How Important Is Health Inequality for Lifetime Earnings Inequality?*

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Abstract

Health and earnings are positively correlated due to several reasons. First, individuals who are in poor health are significantly less likely to work than healthy individuals. Second, conditional on working, individuals in poor health work fewer hours on average. Third, individuals in poor health on average earn lower wages. We document these facts using an objective measure of health called a frailty index which we construct for PSID respondents. The frailty index measures the fraction of observable health deficits an individual has. In previous work, we documented that health, as measured by the frailty index, deteriorates more rapidly and has a larger increase in dispersion with age than self-reported health. It is also more persistent over the life-cycle. These facts put together suggest that health inequality over the life cycle may be an important driver of lifetime earnings inequality. To assess this claim we develop a model of the joint dynamics of health and earnings over the life cycle. Individuals in the model face health, productivity and employment risk, and optimally choose labor supply on both the intensive and extensive margins. Agents are partially insured against these risks through government-run disability insurance, means-tested social insurance, and social security programs. They face a dynamic process for frailty (health) that is estimated using the PSID data. The model is estimated using a method of moments. Targeted moments are constructed off distributions of wages, hours, and employment rates by frailty and age. These distributions are obtained from an auxiliary simulation model that is estimated using PSID data. We find that health inequality can account for a significant share of the variation in lifetime earnings among 70 year-olds. Most of this effect is due to that unhealthy individuals exit the labor force at much younger ages than healthy ones. We find that health inequality has a larger impact on earnings inequality than previous literature for two reason. One, our model is the first in this literature that allows health to impact earnings through all three margins: participation,

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hours, and wages (productivity). Two, previous literature measured health using self-reported health status, and thus understated the extent to which health deteriorates with age for some individuals and the increase in health dispersion with age.

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JEL Classification numbers: D52, D91, E21, H53, I13, I18

1 Introduction

Recent studies have shown that health has important implications for many economic variables including asset accumulation, labor supply, and income and wealth inequality.[1] However, despite the importance of health in economic studies, there is no unified objective measure of health status. In this paper, we adopt a new objective measure of health status that we introduce in Hosseini et al. (2018), and use it to study the role of health inequality in shaping lifetime earnings inequality. Using this new measure, which we call *frailty index*, we first document three facts about the joint dynamics of health and earnings over the life cycle. First, individuals who are in poor health are significantly less likely to work than healthy individuals. Second, conditional on working, individuals in poor health work fewer hours on average. Third, individuals in poor health on average earn lower wages. In addition, our previous work documented that health, as measured by the frailty index, deteriorates more rapidly and has a larger increase in dispersion with age than self-reported health status (SRHS hereafter). It is also more persistent over the life cycle. These facts put together suggest that health inequality over the life cycle may be an important driver of lifetime earnings inequality. Motivated by these observations, we ask how much of the lifetime earnings inequality can be accounted for by rise in health inequality over the life cycle. Particularly, we ask to what extent rapid deterioration of health at the bottom of the health distribution contributes to individuals exit from the labor force (into retirement and or disability).

To this end, we build a life cycle general equilibrium model featuring agents who experience heterogeneous and risky *frailty* dynamics over their life cycle as well as productivity and employment risk. Markets are incomplete, but there exists a government in the model that runs a disability insurance program similar to US SSDI, a social security program, and a tax/transfer system. Agents jointly make consumption, savings, and labor supply decisions in each period over the life cycle. We calibrate the model to the US data, and choose key parameter values to match the joint dynamics of health and earnings that we document here and in Hosseini et al. (2018). We find that our calibrated model is capable of generating the lifetime earnings inequality of 70 year-olds that is observed in the data. We then use the calibrated model to answer the following question: how important is health inequality for lifetime earnings inequality? In particular, how much of the variation in lifetime earnings of 70 year-olds is due to the fact that individuals experience heterogeneous health dynamics over their life cycle?

To quantitatively assess the role of health inequality in shaping lifetime earnings inequality, we compute and examine a counterfactual economy in which individuals are assumed to experience the identical health profile over the life cycle. We find that health inequality over the life cycle is able to account for a substantial share of the variation in lifetime earnings among the 70 year-olds. Overall, relative to previous studies that use other health measures of health status, such as SRHS, we find that health (frailty index) has a larger impact on labor supply and earnings. This is largely due to the fact that frailty index is better at capturing evolution of the distribution of health status over the life cycle, which we discuss below.

[1] See De Nardi et al. (2010), Kopecky and Koreshkova (2014), Capatina (2015), De Nardi et al. (2017), and Prados (2017) among others.

Frailty index, is simply the accumulated sum of all adverse health events that has occurred to an individual. Our construction of this health measure is inspired and based on findings in gerontology literature.[2] The idea behind frailty index is as follows. As individuals age, they accumulate health problems. These health problems can range from symptoms to clinical signs and laboratory abnormalities to diseases and disabilities. These health problems are referred to as *deficits*. Mitnitski et al. (2001) and Mitnitski et al. (2002) have demonstrated that health status can be represented by combining deficits in an index variable, called frailty index. Mitnitski et al. (2005) and Goggins et al. (2005) find that frailty index is comparable between databases even when list of deficits used to construct the index do not coincide. They also find the frailty index to be a better predictor of mortality and institutionalization than age.

In our previous work (Hosseini et al. (2018)), we show that the frailty index is highly correlated with the main existing health measure, SRHS, and it has several advantages compared to SRHS. In particular, the frailty index gives a more accurate picture of how an individual's health evolves with age. That is, individuals' health decays at a substantially faster pace over the life cycle when measured by frailty as opposed to SRHS, and in addition health status measured by frailty is more persistent. Based on these findings, we argue that using the frailty index would also allow us to better capture the joint dynamics of health and earnings over the life cycle.

Our paper is closely related to a number of recent studies that uses quantitative life-cycle models to analyze the interactions between health and earnings over the life cycle.[3] For example, Kitao (2014) builds a life-cycle model of individuals who face employment and health risks, and use the model to study the impact of disability insurance policies on employment decisions. Capatina (2015) studies the life-cycle effects of health risks for different education groups, and finds that the effect of health risks is the largest among the non-college group. However, both studies (similar to many other studies in the literature) measure health status using the subjective measure, SRHS, which is known to suffer several limitations (see Hosseini et al. (2018) for a detailed explanation). Relative to SRHS, we argue that our constructed measure of frailty is better at capturing joint dynamics of health status and earnings particularly for middle aged poor and unhealthy individuals. This is an important contributing factor in our findings.

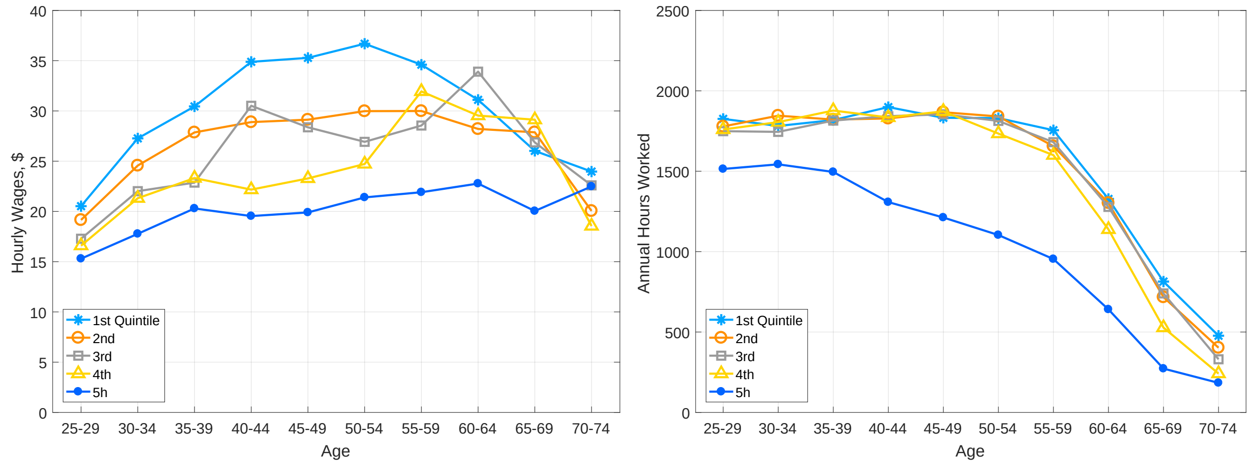
Our paper belongs to the fast-growing broadly-defined literature that studies extended life-cycle models with health and health expenditure.[4] While studies in this literature differ substantially in terms of the question of interest and modeling strategy, they share one common issue, that is, how to measure health. Therefore, we believe that our use of frailty index in this paper is relevant and can be potentially useful for other studies in this literature.

The remainder of the paper is organized as follows. In Section 2 we document empirical facts on relationship between health status and earnings. Section 3 presents the benchmark model. The calibration of the model and the main quantitative findings are presented in Section 3 and 4. Section 5 provides the concluding remarks.

[2]See Searle et al. (2008); Rockwood and Mitnitski (2007); Rockwood et al. (2007); Mitnitski et al. (2001, 2005); Kulminski et al. (2007a,b); Goggins et al. (2005); Woo et al. (2005), and among others.

[3]See Kitao (2014), Capatina (2015), Prados (2017), Michaud and Wiczer (2017), and among others.

[4]See De Nardi et al. (2010), Suen (2006), Kopecky and Koreshkova (2014), Zhao (2014), Ozcan (2013), and among others.



(a) Wage rates by frailty quintile among workers who work at least 260 hours annually and earn at least $3 per hour.

(b) Hours worked by frailty quintile, total sample.

Figure 1: Wage rates by frailty quintiles (left), and hours worked by frailty quintiles (right)

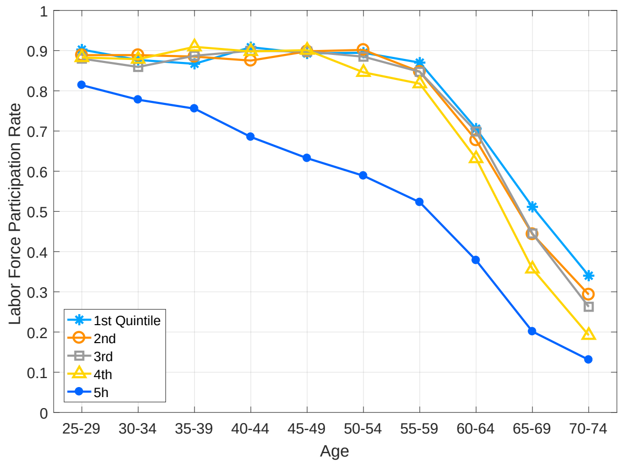
2 Health Status and Earnings: Empirical Facts

We start by presenting empirical facts on how wages and hours worked varies with health status (measured by frailty) in cross section. These observations are based on PSID data. Detailed description of the data is presented in Appendix A.

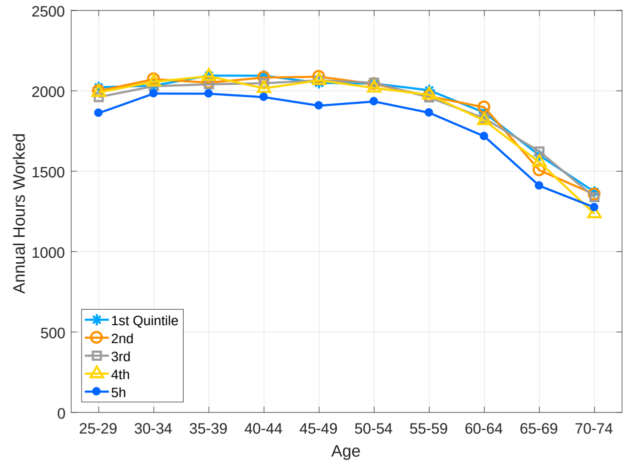
Labor Productivity. We first examine how frailty and labor productivity jointly evolve by age for working individuals. Here labor productivity is measured by wage rates. Figure 1a presents the average wage rates by frailty quintiles for each age group from age 25-29 to age 70-74. Note that higher frailty index correspond to worse health status. Therefore the first quintile of frailty is the healthiest and the fifth quintile is the unhealthiest. As can be seen, the mean wage rates display a hump shape over the life cycle for the first four frailty quintiles, while the wage profile is relative flat for the fifth one (the most frail quintile). In addition, for any given age group, the wage rates decrease as individuals become more frail. The wage gap between different frailty quintiles is relatively small in 20s and 30s, and it becomes larger in 40s. Another interesting feature of the frailty-wage relationship is that the wage gap among the first four frailty quintiles starts shrinking after age 50, while the wage rate of the most frail workers remain substantially lower than the rest of the workers except the 70-74 age group.

Hours Worked and Labor Force Participation. Frailty also has important implications for labor supply decisions. Figure 1b displays the average hours worked by individuals in each frailty quintiles for each age group over the life cycle. Among the first four quintiles, the average hours worked are similar for age groups until 60. After that, the hours worked start to differ significantly with the more frail individuals work fewer hours. However, for the fifth frailty quintile, the average hours worked are always substantially below those of other four quintiles for the entire life cycle.

Note that the average hours worked per person can be simply decomposed into two



(a) Employment rate by frailty quintile



(b) Hours worked by frailty quintile for workers

Figure 2: Employment rate (left) and hours worked for workers (right). We only consider workers who work at least 260 hours annually and earn at least \$3 per hour.

components: the average hours worked per worker (intensive margin) and the employment rate (the extensive margin). In Figures 2a and 2b, we examine the relationship between frailty and each of the two components. As can be seen, the relationship between frailty and hours worked is largely driven by the extensive margin. Individuals in the most frail quintile are much less likely to work than the other four quintiles. For instance, for age group 45-49, the employment rate is around 90% among the first four frailty quintiles while this rate is only around 60% in the fifth quintile. On the other hand, conditional on working, the impact of frailty on hours worked is much smaller, though still significant.

2.1 Effect of Health Status on Earnings and Hours

So far we documented that individuals in top quintile of frailty have lower employment rate. Moreover, there is not much variation in hours among workers with different level of frailty. We are now estimating the causal relationship between frailty and earnings (and hours). In particular, we are interested in measuring the effect of accumulating one more health deficit on earnings and hours worked. To do this we estimate the following empirical model

$$y_{i,t} \quad = \quad b_i + \lambda_t + \gamma f_{i,t-1} + \alpha_1 y_{i,t-1} + \alpha_2 y_{i,t-2} + \beta \boldsymbol{X}_{i.t} + \varepsilon_{i,t} \tag{1}$$

in which $y_{i,t}$ is logarithm of earnings (or hours) for individual i at time t, $f_{i,t}$ is frailty, and $\boldsymbol{X}_{i,t}$ is a vector of controls that includes marital status, marital status interacted with gender, number of kids, number of kids interacted with gender and cubic polynomial in age. Finally, λ_t is the time effect, b_i is the individual fixed effect, and $\varepsilon_{i,t}$ is random error term.

Individuals vary in unobservable ways (such as innate ability, genes, etc) that could potentially be correlated with their earning ability and as well as overall health (and therefore frailty). This motivates the inclusion of fixed effect in equation (1).[5] Moreover, we are

[5]Individual fixed effect can also pick up variations by gender and education.

interested in estimating the impact of frailty on earnings. However, earnings may also impact frailty. For example, on the one hand decline in health may affect productivity and lead to lower wages (or loss of employment). On the other hand, lower income (or loss of employment) may impact access to health insurance or affect choice of medical care. This, in turn, can impact health status. To avoid this simultaneity issue, we include lagged value of frailty on the right hand side. However, we still need to control for the fact that past earnings can have affect on current frailty as well as current earnings (since earnings is a persistent variable). Therefore, we include lagged values of earning on the right hand side to control for this potential endogeneity.

We are interested in estimating the coefficient γ, which we refer to as *short run effect,* and $\frac{\gamma}{1-\alpha_1-\alpha_2}$ which we refer to as *long run effect*. The difference is that the former only captures the effect of incremental change in frailty this period on earnings next period. However, since earnings is a persistent variable, this leads to further changes in earnings over time which is measured by the latter.

It is well known that these coefficients cannot be consistently estimated using OLS or fixed effect estimators (see Nickell (1981) and Wooldridge (2010) for details). Therefore, to obtain a consistent and unbiased estimates of the effect of frailty on earnings we use dynamic GMM panel estimator. This estimator was introduced by Holtz-Eakin et al. (1988) and Arellano and Bond (1991), and further developed by Blundell and Bond (1998) (and many others).[6] In what follows we assume unobserved heterogeneity is time invariant. The basic estimation procedure consists of two steps. First step is to write equation (1) in first difference form:

$$\Delta y_{i,t} \quad = \quad \eta + \gamma \Delta f_{i,t-1} + \alpha_1 \Delta y_{i,t-1} + \alpha_2 \Delta y_{i,t-2} + \beta \Delta \boldsymbol{X}_{i.t} + \Delta \varepsilon_{i,t} \tag{2}$$

and therefore, eliminate time-invariant unobserved heterogeneity. The second step is to use lagged values of frailty, earnings and controls as instruments and estimate equation (2) using GMM. As we argued above, lagged values of frailty and earnings are predictors of current levels of earnings and frailty. Therefore, they provide sources of variations for current values. However, for instruments to be valid, the past levels of earnings and frailty must be uncorrelated with $\varepsilon_{i,t}$. In other words, the following orthogonality conditions must hold

$$E\left(y_{i,t-s}\varepsilon_{i,t}\right) = E\left(f_{i,t-s}\varepsilon_{i,t}\right) = E\left(\boldsymbol{X}_{i.t}\varepsilon_{i,t}\right) \qquad \text{for } \forall s > 2. \tag{3}$$

With (3) imposed, equation (2) can be estimated using GMM. However, there are still a few shortcomings. For example, differencing can reduce variation in explanatory variable and therefore reduce accuracy of estimates (see Beck et al. (2000)). Moreover, as Arellano and Bover (1995) point out, variables in level may be weak estimates for first-differenced variables. This is specially true for highly persistent variables.[7] To mitigate these shortcomings, we

[6] This estimator is widely used in many areas of economics and finance. Example include the effect of board structure on firm performance (Wintoki et al. (2012)), capital accumulation and firm investment (Whited (1991)), the sensitivity of firm investments to available internal funds (Bond and Meghir (1994)), economic growth convergence (Caselli et al. (1996)), estimation of a labor demand model (Blundell and Bond (1998)), the relation between financial intermediary development and economic growth (Beck et al. (2000)), and the diversification discount (Hoechle et al. (2012)), among many others.

[7] As an stark example, imagine a random walk process. In that case, past values are uncorrelated with first differences.

follow Blundell and Bond (1998) and Blundell and Bond (2000) and improve the GMM estimator by also including the equations in levels in the estimation procedure. This equation is then estimated using first-differences as instrument. More precisely, we stack levels and first differences in the following equation

$$\begin{bmatrix} y_{i,t} \\ \Delta y_{i,t} \end{bmatrix} = \eta + \gamma \begin{bmatrix} f_{i,t-1} \\ \Delta f_{i,t-1} \end{bmatrix} + \alpha_1 \begin{bmatrix} y_{i,t-1} \\ \Delta y_{i,t-1} \end{bmatrix} + \alpha_2 \begin{bmatrix} y_{i,t-2} \\ \Delta y_{i,t-2} \end{bmatrix} + \beta \begin{bmatrix} \boldsymbol{X}_{i.t} \\ \Delta \boldsymbol{X}_{i.t} \end{bmatrix} + \varepsilon_{i,t}, \quad (4)$$

which we can estimate using "system" GMM estimator. Note, however, the level equations include unobserved (time invariant) heterogeneity. For first differences to be valid instruments of the levels, the following additional orthogonality conditions must hold

$$E\left(\Delta y_{i,t-s}\left(b_i + \varepsilon_{i,t}\right)\right) = E\left(\Delta f_{i,t-s}\left(b_i + \varepsilon_{i,t}\right)\right) = E\left(\Delta \boldsymbol{X}_{i.t}\left(b_i + \varepsilon_{i,t}\right)\right) \quad \text{for } \forall s > 2. \quad (5)$$

To summarize, we carry out GMM panel estimation using the orthogonality conditions (3) and (5). These conditions imply that we can use lagged levels as instruments for our differenced equations and lagged differences as instruments for the levels equations, respectively. We further assume that there is no serial correlation in the error term. To test these restrictions and assumptions, we use a series of tests suggested by Arellano and Bond (1991) and Blundell and Bond (1998).

The first test is a test of second-order serial correlation. This is really a test of whether our original specification of empirical model is valid. More precisely, we need to know whether we have included enough lags in (1). If we have, then any historical value of earnings beyond those lags is a potentially valid instrument since it will be exogenous to current shocks. For the purpose of our GMM estimates, if the assumptions of our specification are valid, then by construction the residuals in first differences should be correlated, but there should be no serial correlation in second differences.

The second test is a Hansen-Sargan test of over-identification. The dynamic panel GMM estimator uses multiple lags as instruments. This means that our system is over-identified and provides us with an opportunity to carry out the test of over-identification. The Hansen test yields a J-statistic which is distributed χ^2 under the null hypothesis of the validity of our instruments.

2.2 Estimation results

We use PSID data on frailty, earnings and hours over the period 2003-2015 to carry out the system GMM estimation outlined above. Details of data, sample selection and summary statistics can be found in Appendix A. To highlight the differences in effect of change in frailty on intensive vs. extensive margin of labor supply, we estimate coefficients in (1) separately for everyone in our sample (regardless of whether they exit labor market) and those who continuously work. Table 1 reports the system GMM estimation results for earning regression.[8] Left panel (columns (1) to (3)) shows the regression results for the entire sample. Right panel (columns (4) to (6)) shows results only for workers (meaning for those who do not exit employment during sample period). First, notice that for the diagnosis tests for the

[8]For sake of comparison we also report estimation results using OLS, fixed effect estimator as well as system GMM. These are reported in separate tables in the appendix ****

Table 1: Effect of Frailty on Earnings

	Everyone			Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
log(earnings$_{t-1}$)	0.765***	0.754***	0.754***	0.566***	0.552***	0.558***
	(0.124)	(0.121)	(0.115)	(0.180)	(0.175)	(0.167)
log(earnings$_{t-2}$)	0.019	0.024	0.021	0.289*	0.290*	0.296*
	(0.061)	(0.060)	(0.056)	(0.174)	(0.170)	(0.162)
frailty$_{t-1}$	-3.204***			-0.068		
	(1.132)			(0.171)		
frailty$_{t-1}$ × Young (age ≤ 45)		-3.688**			0.471	
		(1.415)			(0.326)	
frailty$_{t-1}$ × Old (age > 45)		-3.081***			-0.306*	
		(1.088)			(0.176)	
frailty$_{t-1}$ × Good Health			-1.311			0.065
			(1.118)			(0.214)
frailty$_{t-1}$ × Bad Health			-4.338***			-0.370
			(1.275)			(0.301)
Controls	YES	YES	YES	YES	YES	YES
Observations	44,879	44,879	44,879	21,919	21,919	21,919
AR(1) test (p-value)	0.000	0.000	0.000	0.046	0.043	0.034
AR(2) test (p-value)	0.071	0.078	0.058	0.431	0.409	0.370
Hansen test (p-value)	0.533	0.460	0.376	0.091	0.095	0.100
Diff-in-Hansen test (p-value)	0.120	0.072	0.189	0.347	0.182	0.250

Notes: Columns (1) to (3) show regression results for entire sample, regardless of employment status. Columns (4) to (6) show results conditional on continued employment. All regressions include controls (marital status, marital status interacted with gender, number of kids, number of kids interacted with gender and cubic polynomial in age). 'Good Health' is self reported health status of Excellent/Very Good/Good. 'Bad Health' is self reported health status of Fair/Poor. Standard errors on parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

system GMM estimators, the null hypotheses are not rejected at 5 percent confidence. In other words, error terms are not second order serially correlated and instruments are valid. Second, notice that frailty has a significant effect on earnings in the entire sample (column (1)). However, there is no effect on the earnings of those who continue to work (column (4)). This suggests that the effects on earnings come from extensive margin (of unhealthy workers leaving employment) rather than intensive margin (or unhealthy workers work fewer hours).

Column (2) shows that there is little difference in the effects of frailty on earnings between those younger than 45 and those older than 45. For both age groups frailty has a significant effect on earnings unconditional on work status. However, as column (5) shows, once the sample is restricted to only those who continue to stay employed, the effect goes away (except maybe for older workers). Finally, columns (3) and (6) suggests that the effect of frailty on earnings is driven by those who are in bad health (meaning those with self reported health status of 'Fair' or 'Poor') and leave employment as the result. These results are consistent with patterns observed in Figure 2a which shows that participation in top frailty quintile is significantly lower in all ages than the rest of the frailty quintiles.

Table 2 shows the results on the effect of frailty on hours worked. The results are consistent with the ones reported earlier for earnings, and surprisingly even the magnitudes

Table 2: Effect of Frailty on Hours

	Everyone			Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{hours}_{t-1})$	0.610***	0.623***	0.649***	0.162	0.220	0.138
	(0.130)	(0.130)	(0.124)	(0.143)	(0.149)	(0.140)
$\log(\text{hours}_{t-2})$	0.090	0.083	0.067	0.167	0.125	0.194
	(0.063)	(0.063)	(0.060)	(0.133)	(0.135)	(0.137)
frailty_{t-1}	-3.328***			0.029		
	(0.854)			(0.134)		
frailty_{t-1} × Young (age ≤ 45)		-3.486***			0.452	
		(1.097)			(0.275)	
frailty_{t-1} × Old (age > 45)		-3.047***			-0.118	
		(0.824)			(0.138)	
frailty_{t-1} × Good Health			-1.152			-0.029
			(0.836)			(0.195)
frailty_{t-1} × Bad Health			-4.043***			0.140
			(0.983)			(0.272)
Controls	YES	YES	YES	YES	YES	YES
Observations	44,879	44,879	44,879	21,919	21,919	21,919
AR(1) test (p-value)	0.000	0.000	0.000	0.013	0.008	0.016
AR(2) test (p-value)	0.697	0.611	0.416	0.471	0.757	0.358
Hansen test (p-value)	0.587	0.543	0.489	0.065	0.045	0.102
Diff-in-Hansen test (p-value)	0.115	0.079	0.288	0.071	0.060	0.083

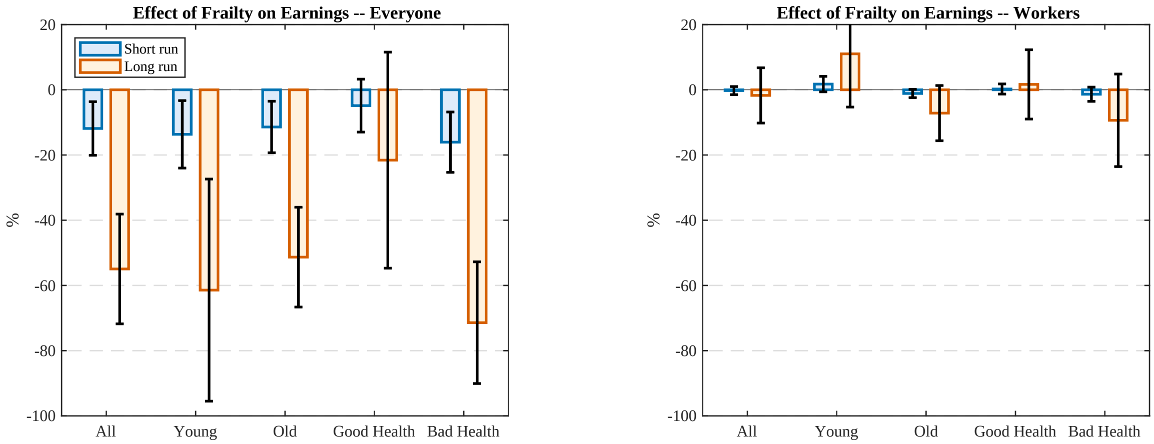
Notes: Columns (1) to (3) show regression results for entire sample, regardless of employment status. Columns (4) to (6) show results conditional on continued employment. All regressions include controls (marital status, marital status interacted with gender, number of kids, number of kids interacted with gender and cubic polynomial in age). 'Good Health' is self reported health status of Excellent/Very Good/Good. 'Bad Health' is self reported health status of Fair/Poor. Standard errors on parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

are similar. Tables 1 and 2 highlight four key findings. One, rise in frailty significantly reduces earnings and hours worked. This effect is mainly due to the extensive margin. Two, rise in frailty has the same effect on younger and older workers. Three, the effect of frailty on hours worked and earnings are largely due to its effect on individuals in bad health. Four, the fact that the magnitudes of the effects are similar for hours worked and earnings suggests that there is little or no effect on wages.[9]

To quantify the magnitude of the effect of an increase in frailty on earnings and hours we calculate the percentage changes in earnings (or hours) in response to one incremental change in frailty. By incremental change in frailty we mean the event that individual accumulates one more deficit. Note that in PSID sample we have total of 27 potential deficits. Therefore, accumulating one more deficit increases frailty by $\frac{1}{27}$. Figures 3 and 4 show short run effects (γ) and long run effects ($\frac{\gamma}{1-\alpha_1-\alpha_2}$) on earnings and hours, respectively, in response to a 1/27th increase in frailty. The solid lines show the 95 percent confidence interval.

Overall, accumulating one more deficit reduces earnings/hours by about 12 percent in

[9] We confirm this by running same regressions on hourly wage. Results are reported in Appendix A.



(a) Everyone

(b) Workers

Figure 3: Response of earnings to accumulation of one more health deficit (an incremental increase in frailty). Left panel shows the responses for everyone on the sample. Right panel shows the responses for those who stay employed. Solid lines show 95 percent confidence intervals.

the short run (two years). The long run effect is 55 percent on earnings and 40 percent on hours.

To capture all channels through which health affects earnings, in the next section we will develop a life cycle general equilibrium model with agents who make jointly decisions of consumption, saving, and labor supply in face of risky *frailty* dynamics as well as productivity and employment risk over the life cycle.

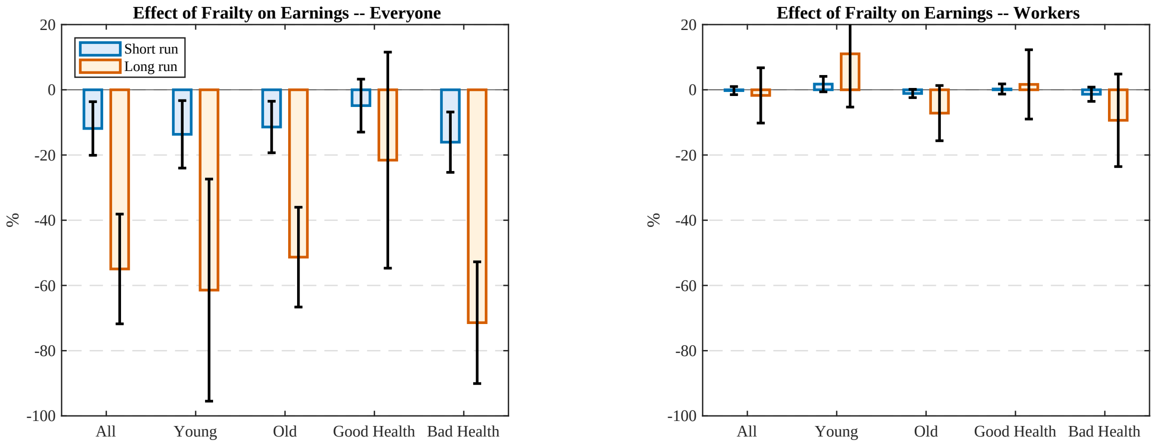
3 The Model

In this section, we describe our benchmark model.

3.1 Demographics

Time is discrete and the economy is populated by continuum of individuals in J overlapping generations. Individuals are born at age 1, and can live up to the maximum age J, that is, age $j = 1, 2, ..., J$. Individuals experience shock to their health status, measured by frailty index f, and they also face medical expenditure shock (out of pocket) and mortality risk, both depending on their frailty. At each age, the probability of surviving to the next period is denoted by $P(j, f)$. Individuals are ex ante heterogeneous with respect to their education level s, and they face uncertain labor productivity. There is an age $R < J$, after which individuals can choose to retire. Each period a new cohort is born at rate n and enters the economy.

Individuals derive utility from consumption c and suffer disutility from working hours l. The disutility from working also depends on frailty and is denoted by $\nu(l, f)$ with $\nu(0, f) = 0$.



(a) Everyone (b) Workers

Figure 4: Response of hours to accumulation of one more health deficit (an incremental increase in frailty). Left panel shows the responses for everyone on the sample. Right panel shows the responses for those who stay employed. Solid lines show 95 percent confidence intervals.

The markets are incomplete. However, everyone has access to a risk-free asset a that pays return r, and there are no other assets. Before retirement, each individual can be either employed, nonemployed or enrolled in Disability Insurance (DI). Employed workers earn wage $w(j,s,\epsilon)$ that depends on age j, education s, and a stochastic shock ϵ. The stochastic component ϵ evolves according to transition probability $\pi^e(\epsilon'|\epsilon,j)$. Employed workers may choose to quit and become nonemployed. They may also separate from their job exogenously with probability θ_s.

Nonemployed individuals can apply for DI or choose to go back to work immediately. If applied for DI, they are awarded DI with probability $\theta_d(j,s,f,n_a)$ in the next period, where n_a indicates the number of times they have applied for DI consecutively in the past. An individual who is awarded DI benefit remains DI beneficiary until he retires. Those who choose to go back to work immediately have to pay some penalty $pen(w)$, which is a function of his wage and cam be understood as cost of job search.

Individuals can choose to retire after reaching the retirement age ($j \geq R$). If chose to retire, they remain retired until they die. During retirement, individuals receive social security security benefit $SS(\bar{e})$, which is a function of their past earning histories, $\bar{e}$.

3.2 Health status and medical expenditure

Individuals' health status is measured by their frailty index, f, which evolves stochastically. An individual at age j who has frailty f will have frailty f' next period with probability $\pi^f(f'|f,j)$. As mentioned before frailty affects mortality risk, disutility from work, chance of successful DI award. Moreover, frailty affects the medical expenditure. An individual of age j and education s who has frailty f experience medical expenditure $m^i(j,s,f)$ for

$i = e, n, d, r$ depending on whether he is employed (e), nonemployed (n), DI beneficiary (d) or retired (r).

3.3 Government

Government makes three distinct transfers to different type of individuals:

- Disability insurance (DI): a DI beneficiary with earning history $\bar{e}$ receives DI benefit $B_d(\bar{e})$.
- Social Security (SS): a retired person with earning history $\bar{e}$ receives social security benefit benefit $SS(\bar{e})$.
- Means-tested transfer: it guarantees a minimum consumption floor for everyone.

To finance these transfers government levies a nonlinear tax on labor income $T(wl)$. In addition, government collects the asset of deceased and make lump-sum transfer to all individuals who are alive.[10]

3.4 Individual decision problems

We now describe the individual decision problem. Let $V^e(j, a, f, s, \epsilon, \bar{e}, n_a)$ be the value function for employed, $V^n(j, a, f, s, \epsilon, \bar{e}, n_a)$ be value function for unemployed, $V^d(j, a, f, s, \bar{e}, n_d)$ be value function for DI beneficiary, and $V^r(j, a, f, s, \bar{e})$ be value function for retiree. Here n_a is the state variable representing how many periods the individual has been in nonemployment consecutively in the past, which is equal to how many periods the individual has applied for DI consecutively in the past if he is nonemployed. n_d represents how many periods the individual has been in DI, which will be used to determine his Medicare benefits. In the rest of the section, we describe problems facing each type of individuals.

The employed worker's problem: when $j < R$, the employed worker has two choices, quit or work at the current wage. Those who choose to work, face the risk of exogenous separation θ_s at the beginning of next period. Their utility-maximization problem can be specified as follows,

$$V^e(j, a, f, s, \epsilon, \bar{e}, n_a) = \max \Big\{ V^n(j, a, f, s, \epsilon, \bar{e}, 0), \quad \max_{c,l,a'} \{ u(c) - \nu(l, f) \tag{6}$$

$$+\beta P(j, f) E[(1-\theta_s) V^e(j+1, a', f', s, \epsilon', \bar{e}', 0) + \theta_s V^n(j+1, a', f', s, \epsilon', \bar{e}', 0)] \} \Big\}$$

subject to

$$\frac{a'}{1+r} + c + m^e(j, f, s) = a + w(j, s, \epsilon) l - T(wl) - pen(w) I_{n_a > 0} + tr(.), \tag{7}$$

$$\bar{e}' = \frac{(j-1)\bar{e} + w(j, s, f, \epsilon) l}{j},$$

[10] To minimize notations, we combine lump-sum transfer from accidental bequests with means-tested transfers, and denote them by $tr(.)$.

$$c, a' \geq 0, \text{ and } l = \{l_{pt}, l_{ft}\},$$

where $I_{n_a>0}$ is the indicator function with 1 representing that the worker has just come back to work from nonemployment and 0 being otherwise. When the individual just came back from nonemployment, he has to pay a penalty $pen(w)$, which is a function of his wage rate and can be understood as job search related cost.

When $j \geq R$, the employed worker can only choose to retire or keep working at the current wage. They face the following optimization problem,

$$V^e(j,a,f,s,\epsilon,\bar{e},n_a) = \max\Big\{V^r(j,a,f,s,\epsilon,\bar{e}), \quad \max_{c,l,a'}\{u(c) - \nu(l,f) + \beta P(j,f) E[(1-\theta_s) V^e(j+1,a',f',s,\epsilon',\bar{e}',0) + \theta_s V^e(j+1,a',f',s,\epsilon',\bar{e}',1)]\}\Big\} \quad (8)$$

subject to 7.

The nonemployed's problem: when $j < R-1$, nonemployed individuals can choose to apply DI or go back to work immediately by paying penalty $pen(w)$. Those who apply for DI, become DI beneficiary with probability $\theta_d(j,f,s,n_a)$ at the beginning of the next period, otherwise they remain nonemployed. The chance of approval also depends on how many times they have applied for DI consecutively in the past, n_a.[11] The nonemployed individual's problem can be specified as follows,

$$V^n(j,a,f,s,\epsilon,\bar{e},n_a) = \max\Big\{\max_{c,a'} u(c) + \beta P(j,f) E\big[\theta_d(j,f,s,n_a) V^d(j+1,a',f',s,\bar{e},0) + (1-\theta_d(j,f,s,n_a)) V^n(j+1,a',f',s,\epsilon',\bar{e},n_a+1)\big], \quad V^e(j,a,f,s,\epsilon,\bar{e},n_a+1)\Big\} \quad (9)$$

subject to

$$\frac{a'}{1+r} + c + m^n(j,f,s) = a + tr(.), \quad (10)$$
$$c, a' \geq 0.$$

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

$$V^n(j,a,f,s,\epsilon,\bar{e},n_a) = \max\Big\{\max_{c,a'} u(c) + \beta P(j,f) EV^r(j+1,a',f',s,\bar{e}), \quad V^e(j,a,f,s,\epsilon,\bar{e},n_a+1)\Big\} \quad (11)$$

subject to 10.

[11] When a worker becomes nonemployed n_a is set to 0. Upon first DI application n_a is set to 1, and its value keeps increasing by 1 for each additional DI application until the DI is awarded or individual finds a job.

DI beneficiary: DI recipients only make consumption and saving decision. It is important to note that DI recipients can also get access to Medicare benefits after enrolled in DI for 2 years. In the model, this eligibility is determined by the state variable n_d, which represents the number of periods the individual has been in DI. DI recipients face the following problem,

$$V^d\left(j,a,f,s,\bar{e},n_d\right)=\max_{c,a'} u\left(c\right)+\beta P\left(j,f\right)E\left[V^d\left(j+1,a',f',s,\bar{e}',n_d+1\right)\right] \tag{12}$$

subject to

$$\frac{a'}{1+r}+c+m^d\left(j,f,s,n_d\right)=a+B_d\left(\bar{e}\right)+tr(.), \tag{13}$$

$$c,a'\geq 0.$$

When DI enrollees reach retirement age R, they automatically move from disability insurance to social security. Thus

$$V^d\left(R,a,f,s,\bar{e},n_d\right)=V^r\left(R,a,f,s,\bar{e}\right).$$

We define $V^r\left(j,a,f,s,\bar{e}\right)$ below.

Retiree: retirees remain retired until they die. They receive social security benefits and only make consumption and saving decision.

$$V^r\left(j,a,f,s,\bar{e}\right)=\max_{c} u\left(c\right)+\beta P\left(j,f\right)E\left[V^r\left(j',a',f',s,\bar{e}'\right)\right] \tag{14}$$

subject to

$$\frac{a'}{1+r}+c+m^r\left(j,f,s\right)=a+SS\left(\bar{e}\right)+tr(.) \tag{15}$$

3.5 Technology

There is a representative firm that produces a single 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 capital and labor input, and A is the total factor productivity. Capital depreciawtes at a constant rate $\delta\in(0,1)$. The representative firm maximizes profits such that the interest rate, r, and the wage rate $\hat{w}$, are given by:

$$r=\ \ \alpha A(K/N)^{\alpha-1}-\delta \quad and \quad \hat{w}\ \ =\ \ (1-\alpha)A(K/N)^{\alpha}. \tag{16}$$

3.6 Recursive competitive equilibrium

Let $\{X^i(.)\}$ represent the time-invariant measures of households of type i. We assume that they are the population measures after the labor participation decisions and DI application decisions are made. The concept of a stationary recursive competitive equilibrium can be defined as follows.

Stationary recursive competitive equilibrium (steady state): Given a fiscal policy $(G,T(.),DI,SS,\underline{c})$, a stationary recursive competitive equilibrium is a set of value functions $\{V^i(.)\}$, households' consumption and saving decisions $\{c^i(.), a'^i(.),\}$ and time-invariant measures of households $\{X^i(.)\}$ for each type of households $i = e, n, d, r$; labor participation decisions $I_w()$ for currently employed individuals and DI application decisions $I_d(.)$ for currently nonemployed individuals; relative prices of labor and capital $\{\hat{w}, r\}$, such that:

1. Given the fiscal policy and prices, households' decision rules solve households' decision problem in equation 6,9,11,12,14.

2. Factor prices solve the firm's profit maximization policy by satisfying equation 16.

3. Individual and aggregate behavior are consistent :

$$K = \sum_i \sum_{\{...\}} a^i(.)X^i(.)$$

$$N = \sum_{\{a,f,s,\epsilon,\bar{e},n_a\}} e_j e_s \epsilon l(.) X^e(a, f, s, \epsilon, \bar{e}, n_a)$$

4. The measures of households $\{X^i(.)\}$ satisfy:

   (a) Employed: for any $j < J$,

   $$X^e(j+1, a', f', s, \epsilon', \bar{e}', n'_a) = I_w(.)\bar{X}^e(j+1, a', f', s, \epsilon', \bar{e}', n'_a) + (1-I_d(.))\bar{X}^n(j+1, a', f', s, \epsilon', \bar{e}', n'_a-1)I_{n'_a \geq 1}.$$

   Here $\bar{X}^e$ and $\bar{X}^n$ are the population measures of employed and unemployed at the beginning of period before the labor participation decision and the DI application decisions are made, which will be defined later.

   (b) Nonemployed: for any $j < R - 1$,

   $$X^n(j+1, a', f', s, \epsilon', \bar{e}', n'_a) = (1-I_w(.))\bar{X}^e(j+1, a', f', s, \epsilon', \bar{e}', n'_a) + I_d(.)\bar{X}^n(j+1, a', f', s, \epsilon', \bar{e}', n'_a)$$

   (c) DI enrollee: for any $j <$ R-1,

   $$X^d(j+1, a', f', s, \epsilon', \bar{e}', n'_d) = \frac{1}{1+n} \sum_{\{a,f,s,\epsilon,\bar{e}\}} \pi^e(\epsilon'|\epsilon, j)\, \pi^f(f'|f, j)\, I_{a'=a'()}(1-I_{n'_d=0})X^d(j, ..., n'_d-1)$$

   $$+\frac{1}{1+n} \sum_{\{a,f,s,\epsilon,\bar{e},n_a\}} \theta_d(j, f, s, n_a)\pi^e(\epsilon'|\epsilon, j)\, \pi^f(f'|f, j)\, I_{a'=a'()}I_{n'_d=0}X^n(j, ...),$$

   (d) Retiree: for any $J > j \geq R$,

   $$X^r(j+1, a', f', s, \epsilon', \bar{e}) = \frac{1}{1+n} \sum_{\{a,f,s,\epsilon,\bar{e}\}} \pi^e(\epsilon'|\epsilon, j)\, \pi^f(f'|f, j)\, I_{a'=a'()}X^r(j, ...)$$

   $$+\sum_{n_a}(1 - I_w(.))\bar{X}^e(j + 1, a', f', s, \epsilon', \bar{e}, n_a).$$

   For $j = R - 1$,

   $$X^r(j + 1, a', f', s, \epsilon', \bar{e}) = \frac{1}{1+n} \sum_{\{a,f,s,\epsilon,\bar{e},n_d\}} \pi^e(\epsilon'|\epsilon, j)\, \pi^f(f'|f, j)\, I_{a'=a'()}X^d(j, ...)+$$

   $$\frac{1}{1+n} \sum_{\{a,f,s,\epsilon,\bar{e},n_a\}} \pi^e(\epsilon'|\epsilon, j)\, \pi^f(f'|f, j)\, I_{a'=a'()}X^n(j, ...)+\sum_{n_a}(1-I_w(.))\bar{X}^e(j+1, a', f', s, \epsilon', \bar{e}, n_a).$$

(e) The population measures of employed and unemployed at the beginning of period before the labor participation decision and the DI application decisions are made, $\bar{X}^e$ and $\bar{X}^n$, satisfy,

$$\bar{X}^e(j+1, a', f', s, \epsilon', \bar{e}', 0) = \frac{1}{1+n} \sum_{\{a,f,s,\epsilon,\bar{e},n_a\}} (1-\theta_s)\pi^e(\epsilon'|\epsilon, j)\,\pi^f(f'|f, j)\,I_{a'=a'()}X^e(j, ...),$$

for $j < J$.

$$\bar{X}^n(j+1, a', f', s, \epsilon', \bar{e}', n_a') = \frac{1}{1+n} \sum_{\{a,f,s,\epsilon,\bar{e}\}} (1-\theta_d)\pi^e(\epsilon'|\epsilon, j)\,\pi^f(f'|f, j)\,I_{a'=a'()}X^n(j, ..., n_a'-1),$$

for $j < R-1$, and, $n_a' \geq 1$.

(f) The measures of age $j = 1$ individuals are zero except:

$$X^e(1, 0, f, s, \epsilon, 0, 0) = const_{in} I_w(1, 0, f, s, \epsilon, 0, 0)\bar{\pi}(f)\bar{\pi}(\epsilon)\bar{\pi}(s),$$

$$X^n(1, 0, f, s, \epsilon, 0, 0) = const_{in}(1 - I_w(1, 0, f, s, \epsilon, 0, 0))\bar{\pi}(f)\bar{\pi}(\epsilon)\bar{\pi}(s),$$

where $const_{in}$ is normalized so that the measure of total population (the sum of $\{X^i(.)\}$) is equal to one.

5. The government's budget holds, that is, (to be updated)

$$\sum_{\{j,a,f,s,\epsilon,\bar{e},n_a\}} T(w(j, s, \epsilon)l(.))X^e(.) = \sum_{\{...\}} X^d(.)DI(\bar{e}) + \sum_{\{...\}} X^r(.)SS(\bar{e}) + G$$

4 Calibration (preliminary)

We calibrate the benchmark model to the U.S. data. Our calibration strategy consists of two stages. In the first stage, we predetermine the values of some standard parameters based on independent estimates or the existing literature. In the second stage, we calibrate the rest of the parameters to match some key moments of the U.S. data. In particular, we determine the key parameter values to match the joint dynamics of health and earnings over the life cycle that we documented in Section 2 using the frailty index as the health measure.

4.1 Demographics

One model period is one year. We assume age $j = 1$ corresponding to 25 year old and $J = 70$ corresponding to 94 year olds. Retirement age is $R = 41$ (66 year olds). Conditional survival probability at each age is assumed to be a function of frailty, age, and education. Specifically, we estimate it by running the following probit regression in the PSID data:[12]

$$y_{ji} = constant + \beta_1 f_{ji} + \beta_2 f_{ji}^2 + \beta_3 j_i + \beta_4 j_i^2 + \beta_5 s_i + \gamma_i X_{ji} + \epsilon_{ji},$$

where y_{ji} is the conditional survival probability agent i faces at age j, and X_i is a set of covariates. We adjust the value of the estimated constant so that population mortality is consistent with life-table in Bell and Miller (2005).

[12] The detailed description of the PSID sample used in our analysis can be find in section A.

4.2 Preference , labor productivity and job search

We assume a separable utility function in consumption and hours worked. Individuals have CRRA utility over consumption and constant Frisch elasticity disutility over hours. Moreover, a person at age j who has frailty f suffer an extra disutility from working. Therefore period utility is given as,

$$\frac{c^{1-\sigma}-1}{1-\sigma}-\nu\left(l,f\right)$$

for workers and

$$\frac{c^{1-\sigma}-1}{1-\sigma}$$

For everyone else.

In the benchmark calibration, we set $\sigma=2$, which is in the middle of the range of values used in the standard macro literature. We choose the function $\nu\left(l,f\right)$ to match labor force participation by age and frailty that we documented in Figure 2a. Specifically, to capture the fact that more dispersion in LFP among frail, we assume disutility from working as an increasing and convex function of frailty, that is,

$$\nu\left(l,f\right)=a_l\frac{l^{1+\frac{1}{b_l}}}{1+\frac{1}{b_l}}+a_\nu f^{b_\nu},$$

where $a_l>0$, $a_\nu>0$, $b_\nu>1$, and b_l is the Frisch elasticity. The current parameterization assumes the following: $l\in 0.2,0.4$, $a_l=1$, $b_l=1$, $a_\nu=100$ and $b_\nu=3$.

The stochastic component ϵ in wage is assumed to evolve according to the standard AR(1) process as in the literature, and we are currently using Guvenen (2009)'s estimates for the parameter values in the process. It is discretized into a 5-state Markov chain. Job separation rate is set to 5%.

4.3 Frailty and medical expenditure

We model the dynamics of frailty index, f, based on our previous work Hosseini et al. (2018). That is, we assume that the frailty index f_{it} for individual i at age t is the sum of a deterministic component whose effect is common to all individuals and a residual that is individual-specific:

$$f_{it}=X_{it}'\beta+R_{it},$$

where X_{it} is a set of covariates.[13] The residual consists of two components and is given by

$$R_{it}=\alpha_i+\gamma_i t+z_{it}+u_{it}.$$

The first component, $\alpha_i+\gamma_i t$, allows for individual-specific effects on the levels and growth rate of frailty. As shown in Hosseini et al. (2018), this is an important component of the model as it allows us to capture ex-ante heterogeneity in individuals' initial frailty levels and the growth rate of frailty over their life cycles. We assume that (α_i,γ_i) is randomly

[13]The set of covariates include age, age-squared, gender, marital status and education. It also includes a full set of cohort dummies.

distributed across individuals with mean zero, variances σ_α^2 and σ_γ^2, and covariance $\sigma_{\alpha\gamma}$, and we discretize each of them into a 3-state discrete variable. The second component is the sum of an AR(1) process and a transitory shock u_{it}. Thus

$$z_{it} = \rho z_{it-1} + \varepsilon_{it},$$

where $z_{i,0} = 0$.[14] The shocks ε_{it} and u_{it} are assumed to be independent of each other and over time, and independent of α_i and γ_i. We assume that ε_{it} has mean zero and variance σ_ε^2, and u_{it} has mean zero and variance σ_u^2.

We choose the values of the parameters in the frailty shock process based on our empirical estimation results reported in Hosseini et al. (2018). We discretize the AR (1) process into a 15-state Markov chain by using the Rouwenhorst (1995) method, where the permanent component is discretized in to 5 states and the transitory shock is discretized into 3 states.[15]

Medical expenditure is currently set to zero.

4.4 DI application

Unemployed individuals who apply for DI, become DI beneficiary with probability $\theta_d(j, f, I_d)$. Here we choose the functional form for $\theta_d(j, f, I_d)$ to match DI enrollment by age and frailty quintiles that are documented in Figure 6a. Specifically, we assume the probability of receiving DI is an increasing and convex function in frailty, that is,

$$\theta_d = \min(1.0, a_d f^{b_d}),$$

where $a_d > 0$ and $b_d > 1$. The current parameterization assumes: $a_d = 100$ and $b_d = 3$)

4.5 Policy parameters

For social security and disability insurance benefits, we use social security benefit formula for primary insurance amount (PIA). They are a non-linear function of individuals' average past earnings. Following Fuster, Imrohoroglu, and Imrohoroglu (2007) and among others, the benefit formula is specified as in Table 3. We rescale the social security benefits to match the total social security and disability insurance benefits as a share of GDP in the U.S. data.

The tax function $T(.)$ has two component. One is the nonlinear component mimicking the U.S. tax/transfer system, and the other is the social security payroll tax function (subject to maximum taxable earning cap) to finance the disability insurance and public pension programs. We model the non-linear component of the tax function in the fashion of Benabou (2002) and Heathcote et al. (2017). That is, the tax function $T(\cdot)$ is given as follows,

$$T(e) = e - \tau e^{1-\lambda} + \pi_{ss} e.$$

[14]Note that t represents age and not time which means we are assuming that the stochastic component of frailty can vary with age but is time-invariant. The variance of frailty increases with both age and time in both the PSID and HRS samples. However, the increase with age is much more dramatic so we went with an age-dependent but time-invariant stochastic component.

[15]Kopecky and Suen (2010) show that the Rouwenhorst (1995) method is more precise than the Tauchen (1986) method for persistent income processes.

Table 3: Social Security and DI Benefit Formula

average lifetime earnings	Replacement rate
$[0, 0.2\bar{e}_a)$	90%
$[0.2\bar{e}_a, 1.25\bar{e}_a)$	33%
$[1.25\bar{e}_a, 2.47\bar{e}_a)$	15%
$[2.47\bar{e}_a, \infty)$	0%

Note: $\bar{e}_a$ is the average lifetime earnings of the economy.

Here λ controls the progressivity of the tax function, which is set to 0.16 based on the estimate by Straub (2018). We calibrate the value of τ to match the total tax revenues in the U.S. data (i.e., $\tau = 0.3$ for now). The social security payroll tax rate π_{ss} is 12.4%.

4.6 Rental rate and wages

Currently, we assume partial equilibrium. We set $r = 0.04$ as after tax return on asset and drop asset taxes. We normalize aggregate wages to 1, and choose β to match wealth-income ratio ($\beta =$). As for the employed workers who just came back from nonemployment, we assume that they suffer a wage penalty, which mimics the forgone earnings during job search within the period. According to the data available at the St Louis Fed, the average duration of unemployment in the pre-crisis U.S. was approximately 15-20 weeks. Therefore, we set the wage penalty to be a third of one year's earnings.

5 Quantitative Results (preliminary)

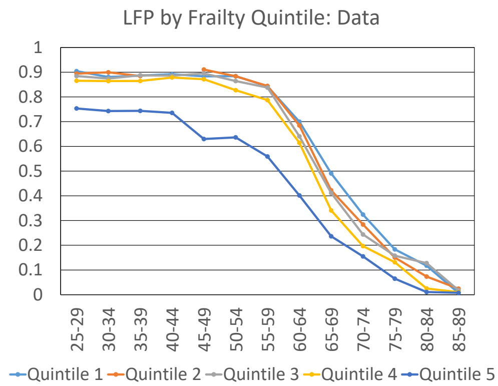
In this section, we use the calibrated model to assess the quantitative importance of the impact of health inequality on lifetime earnings inequality. We ask the quantitative question: To what extent can different health profiles over the life cycle account for the lifetime earnings inequality among the 70 year-olds? Specifically, we consider a counterfactual experiment in which everyone is assumed to experience the same health profile over the life cycle, and investigate how much less lifetime earnings inequality there would be among the 70 year-olds in this counterfactual economy.

5.1 The Benchmark Economy

We start this section by examining the key statistics of the calibrated benchmark economy. As shown in Table 4, our current calibration implies a wealth-income ratio of xx, and an average income tax rate of xx.

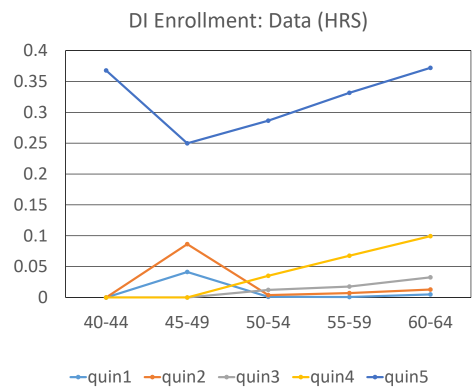
Figure 5 plots the employment rates by age and frailty quintiles in the benchmark model together with their data counterparts from PSID. Figure 6 plots the DI enrollment rates by age and frailty quintiles in the benchmark model together with their data counterparts we documented from MEPS.

Table 5 presents the lifetime earnings distribution of 70 year-olds in the benchmark model together with their data counterpart we documented from the HRS data. As can be seen,



(a) Data (b) Model

Figure 5: Employment rate by age and frailty quintile.



(a) Data (b) Model

Figure 6: DI Enrollment by age and frailty quintile

the benchmark model matches the data fairly well for the lifetime earnings distribution of 70 year olds except the very top tail. The lifetime earnings gini is 0.4 among the 65-70 year-olds in HRS, while the lifetime earnings gini is xx for the 70 year-olds in the model.

Table 4: Properties of the Benchmark Economy

Statistic	Data	Benchmark Model
Interest Rate		
Wage rate		
Average income tax rate		
Wealth-income ratio		
..		
..		

Table 5: Lifetime Earnings Distribution: data vs. model

	as % of Total								Gini
	Each Quintile					Top shares			
	1st	2nd	3rd	4th	5th	10%	5%	1%	
Data	3.1	10.2	16.4	24.0	46.3	29.6	18.7	7.0	0.40
Benchmark									
Counterfactual									

Data source: HRS?

5.2 Counterfactual Economy without Heterogeneous Health Profiles

To evaluate the role of health inequality over the life cycle in shaping lifetime earnings inequality, we construct and analyze a counterfactual experiment in which everyone is assumed to experience the same health profile over the life cycle. Specifically, to construct the counterfactual economy we assume that everyone experiences the average health profile in the benchmark economy while everything else is kept unchanged. We quantify the impact of health inequality by comparing the lifetime earnings inequality in the benchmark model (with health inequality) with that in this counterfactual case (without health inequality).

6 Conclusion

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A Appendix

A.1 Data

We use 2003–2015 PSID data. The PSID is biennial over this period. We do not use years prior to 2003 because the PSID expanded its disability and health-related questions in 2003 to include questions on specific medical conditions, activities of daily living (ADL's) and instrumental activities of daily living (IADL's) which we rely on to construct individuals' frailty indices. For the base sample, the only restriction is that a person is a household head or the spouse of a household head and at least 25 years of age. A good description of the PSID household head definition is in Heathcote et al. (2010). The base sample consists of 18,548 individuals (8,765 men, 9,784 women; 13,224 household heads, 7,128 spouses).

Table 6 lists the variables we used to construct the frailty index for PSID respondents. The index is constructed by summing the variables in the first column of the table using their values which are assigned according to the rules in the second column. Then dividing this sum by the total number of variables observed for the individual in the year. The construction of this frailty index mostly follows the guidelines laid out in Searle et al. (2008), and uses a set of PSID variables similar to the index created in Yang and Lee (2009).

Table 6: Health Variables used to construct frailty index for PSID respondents

Variable	Value
Some difficulty with ADL/IADLs:	
Eating	Yes=1, No=0
Dressing	Yes=1, No=0
Getting in/out of bed or chair	Yes=1, No=0
Using the toilet	Yes=1, No=0
Bathing/showering	Yes=1, No=0
Walking	Yes=1, No=0
Using the telephone	Yes=1, No=0
Managing money	Yes=1, No=0
Shopping for personal items	Yes=1, No=0
Preparing meals	Yes=1, No=0
Heavy housework	Yes=1, No=0
Light housework	Yes=1, No=0
Getting outside	Yes=1, No=0
Ever had one of following conditions:	
High Blood Pressure	Yes=1, No=0
Diabetes	Yes=1, No=0
Cancer	Yes=1, No=0
Lung disease	Yes=1, No=0
Heart disease	Yes=1, No=0
Heart attack	Yes=1, No=0
Stroke	Yes=1, No=0
Arthritis	Yes=1, No=0
Asthma	Yes=1, No=0
Loss of memory or mental ability	Yes=1, No=0
Psychological problems	Yes=1, No=0
Other serious, chronic condition	Yes=1, No=0
BMI ≥ 30	Yes=1, No=0
Has smoked ever	Yes=1, No=0

Table 7: Effect of Frailty on Earnings

	Everyone			Workers		
	OLS	F.E.	GMM	OLS	F.E.	GMM
log(earnings$_{t-1}$)	0.594***	0.125***	0.765***	0.624***	0.042 ***	0.566***
	(0.007)	(0.009)	(0.124)	(0.011)	(0.014)	(0.180)
log(earnings$_{t-2}$)	0.183***	-0.079***	0.019	0.254***	-0.062***	0.289*
	(0.007)	(0.008)	(0.061)	(0.010)	(0.011)	(0.174)
frailty$_{t-1}$	-3.089***	-4.354***	-3.204***	-0.157***	0.026	-0.068
	(0.159)	(0.448)	(1.132)	(0.043)	(0.107)	(0.171)
Controls	YES	YES	YES	YES	YES	YES
Obs.	44,879	44,879	44,879	21,919	21,919	21,919
R^2	0.618	0.096		0.707	0.038	
AR(1) test (p-value)			0.000			0.046
AR(2) test (p-value)			0.071			0.431
Hansen test (p-value)			0.533			0.091
Diff-in-Hansen test (p-value)			0.120			0.347
Note: standard errors in parenthesis				$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

Table 8: Effect of Frailty on Earnings – Young vs Old

	Everyone			Workers		
	OLS	F.E.	GMM	OLS	F.E.	GMM
log(earnings$_{t-1}$)	0.594***	0.125***	0.754***	0.624***	0.042***	0.552***
	(0.007)	(0.009)	(0.121)	(0.011)	(0.014)	(0.175)
log(earnings$_{t-2}$)	0.183***	-0.080***	0.024	0.254***	-0.063***	0.290*
	(0.007)	(0.008)	(0.060)	(0.010)	(0.011)	(0.170)
frailty$_{t-1}$ $\times$ Young (<45yo)	-3.527***	-3.759***	-3.688**	-0.227***	0.067	0.471
	(0.277)	(0.593)	(1.415)	(0.070)	(0.138)	(0.326)
frailty$_{t-1}$ $\times$ Old (>45yo)	-2.909***	-4.576***	-3.081***	-0.112**	0.006	-0.306*
	(0.177)	(0.477)	(1.088)	(0.049)	(0.112)	(0.176)
Controls	YES	YES	YES	YES	YES	YES
Obs.	44,879	44,879	44,879	21,919	21,919	21,919
R^2	0.617	0.096		0.707	0.037	
AR(1) test (p-value)			0.000			0.043
AR(2) test (p-value)			0.078			0.409
Hansen test (p-value)			0.460			0.095
Diff-in-Hansen test (p-value)			0.072			0.182
Note: standard errors in parenthesis				$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

Table 9: Effect of Frailty on Earnings – Good Health vs Bad Health

	Everyone			Workers		
	OLS	F.E.	GMM	OLS	F.E.	GMM
log(earnings$_{t-1}$)	0.588***	0.122***	0.754***	0.624***	0.042***	0.558***
	(0.007)	(0.009)	(0.115)	(0.011)	(0.014)	(0.167)
log(earnings$_{t-2}$)	0.180***	-0.079***	0.021	0.253***	-0.063***	0.296*
	(0.007)	(0.008)	(0.056)	(0.010)	(0.011)	(0.162)
frailty$_{t-1}$ $\times$ Good Health	-1.479***	-2.987***	-1.311	-0.095**	0.079	0.065
	(0.191)	(0.464)	(1.118)	(0.047)	(0.109)	(0.214)
frailty$_{t-1}$ $\times$ Bad Health	-4.205***	-5.125***	-4.338***	-0.318***	-0.079	-0.370
	(0.190)	(0.470)	(1.275)	(0.065)	(0.121)	(0.301)
Controls	YES	YES	YES	YES	YES	YES
Obs.	44,879	44,879	44,879	21,919	21,919	21,919
R^2	0.619	0.098		0.707	0.038	
AR(1) test (p-value)			0.000			0.034
AR(2) test (p-value)			0.058			0.370
Hansen test (p-value)			0.376			0.100
Diff-in-Hansen test (p-value)			0.189			0.250

Note: standard errors in parenthesis — $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Good Health: Those with self reported health status of 'Excellent', 'Very Good', or 'Good'

Bad Health: Those with self reported health status of 'Fair', or 'Poor'

Table 10: Effect of Frailty on Hours

	Everyone			Workers		
	OLS	F.E.	GMM	OLS	F.E.	GMM
log(hours$_{t-1}$)	0.592***	0.131***	0.610***	0.371***	-0.094 ***	0.162
	(0.007)	(0.009)	(0.130)	(0.011)	(0.014)	(0.143)
log(hours$_{t-2}$)	0.175***	-0.077***	0.090	0.184 ***	-0.133***	0.167
	(0.007)	(0.008)	(0.063)	(0.009)	(0.011)	(0.133)
frailty$_{t-1}$	-2.237***	-3.247***	-3.328***	-0.061**	-0.026	0.029
	(0.117)	(0.328)	(0.854)	(0.033)	(0.101)	(0.134)
Controls	YES	YES	YES	YES	YES	YES
Obs.	44,879	44,879	44,879	21,919	21,919	21,919
R^2	0.607	0.095		0.289	0.042	
AR(1) test (p-value)			0.000			0.013
AR(2) test (p-value)			0.697			0.471
Hansen test (p-value)			0.587			0.065
Diff-in-Hansen test (p-value)			0.115			0.071

Note: standard errors in parenthesis — $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 11: Effect of Frailty on Hours – Young vs Old

	Everyone			Workers		
	OLS	F.E.	GMM	OLS	F.E.	GMM
$\log(\text{earnings}_{t-1})$	0.592***	0.130***	0.623***	0.371***	-0.094***	0.220
	(0.007)	(0.009)	(0.130)	(0.011)	(0.014)	(0.149)
$\log(\text{earnings}_{t-2})$	0.175***	-0.078***	0.083	0.184***	-0.133***	0.125
	(0.007)	(0.008)	(0.063)	(0.009)	(0.011)	(0.135)
$\text{frailty}_{t-1} \times$ Young (< 45yo)	-2.532***	-2.896***	-3.486***	-0.071	-0.015	0.452
	(0.205)	(0.434)	(1.097)	(0.048)	(0.119)	(0.275)
$\text{frailty}_{t-1} \times$ Old (> 45yo)	-2.116***	-3.378***	-3.047***	-0.055	-0.032	-0.118
	(0.130)	(0.352)	(0.824)	(0.041)	(0.108)	(0.138)
Controls	YES	YES	YES	YES	YES	YES
Obs.	44,879	44,879	44,879	21,919	21,919	21,919
R^2	0.607	0.095		0.289	0.042	
AR(1) test (p-value)			0.000			0.008
AR(2) test (p-value)			0.611			0.757
Hansen test (p-value)			0.543			0.045
Diff-in-Hansen test (p-value)			0.079			0.060
Note: standard errors in parenthesis				$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		

Table 12: Effect of Frailty on Hours – Good Health vs Bad Health

	Everyone			Workers		
	OLS	F.E.	GMM	OLS	F.E.	GMM
$\log(\text{earnings}_{t-1})$	0.585***	0.128***	0.649***	0.370***	-0.094***	0.138
	(0.007)	(0.009)	(0.124)	(0.011)	(0.014)	(0.140)
$\log(\text{earnings}_{t-2})$	0.173***	-0.077***	0.067	0.184***	-0.133***	0.194
	(0.007)	(0.008)	(0.060)	(0.009)	(0.011)	(0.137)
$\text{frailty}_{t-1} \times$ Good Health	-1.020***	-2.251***	-1.152	-0.015	0.051	-0.029
	(0.140)	(0.339)	(0.836)	(0.034)	(0.098)	(0.195)
$\text{frailty}_{t-1} \times$ Bad Health	-3.079***	-3.810***	-4.043***	-0.178***	-0.177	0.140
	(0.140)	(0.347)	(0.983)	(0.059)	(0.125)	(0.272)
Controls	YES	YES	YES	YES	YES	YES
Obs.	44,879	44,879	44,879	21,919	21,919	21,919
R^2	0.609	0.097		0.290	0.043	
AR(1) test (p-value)			0.000			0.016
AR(2) test (p-value)			0.416			0.358
Hansen test (p-value)			0.489			0.102
Diff-in-Hansen test (p-value)			0.288			0.083
Note: standard errors in parenthesis				$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$		
Good Health: Those with self reported health status of 'Excellent', 'Very Good', or 'Good'						
Bad Health: Those with self reported health status of 'Fair', or 'Poor'						

Table 13: Effect of Frailty on Wages of Workers

	Workers		
	(1)	(2)	(3)
$\log(\text{wages}_{t-1})$	0.4234	0.3756	0.5942**
	(0.2691)	(0.2484)	(0.2648)
$\log(\text{wages}_{t-2})$	0.4563*	0.4967**	0.2965
	(0.261)	(0.2413)	(0.2564)
frailty_{t-1}	-0.1765		
	(0.1541)		
frailty_{t-1} × Young (age $\leq$ 45)		0.0091	
		(0.3219)	
frailty_{t-1} × Old (age > 45)		-0.2468	
		(0.1508)	
frailty_{t-1} × Good Health			-0.1365
			(0.2209)
frailty_{t-1} × Bad Health			-0.3696
			(0.2715)
Controls	YES	YES	YES
Observations	21,919	21,919	21,919
AR(1) test (p-value)	0.2621	0.2514	0.1467
AR(2) test (p-value)	0.3446	0.2341	0.7139
Hansen test (p-value)	0.2447	0.2457	0.2863
Diff-in-Hansen test (p-value)	0.8241	0.4769	0.3631

Notes: Columns (1) to (3) show results conditional on continued employment. All regressions include controls (marital status, marital status interacted with gender, number of kids, number of kids interacted with gender and cubic polynomial in age). 'Good Health' is self reported health status of Excellent/Very Good/Good. 'Bad Health' is self reported health status of Fair/Poor. Standard errors on parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.