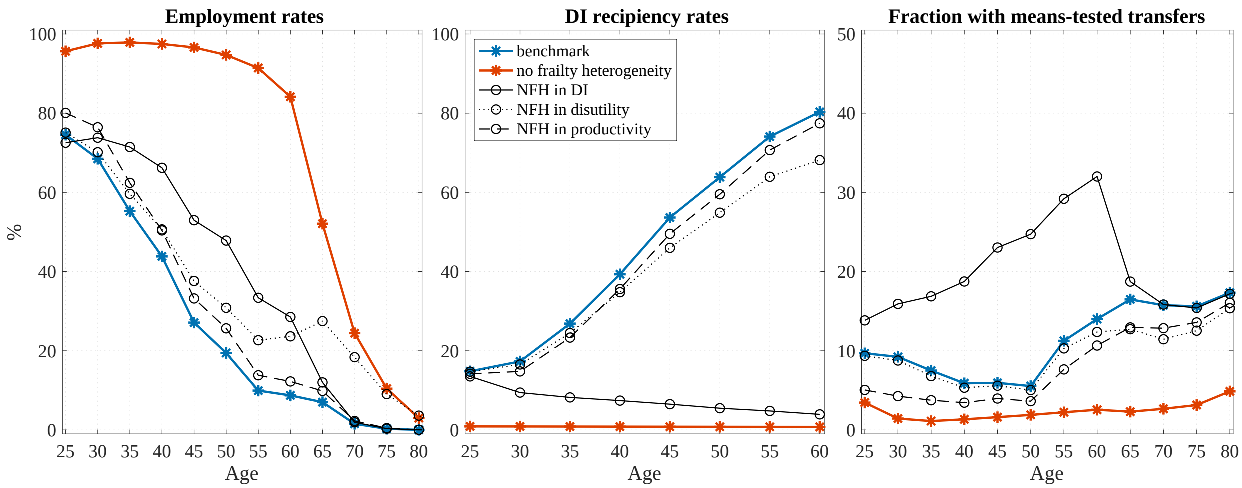

Figure 7: Employment rates (left panel), DI recipiency rates (middle panel), and fraction receiving means-tested transfers (right panel) by age for individuals in the top 5 percentiles of frailty in the benchmark economy, the no-frailty-heterogeneity economy, and counterfactual economies 1–3.

frail college graduates which increases their labor supply. This second effect operates even for the most highly frail individuals as Figure 7 shows.[43] Notice that, at all ages, these individuals have higher employment and lower DI and means-tested transfer recipiency rates in the "NFH in Labor Productivity" economy relative to the benchmark.

The disutility, medical expense, and mortality channels play relatively smaller roles.[44] The smaller role of the mortality channel is due to two offsetting effects of shutting it down. First, it increases the life expectancy of frail individuals which increases their returns to work and labor supply. This effect works to reduce lifetime earnings inequality. Second, since mortality and productivity are negatively correlated in the benchmark (due to both education and health), it raises the survival rates of individuals in the bottom of the lifetime earnings distribution relative to those in the top. This second effect, which grows with age due to the nature of mortality risk, works to increase lifetime earnings inequality.

Finally, notice in Figure 7 that removing the DI channel has no impact on the employment rates of workers after age 65 while removing the disutility channel has a large impact. This fact, which is also true for the other frailty percentile groups (see Online Appendix Figure 12), indicates that the variation in employment by frailty after age 65 is driven by the disutility channel and not the DI channel. The result illustrates that the variation in employment rates at these older ages is indeed determined by the disutility from work parameters consistent with our identification strategy.

[43]See Section 6 of the Online Appendix for a summary of the overall effects of shutting down each channel on labor force, DI, and means-tested program participation rates.

[44]The contribution of the disutilty channel declines from age 55 to 65 due to the increase in DI acceptance rates conditional on frailty at age 55. See Section 4.

6.2 Alternative measures of health

The most common measure of health used to discipline structural models in economics is self-reported health status (SRHS).[45] We now investigate how our analysis would change if we use this measure instead of frailty.

In the PSID and HRS (as in many other surveys), SRHS can take five values: 'excellent', 'very good', 'good', 'fair', and 'poor'. Following the literature, we convert SRHS to a binary measure. This is typically done in one of two ways: classifying 'fair' and 'poor' SRHS as bad health and the rest as good health, or classifying only 'poor' SRHS as bad health. We consider both of them. For each definition, we estimate education and age-specific transition rates across good and bad health states for men ages 25 to 50 in the PSID, and across good health, bad health, and death for men over age 50 in the HRS. We also estimate initial distributions of men ages 25 and 26 across health states in the PSID. These transition rates and distributions are reported in Tables 42–48 of the Online Appendix.

We create two alternative calibrations of the model using SRHS. In calibration 1, bad health includes both fair and poor SRHS. In calibration 2, bad health includes only poor SRHS. For each calibration we model the dynamics of health and mortality using the estimated transition rates and distributions reported in the Online Appendix. In addition to mortality, in the model, frailty impacts labor productivity, medical expenses, the probability of getting DI, and disutility from work. We use a simple mapping between frailty and SRHS to determine the impacts of SRHS on labor productivity and medical expenses. Specifically, we set the effect of each SRHS state to the effect at the average value of frailty for men in that state. The average values of frailty for men with good and bad SRHS under calibration 1 are 0.086 and 0.231, respectively. Under calibration 2 the values are 0.098 and 0.343. So, for instance, the effect of bad SRHS on labor productivity under calibration 1 is equal to the effect on labor productivity of having a frailty value of 0.231.

We then proceed to calibrate the parameters governing the probability of successful DI application and disutility from work by matching employment and DI recipiency rates by age and health state, as we do in Section 4. To give this version of the model a chance at matching these moments, we relax the assumption that DI is an absorbing state. Instead, we assume DI recipients who are in good health exit at a constant rate. We calibrate this exit rate along with the rest of the parameters in the second stage. The aggregate DI exit rate in the calibrated model is 17 percent under calibration 1 and 5 percent under calibration 2. Employment and DI recipiency rates by age and SRHS under calibration 1 and 2, and in the data, are reported in Figure 8. The top row displays the fit for alternative calibration 1, while the bottom row shows the fit for alternative calibration 2.

Assuming that good health types exit DI with a positive probability is key to matching these moments. Absent this assumption, the model is unable to match DI recipiency rates by age and health group. The reason is twofold. SRHS is a coarse measure and does not allow us to concentrate the probability of successfully obtaining DI among a small enough fraction of the working-age population. Moreover, with SRHS, the health grid is less persistent (see Online Appendix Section 8). The coarseness means that, relative to the benchmark model, too many individuals in bad health are eligible for DI. The low persistence means that a large

[45] See Braun et al. (2017), Capatina (2015), Cole et al. (2019), De Nardi et al. (2010), French and Jones (2011), Kitao (2014), Pashchenko and Porapakkarm (2017), and Pashchenko and Porapakkarm (2019).

number of them transition back to good health. As a result, the fraction of DI recipients in good health is too high especially at older ages unless we assume some of them exit. This does not happen when frailty is used because it is a more granular and persistence measure of health. The third column of Figure 8 shows that both calibrations with SRHS fail to match the untargeted transition rates from non-employment to DI. With the low persistence and a positive fraction of good health types exiting DI each period, matching the targeted fractions of individuals on DI requires counterfactually high entry rates from non-employment for bad health types. For instance, when bad health is defined as SRHS equal to poor, the transition rate from non-employment to DI for those in bad health is 77 percent in the model versus 36 percent in the data.

We now repeat the main exercise, removing health heterogeneity, using the two different calibrations of the model with SRHS. SRHS heterogeneity is removed in a way that is comparable to the way frailty heterogeneity is removed in the benchmark economy: the effects of health through each of the five channels (DI acceptance probabilities, labor productivity, disutility of work, amount of out-of-pocket medical expenditures, and mortality risk) are replaced by age profiles of the average effects. For instance, in the DI channel, the SRHS-specific probabilities of successful DI application at each age are replaced with the average probability of successful DI application at that age. The average probabilities are calculated as the weighted averages of the probabilities of successful DI application of each health group where the weights are the age-specific fractions of individuals in good and bad health. Table 9 presents the results. Also shown in Table 9 are the impacts on lifetime earnings inequality of removing SRHS heterogeneity from the DI ("NSH in DI") and disutility-of-work channels ("NSH in Disutility") only.

In the benchmark economy with frailty as the measure of health, health inequality accounts for 27.7 of the variance of log lifetime earnings at age 55 (Table 8). The impact of health inequality on lifetime earnings inequality is significantly smaller when the measure of health is SRHS. Under alternative calibration 1, health inequality accounts for 10.6 of the variance of log lifetime earnings at age 55. Under alternative calibration 2, it accounts for 4.5 percent. Thus, the model with SRHS understates the impact of health inequality on lifetime earnings inequality relative to the benchmark model by 62 to 84 percent depending on how SRHS is aggregated into a binary measure.

The impacts of being in relatively poor health on lifetime earnings are smaller for the same reasons we needed to modify the model. SRHS is both less persistent, and less correlated with the probability of successfully obtaining DI. With lower persistence, the cumulative impacts of bad health on wages and earnings are smaller. With a lower correlation of bad health with DI entry, its contribution to permanent exits from the labor force is understated. Consequently, the significance of the DI channel for the effects of health inequality on lifetime earnings inequality is reduced. In the baseline economy, shutting down the DI channel decreases the variance of log lifetime earnings by 16.2 percent at age 55 and 20.8 percent at age 65 (Table 8). Under alternative calibrations 1 and 2, eliminating the DI channel leads to smaller reductions in lifetime earnings inequality. Specifically, under alternative calibration 1, the reduction is 5.9 percent at age 55 and 5.3 percent at age 65, while under alternative calibration 2, it is 1.1 percent at age 55 and 3.3 percent at age 65.

While the DI channel plays a smaller role in the economies calibrated using SRHS, the disutility channel plays a larger role. Removing it reduces lifetime earnings inequality at

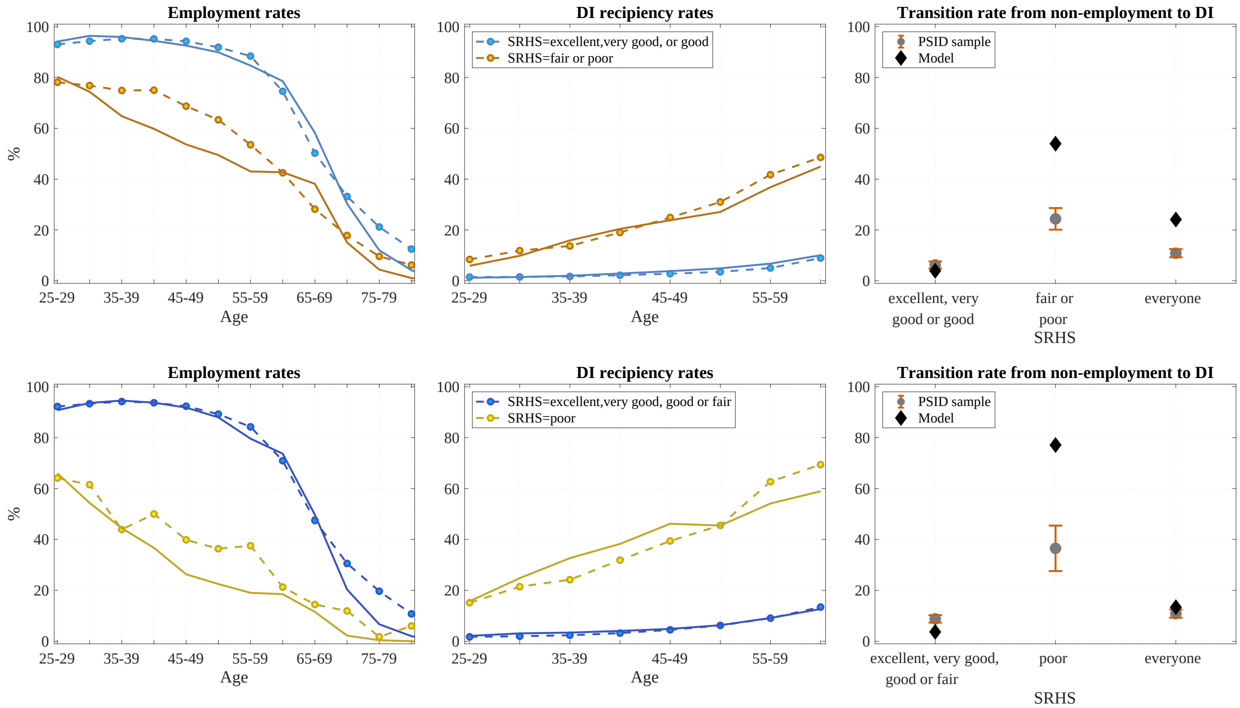

Figure 8: Alternative calibrations using SRHS: solid lines are the model, dashed lines are data. In the top row 'bad health' is defined as SRHS of 'fair' or 'poor'. In the bottom row it is defined as SRHS of 'poor'. The first two columns show targeted moments. The first column shows male employment rates (data source is PSID) and the second column shows male DI recipiency rates (data source is MEPS and Social Security Administration). The third column shows (untargeted) transition rates from non-employment to DI by health status (data source is PSID). Bars are 95% confidence intervals on the data estimates.

age 55 by 8.0 percent under alternative calibration 1 and 1.9 percent under alternative calibration 2 compared to 1.7 percent in the baseline economy. Since the calibrations with SRHS understate the variation in employment with health due to DI recipiency, a greater impact of bad health on the disutility of work is required to generate the targeted variation in employment rates at ages 65–74. For this reason, the calibrations using SRHS not only underestimate the impact of health inequality on lifetime earnings but also exaggerate the importance of the disutility channel. These findings illustrate that using frailty to measure health, as opposed to SRHS, is crucial for our results.

6.3 The value of social security disability insurance

Our findings above indicate that health inequality is a major contributor to inequality in lifetime earnings. They also indicate that the primary channel through which health inequality generates lifetime earnings inequality is the DI program. The incentives for middle-aged frail individuals to work and accumulate labor earnings are significantly reduced by the fact that they have a high probability of obtaining DI benefits if they apply. These results suggest that

Table 9: Variance of log lifetime earnings: results with SRHS.

	% Δ relative to alternative-calibration benchmark				
	age 35	age 45	age 55	age 65	age 75
Alternative calibration 1: bad health = fair or poor SRHS					
No SRHS heterogeneity (NSH)	2.5	−4.7	−10.6	−10.1	−12.0
NSH in DI	6.4	−1.3	−5.9	−5.3	−6.8
NSH in Disutility	−5.5	−5.4	−8.0	−6.0	−7.0
Alternative calibration 2: bad health = poor SRHS					
No SRHS heterogeneity (NSH)	15.2	−1.9	−4.5	−8.0	−7.6
NSH in DI	15.3	2.1	−1.1	−3.3	−2.5
NSH in Disutility	4.1	−1.1	−1.9	−2.3	−2.5

Note: Each row shows the percentage change in the variance of log lifetime earnings in the counterfactual economy relative to the alternative-calibration benchmark. Each counterfactual is identical to the benchmark expect that there is either no SRHS heterogeneity or no SRHS heterogeneity in the listed channel.

one way to reduce lifetime earnings inequality is to eliminate DI. We now assess the long-run welfare implications of such a policy. To remove the DI program we set the probability of getting DI to zero and adjust the payroll tax so that the total payroll tax receipt declines by exactly the amount of expenditures on the SSDI/SSI portion of benefits in the baseline.[46] Two percent of individuals in our benchmark calibration start out on DI. Absent DI, they are assumed to start as non-employed and have zero productivity over their lifetime. Thus, these individuals rely on the means-tested transfer program.[47]

We first consider the direct impact of removing the DI program. We refer to this experiment as *partial equilibrium* since we do not rebalance the overall government budget. The second column of Table 10 shows the steady-state (long-run) welfare and aggregate implications of this experiment. Notice that, consistent with the findings above, eliminating the DI program significantly reduces inequality in earnings and income. The variances of age-65 log lifetime earnings and disposable income fall by about 24 and 10 percent, respectively. It also increases aggregate consumption and aggregate GDP. Yet, it does not reduce consumption inequality. In fact overall inequality in consumption goes up.

Why does the variance of log consumption slightly increase when DI is removed? Removing DI leaves individuals more exposed to the risk of becoming highly frail and incurring high disutility from work. Some individuals offset this increased risk by working and saving more which tends to reduce consumption inequality. Others offset it by relying more heavily on means-tested transfers which tends to increase it. In particular, middle-aged frail workers increase their labor supply as the cost of not working has gone up and they have already accumulated too much wealth to be eligible for means-tested transfers. Their response drives the rise in the aggregate employment rate shown in Table 10. In contrast, the employment rates of younger frail workers, under age 40, decline. This happens because removing the DI program has a similar effect on young frail individuals as using the average frailty profile to determine DI eligibility. That is, it substantially reduces their incentive to work and accumulate lifetime earnings and wealth in anticipation of receiving DI transfers during

[46]Technically, SSI is financed through the general budget and not the payroll tax. However, for the purpose of this exercise, we adjust payroll taxes for changes in both SSDI and SSI expenditures.

[47]In Online Appendix Section 6.4 we show that the welfare results are robust to the alternative assumption that these individuals have similar productivity to individuals who transition to DI shortly after age 25.

Table 10: Aggregate and welfare effects of removing DI

	Benchmark	No DI benefits & tax		
		P.E.	G.E.1	G.E.2
Welfare (% relative to benchmark)				
All	n.a.	0.02	-0.28	-0.72
HSD	n.a.	-2.25	-2.51	-3.89
HS	n.a.	-0.34	-0.64	-1.18
CL	n.a.	1.64	1.31	1.48
Variance				
log lifetime earnings (at age 65)	0.586	0.452	0.453	0.407
log lifetime disp. income (at age 65)	0.390	0.349	0.349	0.341
log consumption (overall)	0.513	0.523	0.523	0.513
Change relative to benchmark (%)				
GDP	n.a.	2.71	2.68	3.08
Consumption	n.a.	2.90	2.57	3.06
Capital	n.a.	2.71	2.68	3.08
Labor input	n.a.	2.71	2.68	3.08
Hours	n.a.	3.55	3.48	4.80
GDP per hour	n.a.	-0.81	-0.77	-1.64
Fraction (%)				
Working (25- to 74-year-olds)	83.70	86.70	86.65	87.75
On DI (25- to 64-year-olds)	6.04	0.00	0.00	0.00
On means tested transfers (all)	3.41	5.68	5.74	4.58
Policy variables				
Payroll tax rate (%)	12.40	10.50	10.50	10.50
Min. consumption (2000 $)	$4375	$4375	$4375	$3995
Tax function parameter (λ)	0.9200	0.9200	0.9173	0.9200

Note: P.E. is the economy without DI in *partial equilibrium*: SSDI/SSI benefits and corresponding fraction of payroll tax are removed. G.E.1 and G.E.2 are *general equilibrium* economies with the overall government budget balanced by adjusting the income tax and minimum consumption, respectively.

middle-age. Instead, they reply more heavily on means-tested transfers which generates the rise in means-tested transfer recipiency rates reported in the table.

The welfare implications of the policy change vary across the three education groups. Whereas college graduates experience a welfare gain equivalent to 1.64 percent of lifetime consumption (mostly due to lower payroll taxes), both high school dropouts and graduates are worse off with welfare declines of 2.25 and 0.34 percent, respectively. These gains and losses aggregate to a small *ex ante* positive welfare gain of 0.02 percent.

The rise in the means-tested transfer recipiency rate leads to an increase in government expenditures. To show the impact of closing this fiscal gap on our welfare calculations, we perform two additional experiments. In the first experiment, we finance the expansion of means-tested programs by raising federal income taxes (by reducing parameter λ in the HSV tax function). The results of this experiment are reported in column G.E.1 of Table 10. As it turns out, the adjustment in taxes required to close the fiscal gap is very small. The reason is that eliminating DI increases labor supply and hence grows the tax base. Alternatively, we close the gap by reducing the maximum level of means-tested transfer benefits ($\bar{c}$). The results for this experiment are reported in column G.E.2. These *general equilibrium* results

Table 11: Welfare effects of a DI program without redistribution across education groups

	No DI		DI w/o redistribution	
	P.E.	G.E.1	P.E.	G.E.1
Welfare (% relative to benchmark)				
ALL	0.02	-0.28	-0.42	-0.46
HSD	-2.25	-2.51	-3.05	-3.08
HS	-0.34	-0.64	-0.85	-0.89
CL	1.64	1.31	1.48	1.43

Note: 'Remove DI' is an economy in which SSDI/SSI benefits and corresponding fraction of payroll tax are removed. 'DI w/o Redistribution' is an economy without redistribution in DI, in which DI benefits of each education group are paid for by education-specific payroll taxes. P.E. is *partial equilibrium* and G.E.1 is *general equilibrium* where the overall government budget is balanced by adjusting the income tax.

reinforce our initial finding. Eliminating the DI program, despite reducing inequality in earnings and income and generating sizable gains in aggregate consumption and GDP, is not welfare improving for lower educated groups. Welfare losses from eliminating the program are even larger in general equilibrium. If we close the fiscal gap by increasing income tax rates, *ex ante* welfare falls by 0.28 percent. If we close the gap instead by reducing the means-tested consumption floor, it falls by 0.72 percent. In both cases, welfare losses are particularly large for high school dropouts whose welfare declines by 2.51 and 3.89 percent depending on which rule is used to clear the government budget.

Before they know their education type, individuals in our model prefer an economy with a DI program. This is true assuming that they anticipate the full tax implications of removing it. However, once education is known, only the non-college individuals prefer to live with DI. The reason for this result is that DI is both an insurance program and a redistribution program. College-educated workers who have higher earnings and better health are more likely to work and less likely to use DI. Consequently, their payroll and income taxes disproportionately finance the program. Would all education groups value the DI program if it did not feature redistribution? To answer this question, we consider a counterfactual DI system that requires SSDI/SSI outlays to be self-financing within each education group. In this counterfactual system, DI benefits are financed by education-specific payroll taxes. Naturally, in this system, the payroll taxes of high school dropouts go up and those of college graduates go down.

We report the welfare results of this experiment in Table 11 and more detailed results in Online Appendix Table 50. For comparison purposes, we also report the results of removing the DI program altogether. When we compare across these two economies in *partial equilibrium*, that is without attempting to close the government budget, the results are surprising. All education groups prefer the 'No DI' economy to an economy that features 'DI w/o redistribution'. To understand these results, we need to think about the alternative insurance program for working-age individuals in the economy: the means-tested program. The interaction between these two programs is important. In the 'DI w/o redistribution' economy, DI transfers within each education group are paid for via payroll taxes. In the 'No DI' economy, however, individuals with poor health instead rely on means-tested transfers which are paid out of the general government budget. In *partial equilibrium* these transfers are free. This makes the 'No DI' economy preferable over the 'DI w/o redistribution' economy for all three education groups in partial equilibrium. Essentially, the presence of a publicly-provided secondary insurer crowds out their desire to have other insurance, even when it is "actuarially fair". This is similar to the findings of Braun et al. (2019) and Brown and Finkelstein (2008) on how Medicaid crowds out demand for private long-term care insurance.

Finally, we repeat the same experiment but close the fiscal gap by adjusting the income tax parameter λ. As Table 11 shows, comparing the 'No DI' economy to 'DI w/o redistribution' in *general equilibrium* changes the ranking of the two only for the college educated. This is because the additional income taxes needed to close the fiscal gap are primarily paid for by them. Non-college individuals still prefer the 'No DI' economy for the same reason as before, absent DI, they can get means-tested transfers essentially for free. In contrast, college graduates are now better off in the 'DI w/o redistribution' economy where the overall tax burden of insurance provision is more equally distributed across the education groups. Consequently, even though both college and non-college graduates prefer having a public DI program, they disagree on which one. Non-college prefer the benchmark DI program and would rather have no program than one featuring no redistribution across education groups. Vice versa, college graduates prefer a DI program featuring no redistribution and would rather have no program than the benchmark one.

7 Conclusion

Our findings indicate that health inequality has a large impact on lifetime earnings inequality: 28 percent of the variation in lifetime earnings of American men at age 55 is due to the fact that they face risky and heterogeneous lifecycle health profiles. A decomposition exercise shows that the impact of poor health on access to social security disability benefits is the most important factor driving this result. This finding indicates that the social security disability insurance program is an important contributor to lifetime earnings inequality. Despite this, we document that it is *ex ante* welfare improving and, if anything, should be expanded.

The analysis is conducted using a fine measure of health, the frailty index and a health process that features fixed heterogeneity, a persistent shock, and a transitory shock. Frailty captures well the variation in health in the poor health tail of the distribution where the impacts of the social security disability insurance program are concentrated. We show that this is crucial to our analysis and results. Using a more standard but coarser measure of health—self-reported health status—and modeling its dynamics in the way commonly done in previous literature leads us to underestimate the importance of health inequality for lifetime earnings inequality and the role of disability insurance.

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