How Important Is Health Inequality for Lifetime Earnings Inequality?*

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January 13, 2020

Abstract

We study the impact of poor health on lifetime earnings inequality. First, using a dynamic panel data approach, we provide empirical evidence that negative health shocks reduce earnings. The effect is primarily driven by the participation margin and is concentrated in less educated and poor health individuals. Next, we build a dynamic, general equilibrium, lifecycle model that is consistent with these findings. Working-age individuals in the model have heterogeneous and risky health profiles. They choose to either work, or not work and apply for social security disability insurance (SSDI). Health impacts individuals' productivity, SSDI access, disutility from work, mortality, and medical costs. Calibrating the model to the U.S, we find that in an economy where all individuals receive the average health profile the variance of log lifetime earnings is 32 percent lower (at age 65) and 29 percent lower (at age 75) relative to the benchmark. The most important factor accounting for the decline is the fact that the removal of health inequality reduces lower-productivity individuals' access to SSDI and, consequently, increases their labor supply.

Keywords: earnings, health, frailty, inequality, disability, dynamic panel estimation, life-cycle models

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

*We would like to thank Hans Schwandt and David Wiczer for insightful discussions. We would also like to thank attendees at the IFS conference on Inequality and Transfers over the Life Cycle, FRB San Francisco conference on Micro-Macro Labor Economics, MRDRC Researcher Workshop, Shanghai Macro Workshop, SED, Midwest Macro, as well as seminar participants at PHBS, University of Hawaii, McMaster University, USC Marshall School, FRB Philadelphia, William and Mary, University of Houston, and University of Tokyo for helpful comments and conversations. We would like to thank Jordan Herring for outstanding research assistance.

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1 Introduction

Individuals in the United States face health risk and those in relatively poorer health have lower earnings, lower wealth and are more likely to be out of labor force.[1] Our goal in this paper is to quantify the impact of health inequality on lifetime earnings inequality. In particular, we are interested in how much of the variation in lifetime earnings among older individuals in the U.S. is due to the fact that they face heterogeneous and risky life cycle health profiles.

We are also interested in understanding the relative contributions of the several channels through which health may impact individuals. The five potential channels we consider are as follows. First, poor health is associated with higher out-of-pocket medical expenses. Second, it is associated with higher mortality risk. Third, individuals in poor health may have a higher cost of working, both physically and psychologically, which can affect their labor supply and, hence, earnings. Fourth, poor health may have direct negative impacts on labor productivity and wages. Finally, in the U.S., individuals who are not working and in poor health have a higher likelihood of being awarded Social Security Disability Insurance (SSDI) benefits.

To quantify the impact of health inequality on lifetime earnings inequality, we build and parametrize a heterogeneous agent life cycle model. Each of the five channels through which health may impact individuals is present in the model. We find that health inequality has a large effect on lifetime earnings inequality. If we give all individuals in the economy the average life cycle health profile, the variance of log lifetime earnings at age 75 declines by 29 percent. Through a series of decomposition exercises, we find that the results are mainly driven by a combination of the SSDI, productivity, and disutility channels. The fact that individuals in poor health can obtain SSDI benefits has the largest impact on the older workers, while the negative impact of poor health on labor productivity is the key factor for younger workers.

Our analysis employs a new objective measure of health status, called the *frailty index*, that we explore extensively in Hosseini et al. (2019).[2] 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*. It is highly predictive of health-related outcomes and widely used in Gerontology.[3]

An important advantage of the frailty index is that it allows for the measurement of health on a finer scale. This is important because, as we show in Hosseini et al. (2019), there is significant variation in frailty among working-age individuals in the United States but most of this variation is concentrated among unhealthy individuals. In other words, the cross-sectional distribution of frailty is highly-skewed. To accurately assess the impact of health inequality on earnings inequality, it is important to have a measure of health that allows us to observe the variation in the unhealthy tail of the distribution and its correlation with earnings and labor supply. In particular, we document that, at any age, moving up

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

[2]We are not the first study that uses the frailty index as a measure of health status. See Dalgaard and Strulik (2014), Schünemann et al. (2017b), and Schünemann et al. (2017b,a) for other instances.

[3]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), among others.

along the thin, unhealthy tail is correlated with lower probabilities of being employed and a higher probability of being on SSDI.

We start out by conducting an empirical analysis that is used to motivate and guide the development of our structural model. In particular, we use data from the Panel Study of Income Dynamics (PSID) and a dynamic panel data approach (see Blundell and Bond (1998)) to estimate the impact of health on current earnings and its components: participation, hours conditional on working, and wages. The fact that we can measure frailty on a finer scale also means that we can treat it as a continuous variable. This is an attractive feature of the frailty index for our empirical analysis because it allows us to use it to estimate the marginal impacts of health on earnings and its components. Estimating marginal impacts is not possible with categorical measures of health such as self-reported health status.

In our dynamic panel data estimation, we find that an incremental deterioration of health (adding one more deficit to frailty) has a large effect on earnings. Accumulating one additional deficit reduces earnings by 20 percent. The impact operates primarily through the employment margin and is more pronounced among individuals who are already in poor health and individuals without a college degree. In particular, we find no statistical significant effect on hours conditional on working and smaller effects of frailty on wages that are only significant for individuals without a college degree. We also use our dynamic panel estimator to estimate the causal effect of earnings on frailty. We fail to find statistical significant effects both overall and, on average, within the education and health groups we consider.

Using our empirical findings as a guide, we build a general equilibrium, life cycle model featuring agents who experience heterogeneous and risky *frailty* dynamics over their life cycle as well as productivity and employment risk. Agents jointly make consumption, savings, and labor supply decisions in each period over their life cycle. Given our empirical findings, 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 and apply for disability insurance. Retirement-age individuals can choose to work or retire. In the model, markets are incomplete, but there exists a government that runs the disability insurance program, as well as, a social security program, and a tax/transfer system.

Since we do not find any statistical significant effects of earnings on frailty, we do not allow for such feedback effects in the model. Instead, we assume that individuals in the model face exogenously-given frailty processes. The processes are estimated using the PSID data following Hosseini et al. (2019). In the data, there is variation in frailty even among younger workers, under the age of 35, and this variation rises with age. To match this feature of the data, our frailty process consists of two components. First, individuals are heterogeneous in their initial levels of frailty when they start their working-life. Second, individuals experience frailty risk. In particular, they incur highly persistent frailty shocks whose variances increase as they age.

In the model, an individual's frailty affects their behavior through five different channels: 1) mortality rates, 2) out-of-pocket medical expenditures, 3) labor productivity, 4) probability of successful DI application, and 5) disutility from working. We estimate the effect of frailty on the mortality rate, out-of-pocket medical expenditures and labor productivity (proxied by wages) directly from the data. To estimate the effect of frailty on productivity we use our dynamic panel data estimator. One concern is that our estimated effect may be biased due to selection. We only observe wages of workers but we want to estimate the effect of frailty on potential wages even for non-participants. Al-Sadoon et al. (2019) show that the effects of selection bias are small in dynamic panel data estimation and propose a simple procedure for correcting for them. We follow their procedure. Correcting for selection bias slightly increases the estimated effects of frailty on productivity as compared to the uncorrected estimates. However, the effects are still only significant for individuals with less than a college degree.

The parameters governing the impact of frailty on the probability of successful SSDI application and the disutility from working are chosen such that the model reproduces the cross-sectional variation in labor force participation and disability recipiency by age and frailty in the data. Since most of the variation in labor supply and SSDI recipiency occurs in the unhealthy tail of the frailty distribution, the set of moments targeted is concentrated in this tail.

To disentangle the effect of the SSDI channel from that of the disutility one we use the following strategy. We target the variation in SSDI recipiency rates and labor force participation rates by frailty for 5-year age groups of individuals ages 25 to 64. However, we also target the dispersion in labor force participation rates by frailty for individuals aged 65 to 74. The variation in labor force participation by frailty after age 65 cannot be directly due to the SSDI channel. In the U.S., after age 65, individuals can no longer receive SSDI benefits. Instead, all individuals (regardless of their health status), are eligible for social security retirement benefits. Thus, these additional moments pin down the effect of frailty on the disutility of working.

To assess the quality of our baseline calibration of the model we assess the model's ability to match a set of non-targeted moments. The moments we focus on are the variation in labor force participation rates and SSDI recipiency rates by education. We have three education groups in the model: individuals with less than a high school degree, high school graduates, and college graduates. We compare both the aggregate labor force participation rates and SSDI recipiency rates by education in the model to the data and the variation in these rates by frailty and age within each education groups. The model is able to replicate the patterns in these rates observed in the data.

We use the calibrated model to run the following counterfactual experiment. We assign the average age profile of frailty to all individuals in the model and compare the variance of log lifetime (cumulative) earnings in the counterfactual model to that in the baseline. Removing health inequality in this way reduces the variance of log lifetime earnings by 14 percent at age 45, 27 percent at age 55, 32 percent at age 65, and 29 percent at age 75. Inspection of the ratios of lifetime earnings at the 5th, 10th, 90th and 95th percentiles relative to the median reveals that the impact of health inequality on lifetime earnings inequality is concentrated in the bottom of the income distribution.

Finally, we conduct a series of counterfactual exercises to explore the relative importance of the various channels through which health operates in the model. In each experiment we turn off the effect of frailty only in one channel and leave the rest as they are in the benchmark. 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 due primarily to the DI channel. The reasons for this finding are as follows. Using the average frailty profile to determine individuals' labor productivity reduces lifetime earnings inequality at all ages. This is because, in the baseline economy, poor health negatively impacts the productivity of less-educated workers only.

In contrast, assuming that DI eligibility is determined by the average frailty profile, has two effects. One, it reduces the incentive for frail young individuals to work. They no longer have a high probability of getting on DI when older. Thus, instead of accumulating lifetime earnings to increase their expected future DI benefits, they prefer to avoid the disutility of work and rely on means-tested welfare programs. Two, it increases the labor supply of older frail individuals. These individuals no longer have a high probability of getting DI either, but, because they have more accumulated wealth, are less likely to obtain means-tested benefits if they stop working. Thus, they prefer to work until retirement age. The importance of the second effect grows larger with age and, by age 65, the DI channel is the most important channel through which health inequality increases lifetime earnings inequality.

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.

1.1 Related Literature

Our paper belongs to the growing macroeconomic literature that uses detailed life cycle models to study the aggregate and distributional economic impacts of health status and health expenditures.[4] In particular, there are a number of recent studies that use a similar framework to ours to analyze the interactions between health status, earnings, and labor supply over the life cycle.

Kitao (2014) studies the joint effect of SSDI benefits and Medicare eligibility on SSDI recipiency and labor supply. Low and Pistaferri (2015) develop a life cycle model where work limitations due to poor health impacts individuals' preferences, wages, mortality and medical expenditures. They estimate the model and use it to evaluate policy reforms of SSDI and means-test welfare programs. Michaud and Wiczer (2017) focus on vocational considerations in the awarding of disability benefits. They develop a detailed life-cycle model of the interactions between occupation and health status. They use their model to measure the impact of health deterioration and concentration of health risks within certain occupations on SSDI claims.

Capatina (2015) studies the effect of poor health on labor supply using a life cycle framework that is similar to ours. There are several differences between our study and hers. The most important difference is that we explicitly model SSDI and the incentive effect it has on labor supply. This allows us to separately identify the impact of health on preferences from the impact on the probability of SSDI award. We find that increased access to SSDI is an important channel through which health inequality impacts lifetime earnings inequality. In contrast to Capatina (2015), we do not find that the effect of health on preferences to be only important for younger workers. Moreover, even for these younger workers the impact of this channel on variance of log lifetime earning is less than half of the effect of health on productivity.

Our paper is also related to the empirical literature that estimates the effect of health on

[4]See French (2005), De Nardi et al. (2010), Suen (2006), Kopecky and Koreshkova (2014), Zhao (2014), Ozcan (2013), Braun et al. (2015), Imrohoroglu and Zhao (2018), among others.

employment and earnings. Blundell et al. (2017) study the effect of health on labor supply near retirement in the US and the UK. They provide estimates using both subjective (self-reported) measures of health and subjective measures instrumented with objective measures. They find significant and large estimates of the impact of health on employment that are robust to the choice of health measure. Moreover, similar to ours, they find the effect to be larger among less educated workers. Bound et al. (1999) use the Health and Retirement Study to assess the impact of health on labor supply. They find that deteriorating health is associated with declines in labor force participation. Finally, Meyer and Mok (2019) find that the prevalence of disability in the U.S. is high and correlated with poor economic outcomes including lower earnings and labor supply.

There is also a large body of literature that uses exogenous and sudden occurrences of specific health events (such as accidents, surgery, cancer diagnostics, etc) to estimate the causal effect of health on labor market outcomes. For example, García-Gómez et al. (2013), Lundborg et al. (2015), and Dobkin et al. (2018) use acute hospitalizations in the Netherlands, Sweden, and the United States. Heinesen and Kolodziejczyk (2013) and Jeon (2017) use cancer diagnoses in Denmark and Canada as specific health shocks, and Pohl et al. (2013) uses hospitalization due to accidents in Chile.

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. Section 5 reports the results of our quantitative exercise and Section 6 concludes.

2 Empirical Facts on Health Status and Earnings

We start by documenting some empirical facts on the relationship between *health status* and earnings that we use to guide the development of our structural model. However, first, we need to introduce and motivate our measure of health status: *frailty index*. This brief overview draws heavily on Hosseini et al. (2019) which includes additional details on the construction and properties of the frailty index. It also includes an extensive comparison of the frailty index to self reported health status (SRHS).

2.1 Frailty index as a measure of health status

As individuals age they develop an increasing number of health problems, functional impairments, and abnormalities. Some of these conditions are rather mild (e.g., reduced vision) while others are serious (e.g., heart disease). However, as the number of these conditions rises, the person's body becomes more frail and vulnerable to adverse outcomes. We refer to each of these conditions as a *deficit*. In their pioneering work, Mitnitski et al. (2001) and Mitnitski et al. (2002) demonstrated that the health status of an individual can be represented by an index variable, called the *frailty index*, which summarizes the individual's accumulated deficits. The index is constructed as the ratio of deficits a person has accumulated to the total number of deficits considered. For example, if 30 deficits were considered and 3 were present for a person, that person is assigned a frailty index of 0.1.[5]

In this paper, we use three datasets to quantify the impact of health inequality on lifetime earnings inequality: the Panel Study of Income Dynamics (PSID), Health and Retirement Study (HRS) and Medical Expenditure Panel Survey (MEPS). To construct frailty indices for individuals in each dataset we include health deficit variables spanning the following broad categories:

- Restrictions or difficulty in Activities of Daily Living (ADL) and Instrumental ADL (IADL): such as difficulty eating, dressing, walking across a room, etc.
- Mental or cognitive impairment: such as psychological problems, mental problems, difficulty with immediate word recall or backwards counting, etc.
- Medical diagnosis/measurement: such as high blood pressure, diabetes, heart disease, cancer, high BMI, etc.

In Hosseini et al. (2019), we show that the frailty index is a consistent measure of health across these three datasets. This is the case even though the datasets vary in the exact set of health deficit variables they contain.

We use the frailty index to measure health for our analysis because it has several attractive properties for studying individuals' life-cycle health dynamics and their implications. First, despite its simplicity, it is well documented in Gerontology that the index is highly predictive of health outcomes. Mitnitski et al. (2004) and Mitnitski et al. (2005) (among others) have found that having a higher frailty index is associated with a higher likelihood of an adverse health outcome, such as death or institutionalization.[6] Motivated by these studies, in Hosseini et al. (2019), we show that the frailty index is a better predictor of health-related outcomes (such as mortality, probability of entering a nursing home, and probability of going on social security disability insurance) than SRHS.

Second, the frailty index measures health at a fine enough level that it can be treated as a continuous variable. This is a desirable feature for two reasons. One, it allows us to quantify the impact of marginal changes in frailty on economic outcomes as we do in our empirical analysis below. Two, the distribution of frailty is significantly right-skewed. In others words, there is substantial variation in the extent of poor health among individuals in the unhealthy right-tail. As we will also show below, the impacts of declines in health on earnings and labor supply are concentrated in the unhealthy tail of the distribution. In Hosseini et al. (2019) we show that much of the variation in frailty in this tail is not captured by variation in the coarse categories used to distinguish health status levels based on SRHS.[7] Yet, observing

[5] We show in Hosseini et al. (2019) that the properties of the index are robust to principal compoent weighting. One could come up with many other alternative weighting schemes. However, equal weighting is simple and works well. This may be, at least in part, because individuals with more severe conditions are likely to have more total deficits. For instance, consider two individuals with cancer. The one with a more serious case will likely also report limitations with ADL's and IADL's.

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

[7] Hosseini et al. (2019) also document that frailty provides a more accurate account of the deterioration of health with age than SRHS.

Table 1: Frailty Summary Statistics in our PSID Sample

Mean	0.11	Median	0.07
by age:		Standard Deviation	0.11
25-34	0.07		
35-44	0.09	$+\Delta$ Frailty	0.29
45-54	0.11	$-\Delta$ Frailty	0.13
55-64	0.15	Effect of 1 additional deficit	+0.037

and, ultimately targeting this variation when calibrating our structural model, is important for accurately quantifying the impact of health on lifetime earnings inequality.

2.2 Empirical strategy to estimate health affects

In this section we estimate the effect of frailty on current earnings and assess the relative importance of the three margins through which the effect may operate: labor force participation, hours conditional on working, and wages. The sample we construct to conduct our analysis is based on 2003 through 2017 PSID data. The sample consists of eight waves covering the period 2002 through 2016.[8] Our extended PSID sample consists of household heads and spouses ages 25 to 94. However, we restrict the sample to ages 25 to 64 for the dynamic panel analysis. Table 1 provides summary statistics on frailty for individuals in the dynamic panel sample.[9] Notice that the cross-sectional distribution of frailty is right-skewed and mean frailty increases with age. We use 27 deficit variables to construct the frailty index in PSID. Thus, incurring one additional deficit increases one's frailty index by 1/27 or 3.7 percent. Wave-to-wave changes in frailty occur for 42 percent of the sample on average, 69 percent of which are increases.

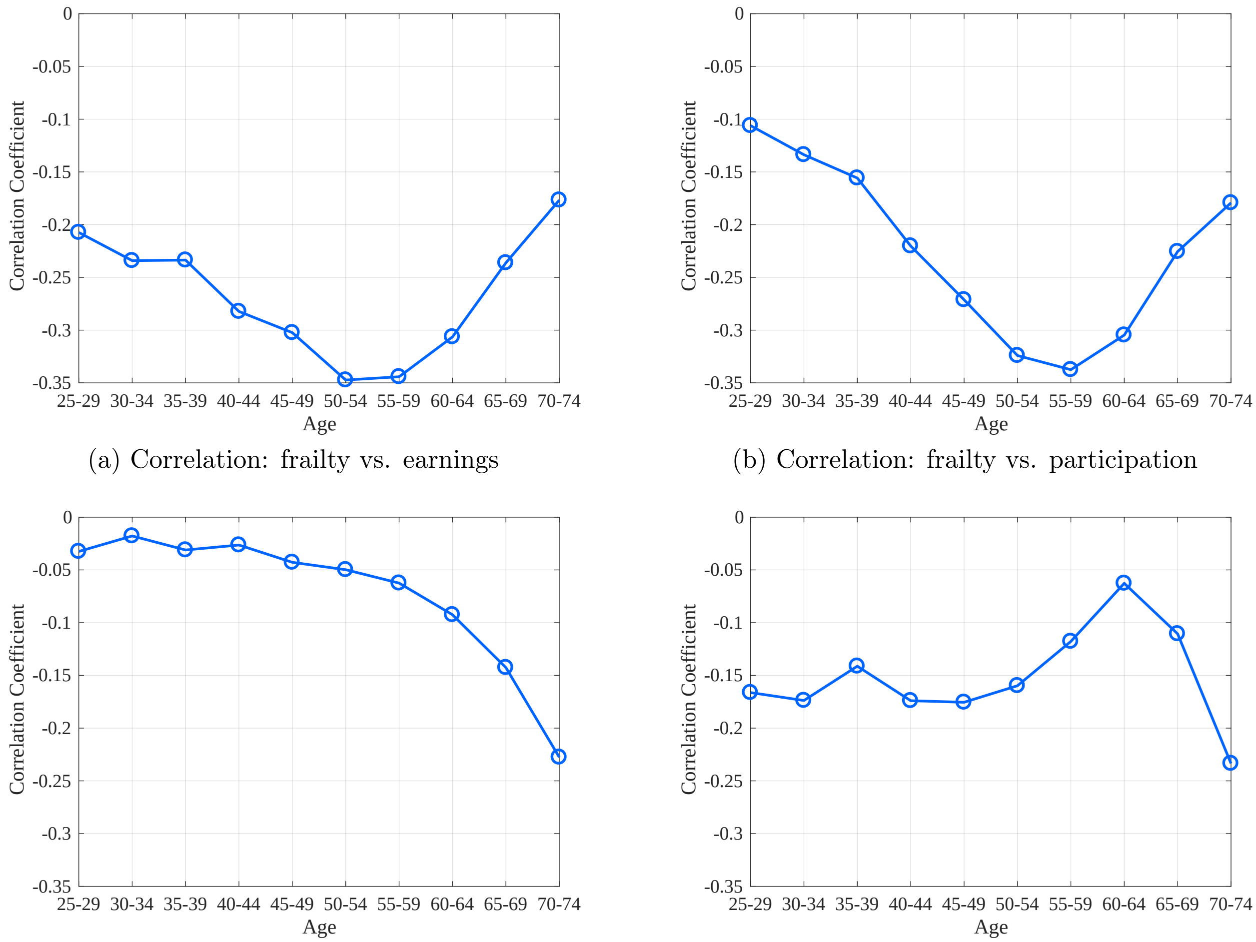
Figure 1 shows the raw correlations of frailty with earnings, participation, hours conditional on working, and wages by 5-year age groups for individuals aged 25 to 74.[10] The figure shows that frailty and earnings are negatively correlated at all ages. The negative correlation is u-shaped over the life cycle with the magnitude peaking during the fifties. Notice that this negative correlation is due to a negative correlation between frailty and all three components of earnings (participation, hours, and wages). However, of the three, the correlation between frailty and participation is the largest and follows a similar life cycle pattern to that of earnings.

How much of the negative correlation between frailty and earnings is driven by declines in health generating declines in earnings and how important are the various margins? To answer this question, we now use a dynamic panel approach to estimate the causal impacts

[8] We start our sample in 2003 because the PSID did not collect enough information on individuals' medical conditions, ADL's and IADL's prior to the 2003 wave to construct frailty indices. The PSID is biennial over this period.

[9] Additional details on sample selection and summary statistics can be found in Appendix A.

[10] Earnings are annual labor earnings where labor earnings of non-workers are set to zero. Individuals are counted as participating in the labor force if they worked at least 260 hours during the year at a wage of at least $3 per an hour. Annual hours worked are calculated as weekly hours times weeks worked. Wages are constructed by PSID using annual labor earnings and annual hours worked.



(a) Correlation: frailty vs. earnings

(b) Correlation: frailty vs. participation

(c) Correlation: frailty vs. hours (workers)

(d) Correlation: frailty vs. wages (workers)

Figure 1: Raw correlations of earnings (top left), participation (top right), hours conditional on working (bottom left), and observed wages (bottom right) with frailty for 25 to 74 year-olds by five-year age groups. Data source: 2003–2017 PSID.

of frailty on earnings, hours and wages. We estimate the following statistical model

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

in which $y_{i,t}$ is the logarithm of either earnings, hours, or wages for individual i at time t. $f_{i,t}$ is frailty and $\boldsymbol{Z}_{i,t}$ is a vector of exogenous controls that includes marital status, marital status interacted with gender, number of kids, and number of kids interacted with gender, year dummies, and a cubic polynomial in age.[11] Finally, b_i is the individual fixed effect and $\varepsilon_{i,t}$ is a random error term with

$$E[b_i] = E[\varepsilon_{i,t}] = E[b_i \varepsilon_{i,t}] = 0.$$

[11] We have also experimented with making marital status, marital status interacted with gender, number of kids, and number of kids interacted with gender endogenous and found that it does not have a significant impact on any of our results.

Individuals vary in unobservable ways (such as innate ability) that could potentially be correlated with both their earning ability and frailty. This motivates the inclusion of a fixed effect in equation (1).[12]

We are interested in estimating the impact of frailty on earnings. However, earnings may also impact frailty. Declines in health may affect productivity and lead to lower wages (or loss of employment). Yet, lower income (or loss of employment) may negatively impact health through its impact on mental health, access to health insurance, or choice of medical care. Moreover, both earnings and frailty are highly persistent variables. In other words, we are concerned about simultaneity but also dynamic endogeneity: past earnings are correlated with current earnings but may also be correlated with both past and current frailty. This concern is the reason why we use a dynamic panel data approach. We need to include lagged values of earnings on the right-hand-side in equation (1).[13]

It is well known that equation (1) 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 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 many others).[14]

The basic estimation procedure consists of two steps. The first step is to write equation (1) in first difference form:

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

which eliminates time-invariant unobserved heterogeneity. The second step is to use lagged values of the left-hand-side variable, frailty, and the endogenous controls in levels as 'internal' 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 or moment conditions must hold

$$E\left(y_{i,t-s} \Delta \varepsilon_{i,t}\right) = E\left(f_{i,t-s+2} \Delta \varepsilon_{i,t}\right) = 0, \quad \text{for } \forall s > 3. \tag{3}$$

[12]The individual fixed effect controls for any non-time-varying heterogeneity across individuals including, for example, differences in gender and education. While we have done are best to include all relevant controls, we cannot completely rule out the possibility that we have omitted time-varying variables that are correlated with both frailty and are left-hand-side variables.

[13]In the Appendix 20 we take a closer look at the effect of past earnings on frailty using a dynamic GMM panel estimator and the same set of exogenous controls. For the groups we consider, we find no evidence of a statistical significant effect of earnings on frailty. However, this does not rule out the possibility that effects do exist for selected subgroups of the population.

[14]Dynamic panel estimators are widely used in many areas of economics and finance. Examples 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.

Using the moment conditions in equation (3) we can estimate equation (2) via GMM. However, there are still a few shortcomings. For example, differencing can reduce variation in explanatory variables and therefore reduce accuracy of estimates (see Beck et al. (2000)). Moreover, as Arellano and Bover (1995) point out, variables in levels may be weak instruments for first-differences. This is especially true for highly persistent variables.[15] To mitigate these shortcomings, we follow Blundell and Bond (1998) and Blundell and Bond (2000) and improve the GMM estimator by jointly estimating the equation in levels and the equation in first-differences. Lagged first-differences are used to instrument levels. More precisely, we stack levels and first differences in the following equation

$$\begin{bmatrix} y_{i,t} \\ \Delta y_{i,t} \end{bmatrix} = \gamma \begin{bmatrix} f_{i,t} \\ \Delta f_{i,t} \end{bmatrix} + \alpha_1 \begin{bmatrix} y_{i,t-1} \\ \Delta y_{i,t-1} \end{bmatrix} + \alpha_2 \begin{bmatrix} y_{i,t-2} \\ \Delta y_{i,t-2} \end{bmatrix} + \delta \begin{bmatrix} \boldsymbol{Z}_{i.t} \\ \Delta \boldsymbol{Z}_{i.t} \end{bmatrix} + \varepsilon_{i,t}, \tag{4}$$

which we can estimate using the "system" GMM estimator. Note, however, that the estimation drops the fixed effect from the levels equation. As a result, for first differences to be valid instruments of the levels, the following additional orthogonality conditions must hold

$$E\left(\Delta y_{i,t-s}\left(b_i + \varepsilon_{i,t}\right)\right) = E\left(\Delta f_{i,t-s+2}\left(b_i + \varepsilon_{i,t}\right)\right) = 0, \quad \text{for } \forall s > 3. \tag{5}$$

To summarize, we carry out GMM panel estimation using the orthogonality conditions (3) and (5). These conditions imply that we can use lagged levels of our endogenous regressors ($y_{i,t}$ and $f_{i,t}$) as instruments for our differenced equations and lagged differences as instruments for the levels equations, respectively. Given the concerns about instrument proliferation and overfitting discussed in Roodman (2009) we do not use all the available lags as instruments. Instead, we use only the fourth through sixth lags for the regressions that include everyone in the sample. To obtain valid instruments for the regressions that are run only on workers requires us to go back further in lag length. Thus, for these regressions we use the fifth through seventh lags. In addition, in all regressions run, we restrict the coefficients on the lags to be the same at each time t by collapsing the instrument matrix.[16]

Following the recommendations in the literature by Roodman (2009), Bond (2002a) and others, we conduct several tests of our specification, approach, and instrument set. In the tables that follow, we report test statistics for two sets of tests.[17] First, we report the results of the tests for first and second-order serial correlation in the residuals of the difference equation. By construction, the residuals of the first-differenced equation should possess first-order serial correction. However, if the assumption of serial independence in the errors in the levels equation is correct, the first-differenced residuals should not exhibit significant AR(2) behavior. Thus, if we pass the test for second-order serial correlation, it means that we have included enough lags to control for the dynamic aspects of our empirical relationship. As a result, any historical value of earnings beyond those lags is a potentially valid instrument since it will be exogenous to current earning shocks.

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

[16]This increases the power of the Hansen-Sargan test for over-identification.

[17]In Appendix B we show the results of additional tests and robustness checks including robustness checks to the number of instruments used, results from difference-in-Hansen tests on subsets of instruments in the levels equation, results of instrument power tests, and a comparison of our dynamic panel GMM estimates to both estimates obtained using an OLS estimator and a within groups (FE) estimator.

The second set of tests statistics we report are tests of the validity of our instruments. The system is over-identified in that we have more instruments than we do endogenous regressors. We conduct a Hansen-Sargan test and report the Hansen J-statistic. The Hansen J-statistic is distributed χ^2 under the null hypothesis that there is no correlation between the error terms and the instruments. Finally, we report the test statistic for the difference-in-Hansen test that our lagged first-difference instruments are uncorrelated with the fixed effects. This must hold for lagged first-differences to be valid instruments of the endogenous variables in the levels equation since the fixed effect is still in the error term.[18]

2.3 Estimation results

We now present the results from our dynamic panel estimation. We report two sets of estimation results that highlight the differences in the effect of changes in frailty on the intensive versus the extensive margin of labor supply. The first set shows the results from estimating equation (1) for everyone in our PSID sample, regardless of their labor force participation status.[19] The second set reports results only for those who are working in all periods we observe them.

Table 2 reports the results from our system GMM estimation of equation (1) where the left-hand-side variable is log earnings. Columns (1) through (4) show the regression results for the entire sample. Columns (5) through (8) show results only for workers. First, notice that the p-values from the AR(2), Hansen, and difference-in-Hansen tests are all above 5 percent. Thus, we cannot reject the nulls of no second-order serial correlation in the error terms and instrument validity. Second, notice that frailty has a statistically significant effect on earnings, on average, for all individuals (column (1)). However, the effect on earnings of workers is relatively small and only significant at the 5 percent level (column (5)).

To aid in the interpretation of the magnitudes of the estimated effects, we also calculate the percentage changes in earnings in response to the accumulation of one additional deficit. Note that in our PSID sample we have a total of 27 potential deficits. Therefore, accumulating one more deficit increases frailty by $\frac{1}{27}$. We are primarily interested in *short-run effects* which are given by the coefficient γ. However, we also compute *long-run effects* given by $\frac{\gamma}{1-\alpha_1-\alpha_2}$. The difference is that the former only captures the effect of incremental changes 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. Note that the long-run effects should be interpreted with caution given that the primary margin is exit from the labor force which is likely often permanent.

Figure 2 shows the short-run effects (γ) and the long-run effects ($\frac{\gamma}{1-\alpha_1-\alpha_2}$) on earnings in response to a 1/27th increase in frailty. The top panel is the estimated effect on the entire sample. The bottom panel shows the effect only on the subsample that continues to work. The solid lines show the 95 percent confidence intervals. The first set of bars in the top panel shows that accumulating one more deficit leads to an 20 percent reduction in earnings (blue bar) in the short-run. This negative impact is as large as 62 percent in the long run (red bar). The bottom panel shows that the effects of accumulating one additional

[18] There can still be correlation between the levels and the unobserved effects but this correlation must be constant over time.

[19] To take logarithms, we shift all observations of annual earnings up by $1.00.

Table 2: Effect of Frailty on Earnings

	Everyone				Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(earnings$_{t-1}$)	0.283	0.370	0.220	0.628**	1.474***	1.371***	1.293***	1.127***
	(0.364)	(0.319)	(0.362)	(0.291)	(0.509)	(0.400)	(0.410)	(0.302)
log(earnings$_{t-2}$)	0.396	0.318	0.444	0.115	-0.640	-0.569	-0.498	-0.308
	(0.298)	(0.259)	(0.297)	(0.239)	(0.454)	(0.356)	(0.377)	(0.273)
frailty$_t$	-5.374***				-0.978**			
	(1.653)				(0.447)			
frailty$_t$ × HSD		-6.269***				-1.846**		
		(1.777)				(0.807)		
frailty$_t$ × HS		-5.591***				-1.239***		
		(1.574)				(0.460)		
frailty$_t$ × CL		-2.519*				-0.558		
		(1.402)				(0.484)		
frailty$_t$ × Good Health			-1.930				-1.765	
			(4.816)				(1.775)	
frailty$_t$ × Bad Health			-5.207***				-0.963**	
			(1.745)				(0.469)	
frailty$_t$ × Young				-4.992***				-1.650**
				(1.784)				(0.673)
frailty$_t$ × Old				-4.030***				-0.293
				(1.317)				(0.365)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	64,965	64,965	64,965	64,965	34,274	34,274	34,274	34,274
AR(1) test (p-value)	0.455	0.319	0.497	0.104	0.030	0.010	0.021	0.008
AR(2) test (p-value)	0.380	0.474	0.298	0.949	0.130	0.082	0.138	0.160
Hansen test (p-value)	0.796	0.132	0.826	0.752	0.434	0.826	0.543	0.465
Diff-in-Hansen test (p-value)	0.652	0.360	0.827	0.464	0.255	0.484	0.259	0.214

Notes: Columns (1) to (4) show regression results for entire sample, regardless of employment status. Columns (5) to (8) 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). 'HSD' is high school dropout, 'HS' is high school graduate, and 'CL' is college graduate. 'Good Health' is frailty at or below the 75th percentile. 'Bad Health' is frailty above the 75th percentile. 'Young/Old' are individuals younger/older than 45 years of age. Standard errors on parenthesis. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

deficit are much smaller when conditioning on those who continue to work. The overall effect is a 4 percent decline in the short-run and it is borderline significant. These findings suggest that, consistent with the magnitudes of the raw correlations in Figure 1, the effects of frailty on earnings are due primarily to the extensive margin (of unhealthy workers leaving employment), rather than the intensive margin (of unhealthy workers working fewer hours or receiving lower wages).

Columns (2) and (6) of Table 2 show how the effects of frailty on earnings differ by education groups: high school dropouts (HDS), high school graduates (HSG), and college graduates (CL). Looking at column (2), frailty has a large and strongly significant effect on the earnings of high school dropouts and those with a high school degree. However, the effect is smaller and less significant for college graduates. The top panel of Figure 2 shows that one additional deficit reduces the earnings of high school dropouts, high school graduates, and college graduates by 23, 21, and 9 percent in the short-run, respectively. Among workers, the effects by education group are substantially smaller and the levels of significance are lower. For instance, accumulating one more deficit reduces the earnings of high-school dropout workers by only 7 percent in the short-run.

Columns (3) and (7) of Table 2 show results by health status. Column (3) shows that frailty has a significant and large effect on the earnings of individuals with bad health. Here, individuals with bad health are those with a value of frailty above the 75th percentile of the overall frailty distribution. The top panel of Figure 2 shows that for these individuals one more deficit leads to a 19 percent drop in earnings in the short-run and a 57 percent decline in the long-run. The effect for individuals with good health (those with a value of frailty at or below the 75th percentile) is small and insignificant. Once we restrict the sample to workers, the coefficient on frailty interacted with bad health becomes substantially smaller and less significant. These results show that the negative effects of frailty on earnings are primarily due to exit from the labor force by individuals who are already in poor health in response to additional health declines.

Finally, columns (4) and (8) of Table 2 and the bottom two sets of bars in each panel of Figure 2 show the effects by age groups. Somewhat surprisingly, that the effects of frailty on earnings are slightly smaller for those older than 45 than those younger than 45. One additional deficit reduces earnings of the young by 18 percent and earnings of the old by 15. In addition, once the sample is restricted to only those who continue to stay employed, the effect is only significant for younger workers. These estimates reveal that the effect of health on earnings for older workers operates primarily through the extensive margin. In contrast, there are potential effects operating through the intensive margin for younger workers. This suggests that younger workers may be more willing to continue working and incur reductions in earnings due to poor health than older workers.

To summarize, the results in Table 2 and Figure 2 tell us that frailty has a large and significant effect on the earnings of low educated individuals and those with bad health. They also indicate that the effect is mainly along the extensive margin. The impact on earnings of workers is either not significant or is relatively small. However, these results do not tell us whether the impacts on workers come from hours or wages, or both. To better understand how frailty affects hours and wages of workers, we repeat the same regressions but replace the independent variable with hours and/or wage. The results of these regressions are reported in Table 3 and Figures 3 and Figure 4.

The left panel in Table 3 (Panel A) shows results on the effect of frailty on hours worked. The results in columns (1) to (4) show the impact of frailty on hours worked for all individuals in the sample. The top panel in Figure 3 shows that the impact of accumulating one additional deficit on hours is very similar to the impact on earnings in the entire sample. Overall, accumulating one more deficit cause a 14 percent drop in hours in the short run and 43 percent drop in hours in the long run. High school dropouts and those in bad health experience the largest declines in hours. College-educated and those in good health have the smallest impact.

Columns (5) through (8) of Table 3 show the effect of frailty on hours for workers only. Note that we do not find any evidence of a significant effect either overall or in any of the subgroups we consider. This indicates that the impact of frailty on hours worked is almost entirely through exit from employment (as opposed to adjustment of working hours). In other words, if an adverse health event does not drive a worker out of employment, there

Table 3: Effect of Frailty on Hours and Wage

	Panel A. Hours regression								**Panel B.** Wage regression			
	Everyone				Workers				Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)
$\log(\text{hours}_{t-1})$	0.399	0.383	0.386	0.669***	0.003	0.074	0.040	0.382				
	(0.322)	(0.319)	(0.317)	(0.257)	(0.345)	(0.313)	(0.311)	(0.318)				
$\log(\text{hours}_{t-2})$	0.263	0.269	0.272	0.048	0.304	0.168	0.282	0.254				
	(0.257)	(0.253)	(0.253)	(0.206)	(0.218)	(0.221)	(0.219)	(0.246)				
frailty_t	-3.887***				0.070				-0.623**			
	(1.188)				(0.246)				(0.263)			
$\text{frailty}_t \times$ HSD		-4.770***				-0.533				-1.854***		
		(1.320)				(0.356)				(0.616)		
$\text{frailty}_t \times$ HS		-4.303***				-0.033				-0.889***		
		(1.224)				(0.281)				(0.307)		
$\text{frailty}_t \times$ CL		-2.219**				0.248				-0.216		
		(1.118)				(0.254)				(0.309)		
$\text{frailty}_t \times$ Good Health			-2.216				-0.060				0.348	
			(3.455)				(0.910)				(1.685)	
$\text{frailty}_t \times$ Bad Health			-3.707***				0.026				-0.581*	
			(1.242)				(0.258)				(0.332)	
$\text{frailty}_t \times$ Young				-3.564***				-0.286				-1.106**
				(1.325)				(0.387)				(0.463)
$\text{frailty}_t \times$ Old				-3.131***				0.144				-0.414
				(0.936)				(0.259)				(0.295)
$\log(\text{wage}_{t-1})$									0.212	0.122	0.303	0.511
									(0.541)	(0.368)	(0.449)	(0.399)
$\log(\text{wage}_{t-2})$									0.532	0.600*	0.461	0.272
									(0.489)	(0.328)	(0.419)	(0.359)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	64,965	64,965	64,965	64,965	34,274	34,274	34,274	34,274	34,170	34,170	34,170	34,170
AR(1) test (p-value)	0.287	0.290	0.289	0.043	0.409	0.286	0.335	0.180	0.651	0.518	0.552	0.362
AR(2) test (p-value)	0.596	0.569	0.565	0.706	0.273	0.572	0.312	0.642	0.454	0.189	0.474	0.734
Hansen test (p-value)	0.971	0.317	0.838	0.811	0.060	0.166	0.174	0.051	0.085	0.374	0.207	0.170
Diff-in-Hansen test (p-value)	0.944	0.597	0.713	0.545	0.080	0.062	0.108	0.037	0.044	0.145	0.082	0.104

*Notes:*Panel A (left) shows regression results for the effect of frailty on hours worked. Columns (1) to (4) are regression results for entire sample, regardless of employment status. Columns (5) to (8) are results conditional on continued employment. Panel B (right) shows regression results on the effect of frailty on wage for workers only. 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). 'HSD' is high school dropout, 'HS' is high school graduate, and 'CL' is college graduate.'Good Health' is frailty at or below the 75th percentile. 'Bad Health' is frailty above the 75th percentile. 'Young/Old' are individuals younger/older than 45 years of age. Standard errors on parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

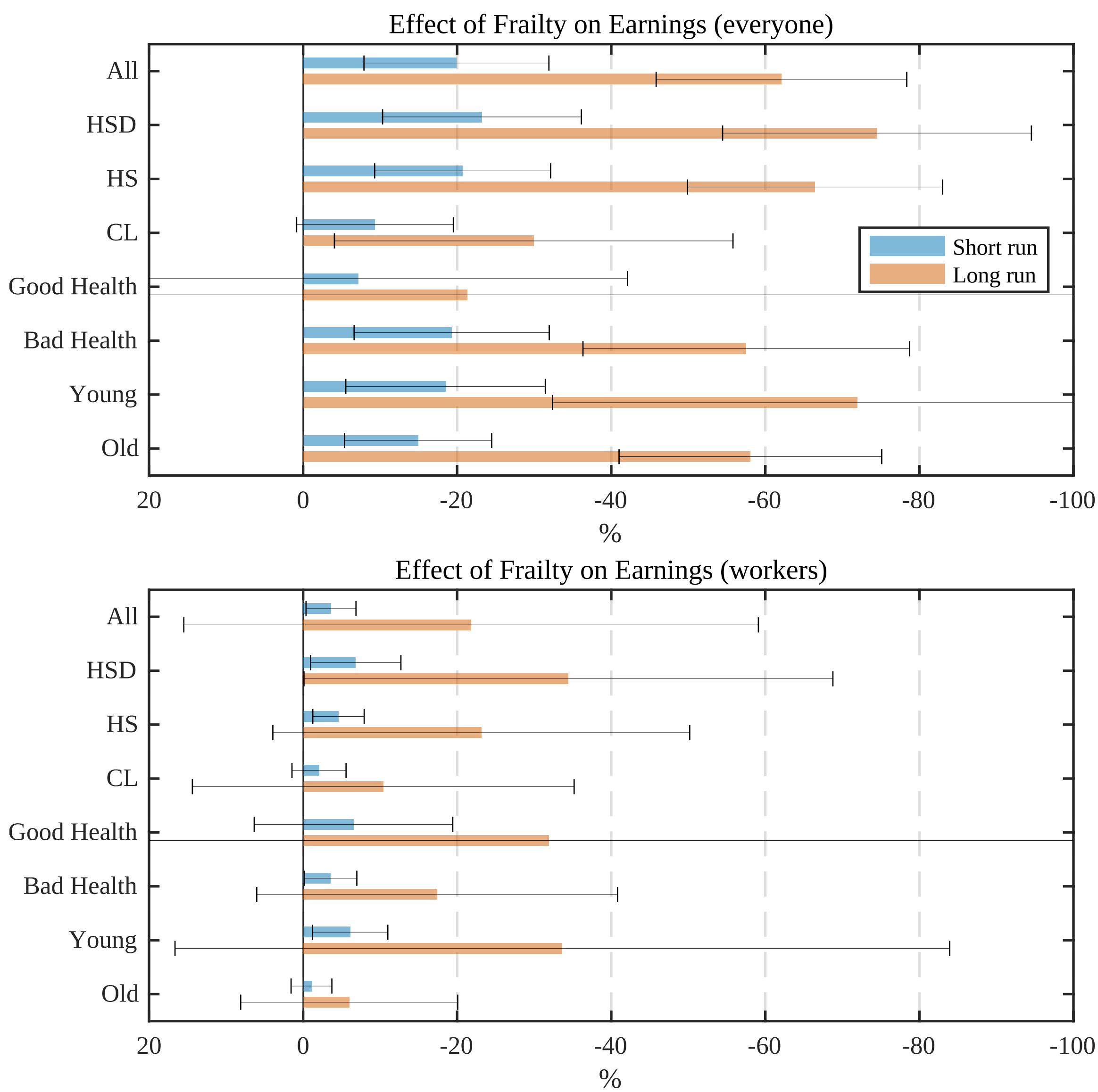


Figure 2: Response of earnings to accumulation of one more health deficit (an incremental increase in frailty). Top panel shows the responses for everyone on the sample. Bottom panel shows the responses for those who stay employed. 'HSD' is high school dropout, 'HS' is high school graduate, and 'CL' is college graduate.'Good Health' is frailty at or below the 75th percentile. 'Bad Health' is frailty above the 75th percentile. 'Young/Old' are individuals younger/older than 45 years of age. Solid lines show 95 percent confidence intervals.

will be no adjustment in hours worked, even among the high school dropouts (who experience the largest decline in earnings while working).

The right panel in Table 3 (Panel B) shows regression results for the effect of frailty on wages of workers. Frailty reduces wages of workers, on average. Figure 4 shows the short and long-run effects on wages of accumulating one more deficit. On average, one more deficit reduces wages of workers by 2 percent in the short-run and 7 percent in the long-run.

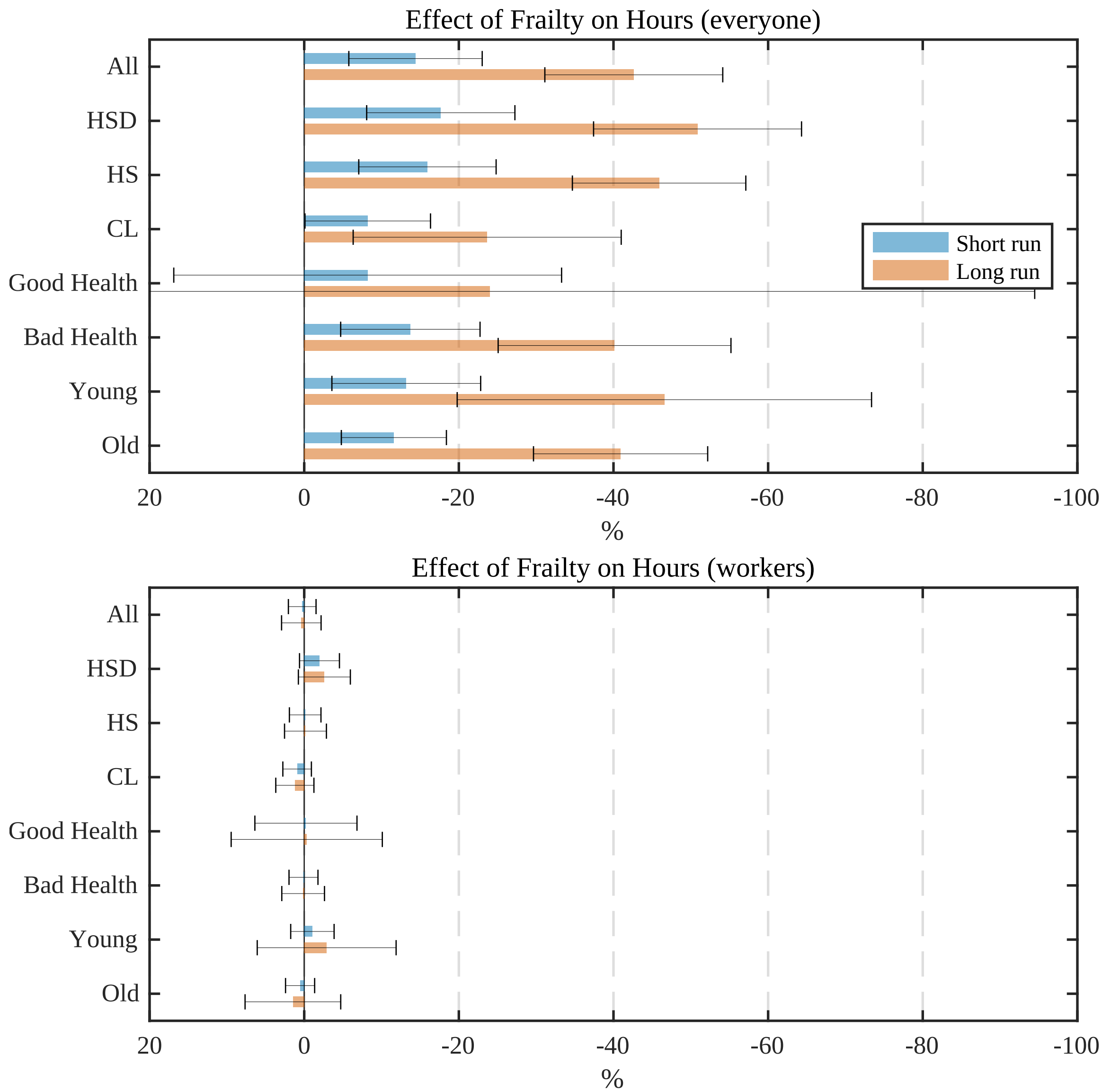


Figure 3: Response of hours to accumulation of one more health deficit (an incremental increase in frailty). Left panel shows the responses for everyone on the sample. Right panel shows the responses for those who stay employed. 'HSD' is high school dropout, 'HS' is high school graduate, and 'CL' is college graduate. 'Good Health' is frailty at or below the 75th percentile. 'Bad Health' is frailty above the 75th percentile. 'Young/Old' are individuals younger/older than 45 years of age. Solid lines show 95 percent confidence intervals.

The effect is negative for all three education groups but decreases with education and is only significant for less educated workers (those without a college degree). Of all subgroups we consider, the effect is largest for the high school dropout group. One additional deficit reduces their hourly wages in the short-run by 7 percent and in the long-run by 25 percent. Notice that the wage effects are similar in magnitude to the effect on earnings of workers reported in the bottom panel of Figure 2.

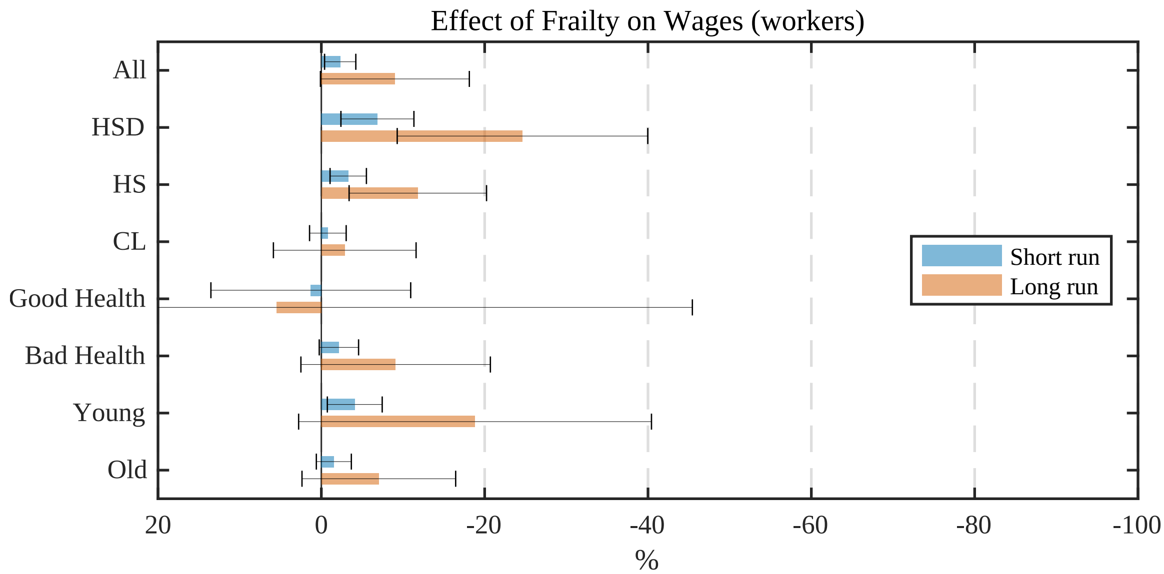


Figure 4: Response of wages to accumulation of one more health deficit (an incremental increase in frailty) for those who stay employed. 'HSD' is high school dropout, 'HS' is high school graduate, and 'CL' is college graduate. 'Good Health' is frailty at or below the 75th percentile. 'Bad Health' is frailty above the 75th percentile. 'Young/Old' are individuals younger/older than 45 years of age. Solid lines show 95 percent confidence intervals.

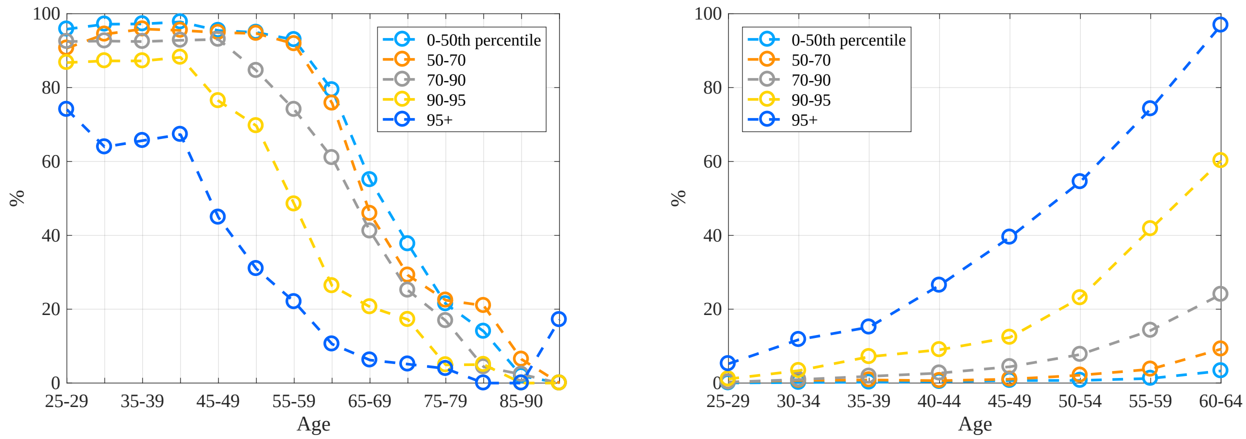
Tables 2 and 3 together with Figures 2 through 4 highlight five key findings. One, the rise in frailty significantly reduces earnings and hours worked. This effect is mainly due to the extensive margin. Two, the overall effect of the rise in frailty on earnings is somewhat similar for younger and older workers. Three, the effect of frailty on hours worked and earnings are largely due to its effect on individuals already in bad health. Four, the magnitudes of the effects are similar for hours worked and earnings. Five, wages of low educated workers (less than college) who stay employed are significantly affected.

The empirical findings from the dynamic panel analysis show that the primary margin through which poor health impacts earnings is the participation margin. The findings also show that the effect is concentrated among less educated individuals and those already in poor health. These finding suggests that the impact of poor health on one's ability to receive SSDI may be an important factor driving the effect. In the U.S., individuals can not apply for SSDI unless they are out of the labor force for at least 12 months. Once on DI, individuals are extremely restricted in the amount they can work without losing benefits. For example, in 2019 SSDI recipients could not earn more than \$1,220 per month without losing some or all of their disability benefits. As a result, nearly all SSDI beneficiaries in the U.S. do not work.[20]

The left panel in Figure 5 shows how employment rates vary by frailty over the life-cycle. This figure is constructed using PSID data.[21] Individuals are considered employed if they

[20] According to Autor and Duggan (2003) earnings exceeding \$500 per month in 1999 would have automatically disqualified a DI applicant.

[21] See the appendix for details on the construction of the PSID sample.



(a) Employment rate.

(b) Fraction on SSDI.

Figure 5: The employment rate (left) and the fraction of individuals on SSDI (right) by frailty percentiles (0 to 50th, 50th to 70th, 70th to 90th, 90th to 95th, and 95th and above) and age. Source: Authors' calculations using PSID data (left) and MEPS and SSA data (right).

work at least 260 hours in a year and earn at least \$3 per hour. Employment rates are plotted by frailty percentiles (0 to 50th, 50th to 70th, 70th to 90th, 90 to 95th, and 95 and above) within 5 year groups ranging from age 25 to 74. The figure shows that there is little variation in employment rates in the bottom 70 percent of frailty distribution in each age group. There is some variation in employment rates between individuals in the 70th to 90th percentiles relative to those below the 70th after age 45. However, individuals with frailty in the top decline, those in the worst health, have significantly lower employment rates over the entire life-cycle. Notice that this difference is most pronounced for individuals in their fifties. In particular, at ages 55-59, only 20 percent of individuals in the 90th to 95th percentile (top 5 percentile) are employed. In contrast, about 80 percent of those in bottom 70 percent of frailty (0 to 50th and 50th to 70th percentile) are employed. The figure is consistent with the findings from the dynamic panel analysis. Highly frail individuals have significantly lower labor force participation rates at all ages.

The right panel of Figure 5 shows the fraction who are on SSDI at each 5 year age group from age 25 to 64 for the same frailty percentiles (0 to 50th, 50th to 70th, 70th to 90th, 90 to 95th, and 95 and above). We use MEPS data to construct this figure. MEPS does not contain information on DI beneficiary status. However, it does include data on whether an individuals receives Medicare benefits. DI beneficiaries are the only group younger than 65 years of age who qualify for Medicare (after being on DI for two years). To construct this figure, we first compute the fraction in each frailty group and each age group who receive benefits from Medicare. We then adjust the total number in each age group by the Social Security Administration population data on DI recipient by age to make sure the numbers are consistent on aggregate. The figure shows that there is a significant difference between the top 30 percentile of frailty (70 to 90th, 90th to 95, and 95 and above) and the rest at any age, specially for those older than 45. By age 65 almost all (60 percent) of individuals at top 5 percentile (90th to 95 percentile) of frailty are on SSDI. However, at the same age only less than 10 percent of those in the bottom 70 percent (0 to 50th and 50th to 70th) are on SSDI.

We now use our empirical findings to guide the development of a structural model. We will use the structural model to quantify the impact of health inequality on lifetime earnings. Individuals in the model will be heterogeneous in their health and face health risk. We focus the model on the participation margin given our findings of its importance. Individual's in the model will chose to participate in the labor market or exit and apply for SSDI. Given that we did not find any statistically significant effects of frailty on hours conditional on working, we do not model the intensive margin of labor supply. However, we do allow for poor health to impact individual's labor productivity and for this effect to be concentrated in individuals with less education. In particular, we assume that shocks to health impact workers' productivity. Finally, we failed to find a statistically significant impact of earnings on health. This result indicates that feedback effects from low earnings to health are either small or concentrated in a small subgroup of the U.S. population. Given that this is the case, we do not model such a feedback effect by endogenizing health.

3 The Model

In this section, we describe our benchmark model.

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 out-of-pocket medical expenditures and mortality risk. At each age, the probability of surviving one more year is denoted by $p(j, f)$. Individuals are ex-ante heterogeneous with respect to their education level s, and they face a labor productivity process that is uncertain due to is dependence on both their frailty and direct labor productivity shocks.

Individuals derive utility from consumption c and (if working) suffer disutility from work which depends on frailty, f. Before retirement, each individual is either employed, non-employed or enrolled in Disability Insurance (DI). An employed individual works a fixed (exogenously given) fraction of his 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 efficient unit of labor services, w. The second term is the efficiency unit of labor services for hours worked, $\eta(j, f, s, \epsilon)$, which 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.[22] It evolves according to transition probability $\pi^e(\epsilon'|j, \epsilon, s)$. Employed workers may choose to quit and become

[22]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 exogenous job separations means that there is a transition component to earnings risk.

non-employed. They can also become exogenously separated from their job with probability σ.

A non-employed individual can apply for DI or choose to go back to work immediately. If he applies for DI, he is awarded benefits with probability $\theta(f, n_a)$ in the next period, where n_a indicates the number of times he has applied for DI consecutively in the past. Individuals who are awarded DI benefits remain on DI until age $R < J$ when they transition to receiving social security retirement benefits. Those who choose to go back to work immediately have to pay a penalty $\chi(w\eta)$, which is a function of their current wage and can be understood as the cost of job search.[23]

Those who are older than 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 social security disability benefits are given by $SS(\bar{e})$, which is a function of the beneficiary's past earning history, $\bar{e}$.

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

3.2 Health status and medical expenditure

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, persistent shock, and transitory shock. An individual whose stochastic component of frailty today is given by ϵ_f will have value ϵ_f' next period with probability $\pi^f\left(\epsilon_f'|j, \epsilon_f, s\right)$. Frailty affects mortality risk, disutility from work, the chance of successful DI award, labor productivity, and out-of-pocket medical expenditures.

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 $m^i(j, f, s)$ where $i = E, N, D, R$ depending on whether he is employed (E), non-employed (N), a DI beneficiary (D) or retired (R).[24]

3.3 Government

The government makes three distinct transfers to individuals that depend on the individuals' state:

- Social Security (SS): individuals aged R and older with earning history $\bar{e}$ receive social security benefit $SS(\bar{e})$ regardless of whether or not they are working.
- Disability insurance (DI): a DI beneficiary with earning history $\bar{e}$ receives DI benefit $SS(\bar{e})$.[25]

[23]We do not explicitly model unemployment and job search. This modeling choice is motivated by the fact that the average duration of unemployment in the US is 15–20 weeks which is shorter than a period in our model. Therefore, we only include the monetary/income costs of short-term joblessness and abstract from the details of unemployment and job search.

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

[25]The U.S. Social Security administration uses the same benefit formula to calculate both retirement and disability benefits.

- Means-tested transfers: individuals with assets, a, and after-tax income net of medical expenditures and job search costs, y, receive transfer $Tr(a, y)$. The transfer is zero if $a + y \geq \underline{c}$. Otherwise, it is just enough to provide a minimum level of consumption of $\underline{c}$.

In addition, the government has exogenous expenditures G. To finance these expenditures and transfers, the government levies a nonlinear tax on labor income $T(w\eta)$ and a proportional tax on capital income τ_K. In addition, the government collects the assets of the deceased and uses them to make lump-sum transfers to all individuals who are alive.[26]

3.4 Individual decision problems

To economize on notation we denote a subset of the state space as $x \equiv (j, a, f, s, \epsilon, \bar{e})$.[27] 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. Variable n_a tracks the number of periods an individual has been in non-employment consecutively in the past. Recall that workers can always go back to employment immediately. If they stay in non-employment, it is because they are applying for DI benefits. Therefore, n_a is also equal to the number of times a worker has applied for DI consecutively in the past. Variable n_d represents the number of periods an individual has been on DI. This variable is used to determine his eligibility for Medicare benefits. We now describe the problems facing each type of individual.

The employed worker's problem: employed workers face the risk of exogenously separating from their employer with probability σ at the beginning of the next period. If separated, they can choose to go back to work immediately. If they survive the separation shock, they can choose to quit the job voluntarily. When $j < R - 1$, their utility-maximization problem can be specified as follows,

$$\begin{aligned} V^E(x, i_s) = & \max_{c, a' \geq 0} u(c, v(f)) \\ & + \sigma \beta p(j, f) E\left[\max\left\{V^E(x', 1), V^N(x', 0)\right\}\right] \\ & + (1 - \sigma) \beta p(j, f) E\left[\max\left\{V^E(x', 0), V^N(x', 0)\right\}\right] \end{aligned} \tag{6}$$

subject to

$$\frac{a'}{1+r} + c + m^E(j, f, s) = a + w\eta(x) - T(w\eta(x)) - \chi(w\eta(x)) i_s + Tr(x, i_s), \tag{7}$$

$$\bar{e}' = \frac{(j-1)\bar{e} + w\eta(x)}{j}.$$

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

[27] To avoid clutter, we use x as the argument of functions with the understanding that not all functions depend on all the elements of vector x.

When workers return from a separation or non-employment ($i_s = 1$), they have to pay a penalty $\chi\left(w\eta\left(x\right)\right)$, which is a function of their hourly wages and can be understood as costs related to job search. Employment decisions of these workers at the beginning of the period are denoted by $I_E(x, i_s)$.

After reaching age R, employed workers can only choose between working and retirement. However, they are eligible to claim social security retirement benefits regardless of whether they are retired or not. They are also eligible for Medicare, which affects their out-of-pocket medical expenditures. Therefore, employed workers of age $j \geq R-1$ face the following optimization problem,

$$\begin{aligned} V^E\left(x, i_s\right) = \max_{c, a' \geq 0} & \, u\left(c, v\left(f\right)\right) \\ & + \sigma p\left(j, f\right) E\left[\max\left\{V^E\left(x', 1\right), V^R\left(x'\right)\right\}\right] \\ & + \left(1-\sigma\right) \beta p\left(j, f\right) E\left[\max\left\{V^E\left(x', 0\right), V^R\left(x'\right)\right\}\right] \end{aligned} \tag{8}$$

subject to

$$\begin{aligned} \frac{a'}{1+r} + c + m^R\left(j, f, s\right) &= a + w\eta\left(x\right) + SS(\bar{e}) - T\left(w\eta\left(x\right)\right) - \chi\left(w\eta\left(x\right)\right) i_s + Tr\left(x, i_s\right), \\ \bar{e}' &= \bar{e}. \end{aligned} \tag{9}$$

The non-employed's problem: non-employed individuals apply for DI. They qualify for benefits with probability $\theta\left(f, n_a\right)$. If awarded, they start receiving them in the following period and will remain on DI until they reach retirement age R. At that time, they move to social security. If not awarded, they can go back to work immediately or remain non-employed and apply again. When $j < R-1$, the non-employed individual's problem can be specified as follows,

$$\begin{aligned} V^N\left(x, n_a\right) = \max_{c, a' \geq 0} & \, u\left(c\right) \\ & + \theta\left(f, n_a\right) \beta p\left(j, f\right) E\left[V^D\left(x', 0\right)\right] \\ & + \left(1 - \theta\left(f, n_a\right)\right) \beta p\left(j, f\right) E\left[\max\left\{V^E\left(x', 1\right), V^N\left(x', n_a + 1\right)\right\}\right] \end{aligned} \tag{10}$$

subject to

$$\frac{a'}{1+r} + c + m^N\left(j, f, s\right) = a + Tr\left(x, n_a\right). \tag{11}$$

Employment decisions of these workers are denoted by $I_N(x, n_a)$.

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

$$V^N\left(x, n_a\right) = \max_{c, a' \geq 0} u\left(c\right) + \beta p\left(j, f\right) E\left[\max\left\{V^E\left(x', 1\right), V^R\left(x'\right)\right\}\right] \tag{12}$$

subject to (11).

The DI beneficiary's problem: 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 two 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. When $j < R-1$, DI recipients face the following problem,

$$V^D(x, n_d) = \max_{c,a' \geq 0} u(c) + \beta p(j,f) E\left[V^D(x', n_d+1)\right] \tag{13}$$

subject to

$$\frac{a'}{1+r} + c + m^D(j,f,s,n_d) = a + SS(\bar{e}) + Tr(x, n_d). \tag{14}$$

When DI beneficiaries reach retirement age R, they automatically move from disability insurance to social security. Therefore, for $j = R-1$,

$$V^D(x, n_d) = \max_{c,a' \geq 0} u(c) + \beta p(j,f) E\left[V^R(x')\right] \tag{15}$$

subject to (14). We define $V^R(x)$ below.

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

$$V^R(x) = \max_{c,a' \geq 0} u(c) + \beta p(j,f) E\left[V^R(x')\right] \tag{16}$$

subject to

$$\frac{a'}{1+r} + c + m^R(j,f,s) = a + SS(\bar{e}) + Tr(x). \tag{17}$$

3.5 Technology

There is a representative firm that produces a single good using a Cobb-Douglas production function such that $Y = AK^{\alpha}N^{1-\alpha}$ 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 wage per an efficient unit of labor services, w, is given by

$$w = (1-\alpha)A(K/N)^{\alpha}. \tag{18}$$

We assume that the economy is in a stationary competitive equilibrium. The full definition of the equilbrium is provided in Appendix C.

4 Calibration

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 from the data or the existing literature. In the second stage, we calibrate the rest of the parameters by minimizing the distance between targets computed using U.S. data and their model counterparts. In particular, the parameters governing DI eligibility and work disutility are chosen by targeting the labor force participation rates and SSDI enrollment rates by age and frailty presented in Section 2.

Demographics

One model period is one year. We assume age $j = 1$ corresponds to a 25 year-old and $J = 70$ corresponds to a 94 year-old. Workers receive social security and Medicare benefits at age $R = 41$ (66 year-olds). This is also the age at which they no longer choose between working and applying for SSDI but instead choose between working and being retired. Conditional survival probability at each age is assumed to be a function of frailty, age, and education. Specifically, we estimate the following probit regression using the PSID data and use the predicted values as mortality rates:

$$m_{j+1i} = \text{Probit}\left(\text{constant} + \beta_1 f_{ji} + \beta_2 f_{ji}^2 + \beta_3 j_i + \beta_4 j_i^2 + \beta_5 s_i + \gamma_i X_{ji}\right) + \epsilon_{ji}.$$

Here m_{j+1i} is the mortality rate of agent i between age j and $j+1$, s_i is years of schooling and X_i is a set of covariates (gender and marital status). The results of this estimation are presented in Table 24.[28] We adjust the value of the estimated constant so that population mortality is consistent with the year 2000 period life-table in Bell and Miller (2005). 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 year 2000 U.S. Census).

Preferences

Individuals have utility over consumption c and suffer disutility from working. The extent of disutility from work depends on frailty. A more frail worker suffers more from working. We assume a non-separable utility function in consumption and leisure. Individuals have CRRA utility over consumption and constant-Frisch-elasticity disutility over hours worked. Moreover, a person at age j who has frailty f suffer an extra disutility from working. Therefore period utility is given as,

$$u(c, f) = \frac{\left(c^{\mu}\left(1 - v(f) \times i_p\right)^{1-\mu}\right)^{1-\gamma}}{1-\gamma},$$

with

$$v(f) = \phi_0\left(1 + \phi_1 f^{\phi_2}\right),$$

and $i_p = 1$ if the individual is working and 0 otherwise. 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 macro literature.[29]

We assume $\phi_0 \geq 0$, $\phi_1 \geq 0$, and $\phi_2 \geq 0$ so that higher levels of frailty increase the disutility of working. If $\phi_2 > 1$ than, $v(f)$ is convex in frailty and the marginal effect of increasing frailty is higher, for more frail individuals. The opposite is true if $\phi_2 < 1$. We choose the parameters ϕ_0, ϕ_1, and ϕ_2 in the minimization routine. However, they are pinned down by the dispersion in labor force participation rates of older workers (ages 65 to 74)

[28] Agents do not have a gender or marital status in the model. Instead, we compute the mortality rate of an agent by giving him the average gender in the population in year 2000, as well as, the average marital status by age.

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

across frailty percentiles. In the model, labor force participation rates are affected by frailty through five channels: labor productivity (i.e. wage), medical expenses, survival, probability of becoming eligible for DI, and disutility from work. As we describe below, the effects operating through the first three channels are estimated directly from the data without using the model. For older workers, the effect of frailty on DI application is irrelevant. These workers are not eligible for disability benefits and social security eligibility does not depend on their level of frailty. Therefore, the only way frailty can affect participation for this age group (in the model) is through preferences (disutility from work). This helps us identify the effect of frailty in preferences.

Labor productivity and job separation

We estimate labor productivity process $\eta(j, f, s, \epsilon)$ separately for each education groups (high school dropouts, high school graduates, and college graduates). We assume labor productivity for each education group is the sum of a deterministic component and a stochastic component. The deterministic component consist of a polynomial on age and linear frailty effect. The stochastic component is a fixed effect AR(1) process. There is however a difficulty due to (potential) selection bias. We do not observe hourly wages (which we use as proxy for labor productivity) for those who do not work. However the decision to work depends on wage/productivity. In other words, it is not enough for us to know how frailty affects wage/productivity of those who work, but we need to know its impact on everyone's wage (whether they choose to work at given wage or not).

To correct for this selection bias we employ a reduced form strategy rather than using our model. We follow closely the estimation procedure of Low and Pistaferri (2015) and use "potential" government transfers and its interactions with frailty level as *inclusion restrictions*. The assumption is that these "potential" transfers have different work incentives for people with different frailty level. Low and Pistaferri (2015) define "potential" government transfers as sum of food stamps benefits, AFDC/TANF payments, unemployment insurance benefits, and EITC payments that individuals would receive in case of program application. These transfers vary across states. Moreover, they depend on marital status and number of kids (which also vary across individuals in our sample). Therefore, instead of using the amount of "potential" transfers as inclusion restrictions we use interaction of states, number of kids and martial status (total of 482 combinations).

More precisely, we follow a two step procedure. In step 1, we estimate a fixed effect linear probability model of employment as function of frailty (interacted with education), age polynomial, and interaction of state, number of kids, and marital status. The result of this regression is presented in Table 25. We use the estimated fixed effects in this regression in the second step.

In step 2 we estimate the wage regression using dynamic panel system GMM procedure outlined in Section 2.2. The only difference is that we include the predicted fixed effects from estimation in step 1 as regressors. In doing this we follow Al-Sadoon et al. (2019) who show that in system GMM the selection bias is mainly due to correlation of fixed effects in selection and outcome equations. To correct for this selection bias they suggest to include the fixed effect from a regression similar to our first step, as a regressor in the dynamic panel estimation. More precisely, to follow Al-Sadoon et al. (2019) recommendation, we estimate log wage as function of two lags of log wage, lagged frailty interacted with education (with frailty treated as exogenous —given our earlier finding of absence of reverse causality), and fixed effects estimated in step 1. The result of this regression is presented in Table 26.

Using procedure outlined above we obtain an equation that relates log wages to frailty and age and is corrected for selection bias. We used estimated coefficients in this regression to remove the frailty effect and run the reminder (separately for each education group) on age polynomial and year dummies. These would be the deterministic components of function $\eta(j, f, s, \epsilon)$. For stochastic component we use the resulting residuals to estimate the process for shocks ϵ. To do this we estimate an AR(1) process with fixed effect for these residuals using GMM (this part closely follows Guvenen (2009)). Here we group together high school dropouts and high school graduates in order to take advantage of larger samples sizes. This means that we assume the same stochastic process of wage (net of frailty and selection effect) for both high school dropouts and high school graduates. The result of these estimations are presented in Table 27. In the appendix we compare our bias correction and estimates wage process to Low and Pistaferri (2015).

Finally, job separation rate is set to $\sigma = 15.15\%$, which is the average (annual) rate of layoffs and discharges between 2005 and 2007 according to the Jobs Opening and Labor Turnover Survey (JOLTS) by the Bureau of Labor Statistics (BLS).

Frailty and medical expenditure

For dynamics of frailty index, f, we use Hosseini et al. (2019) analysis and estimation. 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:

$$f_{ij} = X'_{ij}\beta + R_{ij},$$

where X_{ij} is the set of covariates (polynomial in age, gender, marital status, education, and year dummies). The residual consists of two components and is given by

$$R_{ij} = \alpha_i + z_{ij} + u_{ij}.$$

The first component, α_i, allows for individual-specific effects on the levels of frailty. We assume that α_i is randomly distributed across individuals with mean zero, and variance σ_α^2. We approximate its distribution with a 3-state discrete variable. The second component is the sum of an AR(1) process and a transitory shock u_{ij}. Thus

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

where $z_{i,0} = 0$.[30] The shocks ε_{ij} and u_{ij} are assumed to be independent of each other and over time, and independent of α_i. We assume that u_{it} has mean zero and variance σ_u^2 and that ε_{ij} has mean zero but its variance is age-dependent. Specifically, we assume that the variance of ε_{ij} is given by

[30]Note that j 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. This motivates our choice of an age-dependent but time-invariant stochastic component.

$$\sigma^2_{\varepsilon,j} = \delta_{\varepsilon,1} j + \delta_{\varepsilon,0}, \tag{19}$$

where $\delta_{\varepsilon,0}$ is the initial variance level and $\delta_{\varepsilon,1}$ is the rate at which the variance changes with age. The white noise shock u_{ij} captures both measurement error and acute health events such as a temporary inability to walk due to a broken leg. The persistence ρ and the variances of the innovations to the persistent process $\sigma^2_{\varepsilon,j}$ determine individuals' exposure to persistent health shocks. As we discuss in detail in Hosseini et al. (2019), allowing the variance of the persistent shocks to be age dependent is crucial for matching the qualitative properties of frailty dynamics.

We choose the values of the parameters in the frailty shock process based on our empirical estimation results reported in Hosseini et al. (2019). We then discretize the AR (1) process into a 15-state Markov chain by using the Rouwenhorst (1995) method, where the permanent component is discretized into 5 states and the transitory shock is discretized into 3 states.[31] The estimated parameters are reported in Table 28.

We estimate out-of-pocket medical expenditures separately by labor market status: employed, non-employed, and on Medicare (which includes both retirees and those who are on DI). For each labor market status and each education group we estimate out-of-pocket medical expenditures using MEPS on age polynomial and frailty polynomial. This allows us to capture the nonlinear effect that frailty has on out-of-pocket expenditures. Note that although we do not include any randomness directly in this formulation, the out-of-pocket medical expenditure is random through its dependence on frailty. The results of these estimations are presented in Table 29.

DI application

Social Security Disability Insurance program (SSDI) is an insurance program for covered workers, their spouses and dependents. The program pays benefit based a covered worker's past earnings. The purpose of the program to insure individuals against adverse health shocks that severely affect their ability to work. However, in determining eligibility vocational factors are also considered. The determination of eligibility is implemented through a multi-staged disability determination process involving medical evidence, "vocational" factors (specifically age, education, and past work), and a determination as to resulting activity limitations. The criteria, then, involve not only medical and vocational factors, but judgmental components. Below we describe a brief summary how benefit eligibility is determined. This brief description motivates the way we model this process.

To be eligible for benefits, a worker must have accumulated a sufficient number of SSA work credits. Those with insufficient/no credit are rejected immateriality. Also, claims made by insured workers currently engaged in substantial gainful activity are rejected. Claims are accepted if the applicant provides proof of a severe medical condition expected to last for at least one year or result in death, that meets or is equivalent to a condition the SSA's listing of over 100 specific impairments. Examples include statutory blindness (i.e., corrected vision

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

Table 4: Parameters chosen outside the model

Parameter	Description	Values/source
Demographics		
J	maximum age	70 (94 y/o)
R	retirement/SS eligibility age	41 (66 y/o)
ν	population growth rate	0.02
Preferences		
γ	curvature of utility function	2
μ	weight on consumption	0.5
Job Separation		
σ	annual layoffs/separations in JOLTS	0.15
Technology		
α	capital share	0.33
δ	depreciation rate (Gomme and Rupert (2007))	0.07
r	return on assets	0.04
Government policies		
τ_{SS}, τ_{med}	social security and Medicare tax rates	0.124, 0.029
τ_K	capital tax (Gomme and Rupert (2007))	0.3
τ	tax progressivity (Guner et al. (2014) estimation)	0.036
$\underline{c}$	minimum consumption (% of ave. earnings)	11
G	government purchases (% of GDP)	8

of 20/200 or worse in the better eye) and multiple sclerosis (inset reference in footnote). Claims that reach this stage and are not accepted go through extra review process that involves a combination of medical impairment and vocational factors such as education, work experience, and age. First, the applicant is evaluated in order to identify the types of work the individual is capable of in spite of their disability. If it is deemed the applicant is capable of performing their recent past work, their application will be denied. Otherwise, it will be considered whether the applicant has the vocational skills to adapt to new work feasible given their medical condition or impairment. This is when age and education/skill become a major factor. For example, according to Myers (1993), a former Social Security Administration Deputy Commissioner, "if a worker has a disability so severe that he or she can do only sedentary work, then disability is presumed in the case where the person is aged 55 and older, has less than a high school education, and has worked only in unskilled jobs, but this is not so presumed in the case of a similar young worker."

Motivated by description above, we assume that probability of successful DI application depends on frailty (to proxy for medical conditions/impairment), age (to proxy for vocational consideration), and number times the individual has applied for DI. This last one is motivated by the evidence presented French and Song (2014) who show that almost 70 percent of DI applications are eventually awarded benefit within 10 years, but the rate of successful application declines in number of previous attempts. To capture all this we make the following functional form assumption:

$$\theta\left(f, n_a\right) = \min\left\{1, \kappa_0 f^{\kappa_1} n_a^{\kappa_2}\right\}.$$

Table 5: Parameters calibrated using the model

Parameters	Description		Values
Preferences			
β	discount factor		0.976
Policy			
λ	HSV tax parameter(level)		0.036
Disutility of work			
ϕ_0	level		0.64
ϕ_1	frailty effect		2.5
ϕ_2	frailty effect		3.0
Prob. of successful DI application			
κ_0	level		150
κ_1	frailty effect		4.5
κ_2	decline in number of attempts		-0.7
Targeted Moments		Data	Model
Wealth-earning ratio		3.2	3.2
Federal income tax (% of GDP)		8	8
LFP by frailty quintile at ages 25 to 74		Figure 6	
DI take up rate by frailty quintile at age 25 to 64		Figure 6	
Decline in in number of attempts (French and Song (2014))		Figure 6	

We calibrate parameters κ_0 and κ_1, using the model, to match the DI take up rate at each age group and frailty group (0 to 50th percentile, 50th to 70th, 70th to 90th, 90th to 95th, and 95th and above). Parameter κ_2 is chosen so that the model matches decline of success rate in number of attempts as reported in French and Song (2014).

Policy parameters

For social security retirement and disability insurance benefits, we use social security benefit formula for primary insurance amount (PIA):

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

where $\bar{e}_a$ is the average earnings in the economy.

The tax function $T\left(\cdot\right)$ 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 $T\left(\cdot\right)$ is given as follows,

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

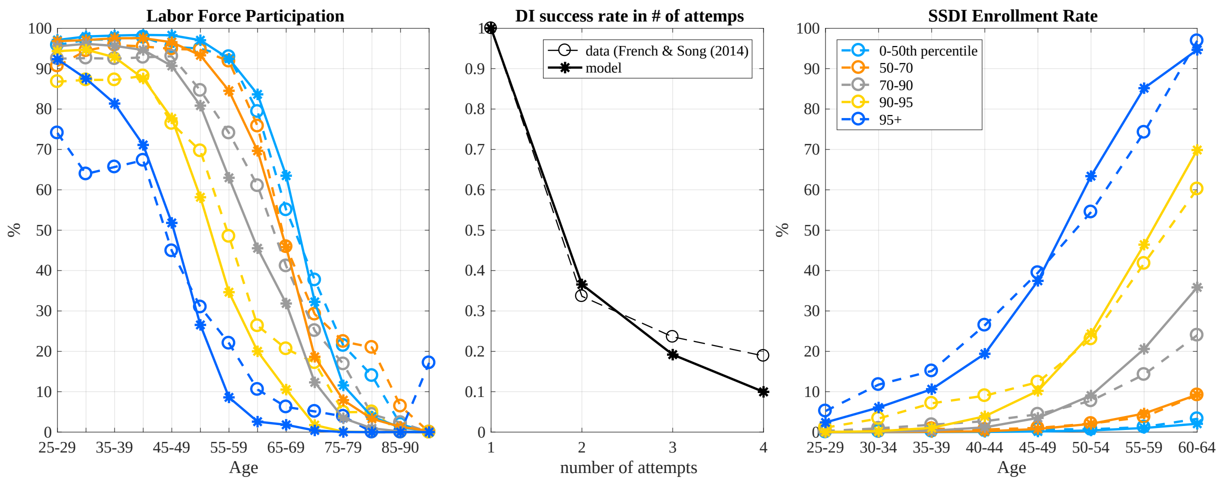


Figure 6: Calibration targets: model vs data. Solid lines are model. Dashed lines are data. Left panel is labor force participation (based on PSID), right panel fraction enrolled and receive SSDI benefit (based on MEPS), and middle panel is rate of success in SSDI application in number of attempts (taken from French and Song (2014) with first attempt normalized to 1).

Here τ controls the progressivity of the tax function, which is set to 0.036 based on the estimate by Guner et al. (2014). We choose the value of λ in the second-stage of the calibration to match the total federal income tax receipts as share of GDP in the U.S. data. The social security payroll tax rate is $\tau_{ss} = 0.124$ (subject to maximum taxable cap) and the medicare tax rate is set to $\tau_{med} = 0.029$. There is also a capital tax $\tau_K = 0.3$ paid by the firm (see Gomme and Rupert (2007)). Minimum consumption c_{min} is set at 11 percent of average earning (see Kopecky and Koreshkova (2014) for details and review of the literature).

Technology

We assume a small open economy and set $r = 0.04$. The capital share α is 0.36. We normalize aggregate wages to 1, and choose β to match wealth-to-earnigs ratio of 3.2. The depreciation rate is set to $\delta = 0.07$. This is based on calculation in Gomme and Rupert (2007)).[32]

For the employed workers who just came back from non-employment, we assume that they suffer a wage penalty, which mimics the forgone earnings 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 15-20 weeks (for period of 2000 to 2007). Therefore, we set the wage penalty to be a third of one year's earnings.

Table 6: Labor force participation rates (top) and DI recipiency rates (bottom) by education groups

	Labor force participation rates (%)		
	High School Dropouts	High School Graduates	College Graduates
Data	78	87	93
Model	84	89	96
	DI recipiency rates (%)		
	High School Dropouts	High School Graduates	College Graduates
Data	9.5	5.0	1.4
Model	8.4	4.9	0.8

4.1 Calibration results

Frailty affects employment (and therefore earnings) through five channels: 1) mortality rates, 2) out of pocket medical expenditures, 3) labor productivity, 4) probability of successful DI application, and 5) disutility from working. As we described above, we estimate the impact of frailty on the first three outside of the model. Moreover, we choose a series of preference, technology, and policy parameters independently from the model. The calibrated values and targets for these parameters are presented in Table 4.

We use these predetermined processes and parameter values to calibrate the probability of successful DI application as well as disutility from working by matching targets using our model. The moments that determine the parameters for the probability of successful DI application are the SSDI enrollment rates by frailty percentiles (0 to 50th, 50th to 70th, 70th to 90th, 90th to 95th, and 95th and above) for each 5 year age group between ages 25 and 64, as well as, the rate of decline in the DI acceptance rate by number of attempts. We also target labor force participation rates by frailty percentiles for age group 25 to 74 to determine the parameters of the disutility of work. Chance of successful DI application does not directly impact the labor supply choices of individuals after age 65. For this reason, the dispersion in the labor force participation rates by frailty for individuals in the 65 to 74 year-old age groups can be used to pin-down the effect of frailty on the disutility from working.

In the second-stage of the calibration we also target the wealth-to-output ratio and the share of revenue raised through non-linear income taxes to pin down the discount factor β and average tax parameter λ, respectively. These parameters that are calibrated using the model are presented in Table 5.

Figure 6 shows calibration targets in data and their model counterparts. All targeted moments are reasonably close except the labor force participation rates of individuals in the top 5 percent of the frailty distribution under age 45. The model overstates the participation rates of these individuals. In general the model overstates participation at younger ages and

[32] Gomme and Rupert (2007) calculate depreciation for four different sectors (Market Structures, Equipment and Software, Housing, and Consumer Durable). We use a weighted average of their calculations. To do this we weight depreciation in each sector by the share of capital in that sector. All of our calculations are based on their reported data and calculations.

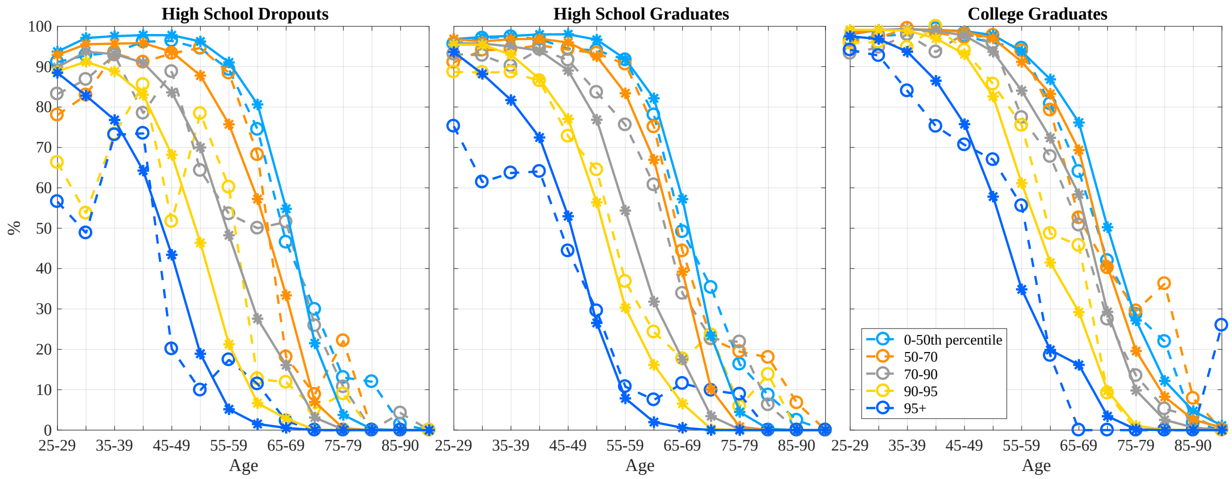


Figure 7: Calibration assessment: participation rate by education, frailty groups (0 to 50th percentile, 50th to 70th, 70th to 90th, 90th to 95th, and 95th and above) and age. Solid lines are model. Dashed lines are data (PSID).

understates it at older ages. Note that the participation rates of individuals ages 75 and above are not targeted.

To assess the model's performance with regards to non-targeted moments, we look at labor force participation and DI take up rates across different education groups. Table 6 shows the overall participation and DI take up rates by education group. Top panel shows that the model does reasonably well in matching participation among college and high school graduates, but overstates the participation among the high school dropouts. The bottom panel shows that the model closely matches the SSDI take up rate for high school graduates, but slightly understates SSDI take up rates for both high school dropouts and college graduates.

To inspect this further we look at participation by age and frailty groups (0 to 50th percentile, 50th to 70th, 70th to 90th, 90th to 95th, and 95th and above) across different education groups. These are presented in Figure 7. Here we see that the model performs reasonably well capturing the pattern of labor force participation for each education group. In particular, it captures well the reduced dispersion in participation rates by frailty at education increases. Among high school dropouts and and high school graduates, the model overstates employment rates among young (under 45) workers who are in top 5 percent of frailty. It also understates the participation rates of workers above age 65. In general the model tends to overstate participation when young and understate participation when old.

Figure 8 present share of workers in each age, frailty group (0 to 50th percentile, 50th to 70th, 70th to 90th, 90th to 95th, and 95th and above), and each education group who are on SSDI. The model captures the pattern of SSDI recipiency by frailty and age within each education group. Importantly, the model replicates the rise in SSDI recipiency of those in the top deciles of the frailty distribution by education. We view these findings as evidence that, overall, our model captures well the extent of poor health, its effects, and the labor supply responses to it for individuals in the unhealthy tail of the frailty distribution.

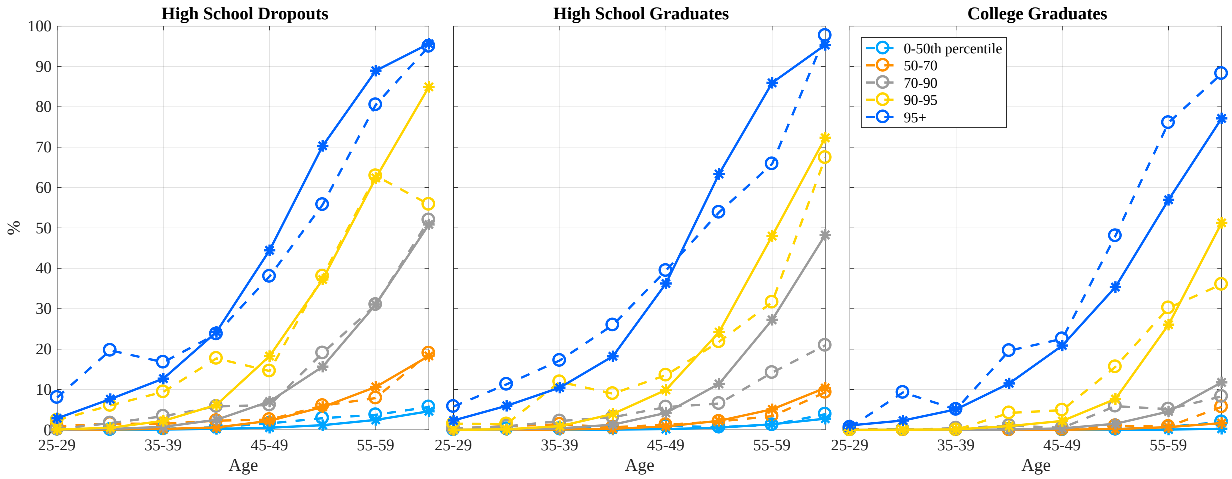


Figure 8: Calibration assessment: SSDI enrollment rate by education, frailty groups (0 to 50th percentile, 50th to 70th, 70th to 90th, 90th to 95th, and 95th and above) and age. Solid lines are model. Dashed lines are data (MEPS).

5 Quantitative Exercise

In this section we use the calibrated model to assess the impact of health inequality on lifetime earnings inequality. To do this we conduct the following experiment. We consider a counterfactual economy in which everyone has the same frailty age-profile. In particular, we give all individuals in the economy the average frailty profile. Giving all individuals in the economy the average frailty profile removes all cross-sectional variation in frailty (due to both individual fixed effects and risk) that is present in the benchmark economy. In doing so, we remove heterogeneity in frailty due to their education levels and fixed frailty types. We also remove heterogeneity in frailty due to the persistent and transitory frailty shocks. With this understanding, we refer to the counterfactual economy as the No-Frailty-Heterogeneity economy (or NFH for short). We compare the inequality in lifetime earnings at different ages between the No-Frailty-Heterogeneity economy and the benchmark. For each individual, our measure of lifetime earnings at each age is simply that individual's accumulated earnings to date.

Figure 9 shows the age-profile of the variance of log lifetime earnings in the benchmark economy and the No-Frailty-Heterogeneity economy. The No-Frailty-Heterogeneity economy has almost the same variation in lifetime earnings as the benchmark economy at younger ages. However, between ages 35 and 65, the variance of log lifetime earnings increases more rapidly with age in the benchmark economy. As a result, there is less variation in lifetime earnings in the No-Frailty-Heterogeneity economy starting around age 40. As reported in Table 7, at age 45 the variance of log lifetime earnings is 13.9 percent lower in the No-Frailty-Heterogeneity economy relative to the benchmark. The relative difference peaks at age 65 when the variance of log lifetime earnings is 32 percent lower.[33]

We also report results for two related counterfactuals in Table 7. The aim is to assess

[33]Everyone in our model chooses to work in the first period of life. Thus, no one in our model has a lifetime earnings of zero at any age. Therefore, we can use the variance of log to measure and compare dispersion.

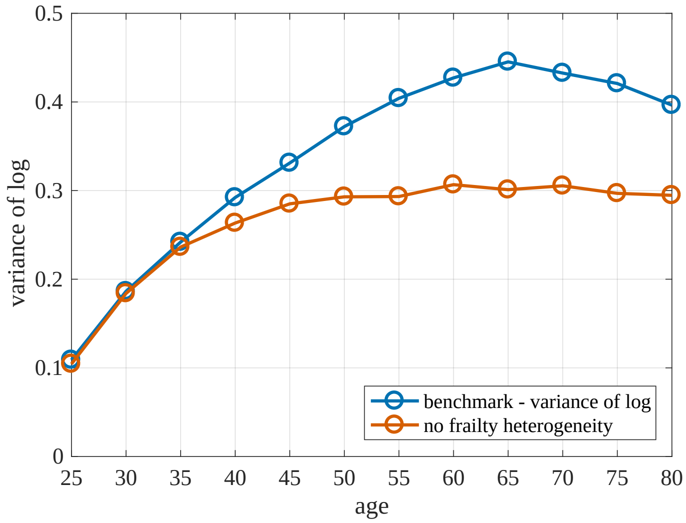


Figure 9: Variance of log lifetime earnings. Benchmark model (blue) vs model without heterogeneity in frailty (red).

whether the decline in the variance of log lifetime earning is driven by removing fixed effect heterogeneity or risk. In the middle panel of table 7 we report the variance of log lifetime earnings for a counterfactual economy that is identical to the benchmark, except that there is no frailty shock. All inequality in frailty in this economy is due to initial fixed heterogeneity. The bottom panel of table 7 shows the results of the same calculation for an economy that does not feature any initial heterogeneity in frailty due to fixed effects. All the inequality in frailty in this counterfactual is driven by the transitory and permanent shocks to frailty. As expected the decline in the variance of log lifetime earnings in both counterfactuals is smaller relative to the main counterfactual (or No-Frailty-Heterogeneity). However, the decline in the variance of log lifetime earning is larger when we only remove shocks, especially at older ages.

To sum up these findings, inequality in frailty appears to have a large effect on the variance of log lifetime earnings. This effect is mainly driven by the initial fixed effect heterogeneity at younger ages (up to 45). However, for older workers (older than 55) more than two thirds of the decline can be attributed to the transitory and permanent frailty shocks. This finding is also important in that it highlights why understanding the dynamics of health status is important for understanding the impact of health status of labor supply and income inequality.

Next, we show that almost all of the deference in variance of log lifetime earning between benchmark economy and the No-Frailty-Heterogeneity economy is due to higher earnings at the bottom of the distribution in the No-Frailty-Heterogeneity economy. To show this we calculate the ratios of lifetime earnings at the 5th percentile to the median, the 10th percentile to the median, the 90th percentile to the median, and the 95th percentile to the median by age. We compare these ratios in the benchmark economy with those in the No-Frailty-Heterogeneity economy. These measures are plotted in Figure 10. Notice that, after age 40, there are large differences in the ratios of the 5th and 10th percentiles relative to the median across the two economies. In contrast, there are little differences in the ratios of

Table 7: Variance of log lifetime earnings in benchmark economy and counterfactual economy without frailty heterogeneity.

	Var. log lifetime earnings			
	age 45	age 55	age 65	age 75
Benchmark	0.33	0.40	0.45	0.42
No frailty heterogeneity	0.29	0.29	0.30	0.30
% change relative to benchmark	-13.91	-27.42	-32.39	-29.45
Removing only frailty shocks	0.31	0.33	0.34	0.33
% change relative to benchmark	-5.49	-17.92	-24.12	-21.06
Removing only frailty fixed effect	0.30	0.37	0.41	0.40
% change relative to benchmark	-8.47	-9.60	-8.12	-4.23

Note: "No frailty heterogeneity counterfactual" removes all frailty shocks as well as cross-sectional (fixed effect) heterogeneity. "Removing only frailty shocks" removes only ex post uncertainty/shocks but retains all the initial fixed-effect heterogeneity. "Removing only frailty fixed effect" only removes initial fixed effect heterogeneity but retains all the shocks and uncertainty.

the 90th and 95th. This figure clearly shows that almost all the decline in the variance of lifetime earnings when health inequality is removed is driven by an increase in the lifetime earnings of individuals at the bottom of the distribution.

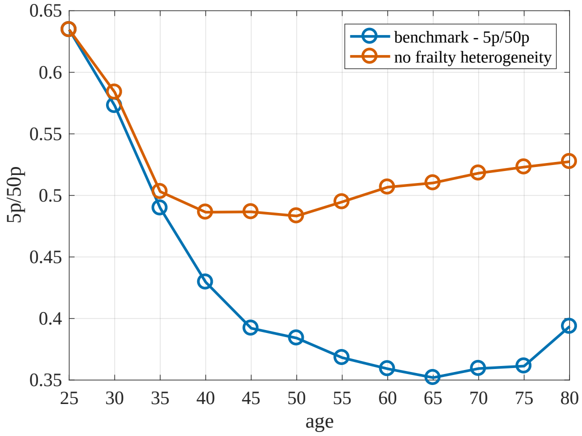
5.1 Breaking down the effect of frailty heterogeneity

As we mentioned before, there are five channels through which frailty can affect earnings and earnings inequality in this model. In our next exercise we assess the importance of each of these five channels in driving the results above. In other words, we want to know how important each channel is in generating the difference in the variance of log lifetime earnings between the benchmark economy and the No-Frailty-Heterogeneity economy. To this end, we run five additional counterfactual economies. In each counterfactual we shut down heterogeneity in frailty in one channel while leaving the rest as they are in benchmark. Here are the five counterfactual economies:

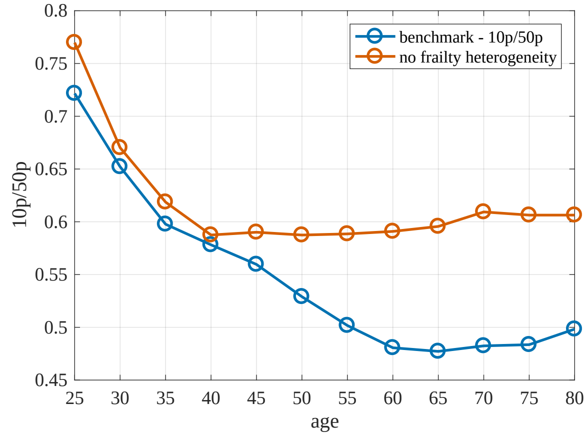
1. Counterfactual economy 1 is equivalent to the benchmark, expect that the probability of successful SSDI application is determined by the average frailty at each age (and independent of individual frailty). We label this experiment "NFH in SSDI" (no frailty heterogeneity in SSDI).

2. Counterfactual 2 is equivalent to the benchmark, expect that labor productivity (wage) is determined by the average frailty at each age. We label this experiment "NFH in Labor Productivity".

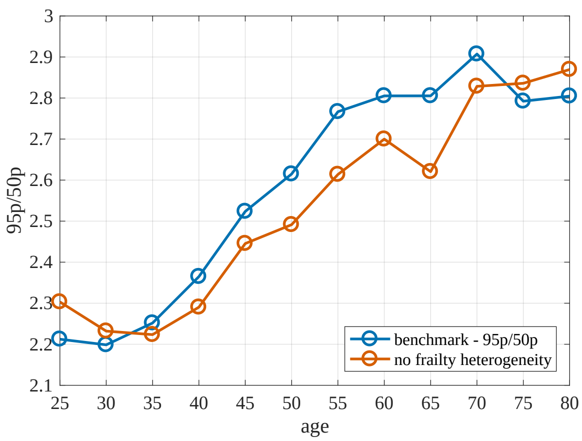
3. Counterfactual 3 is equivalent to the benchmark, expect that the disutility from working is determined by the average frailty at each age. We label this experiment "NFH in Disutility".



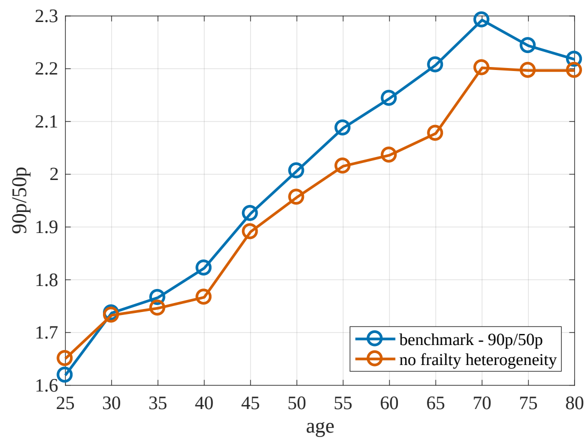
(a) 5th percentile to median



(b) 10th percentile to median



(c) 95th percentile to median



(d) 90th percentile to median

Figure 10: Inequality in lifetime earnings. Benchmark model (blue) vs model without heterogeneity in frailty (red).

4. Counterfactual 4 is equivalent to the benchmark, expect that out-of-pocket medical expenditures are determined by the average frailty at each age. We label this experiment "NFH in Medical Expenditure".

5. Counterfactual 5 is equivalent to the benchmark, expect that mortality rates are determined by the average frailty at each age. We label this experiment "NFH in Mortality".

Table 8 shows the differences in the variance of log lifetime earnings between the benchmark economy and each counterfactual economy at four ages. Note that the SSDI channel generates a large decline especially at older ages. In other words, if SSDI application was decided for everyone on the basis of average health at each age and not on individual health status, the variance of log lifetime earnings would be lower by 12.6, and 18.3 percent, respectively, at ages 65 and 75. However, this is not the case for younger workers. At age 45, the variance of log lifetime earning is 9.4 percent higher in the "NFH in SSDI" counterfactual relative to the benchmark economy. Young frail workers in the benchmark economy have a higher

Table 8: Decomposition of different channels

	Var. log lifetime earnings (%Δ relative to benchmark)			
	age 45	age 55	age 65	age 75
NFH in SSDI	$+9.4$	-1.3	-12.6	-18.3
NFH in Labor Prod.	-10.3	-14.1	-14.7	-11.7
NFH in Disutility	-4.9	-6.3	-6.0	-3.5
NFH in Med. Exp.	$+0.1$	$+0.3$	$+0.3$	$+1.0$
NFH in Mortality	-3.5	-3.8	$+0.7$	$+13.1$

Note: Each row shows the percentage change in variance of log lifetime earnings relative to benchmark. NFH: no frailty heterogeneity. NFH in SSDI: probability of SSDI acceptance is the same for all individuals at same age, NFH in Labor Prod.: there is no heterogeneous effect of frailty on wage, NFH in Disutility: there is no heterogeneous effect of frailty on disutility from work, NFH in Med. Exp.: no heterogeous effect of frailty on out of pocket medical expenditures, NFH in Mortality: no heterogeneous effect of frailty on mortality.

incentive to work. They expect a high chance of going on SSDI in the future and they want to accumulate earnings credit to raise their benefit in anticipation. This incentive becomes a lot weaker if the SSDI benefit is decided based on average frailty (rather than their own high individual frailty). On the other hand, they still suffer high disutility of work and have low wages (similar to the benchmark). These effects push young frail workers out of the labor force, and onto means-tested programs (modeled as a consumption floor in our framework). Therefore, removing the heterogeneous effect of frailty on SSDI causes an increase in the dispersion of lifetime earnings (rather then decrease) for young workers.

Removing frailty heterogeneity in determining the SSDI acceptance rate reduces the chance of going on SSDI for older frail workers as well. However, since they are more likely to have accumulated wealth, they are not eligible for means-tested programs. Therefore, they continue to work. This is the main reason for the large decline in the variance of log lifetime earnings in the “NFH in SSDI" counterfactual relative to the benchmark.

Overall (and across all ages), the largest decline in the variance of log lifetime earnings is due to the labor productivity channel. If frailty did not have a heterogeneous impact on labor productivity, the variance of log lifetime earnings would have been between 10.3 to 14.7 percent lower relative to the benchmark. Since high frailty has the same impact on wages in all ages, removing frailty heterogeneity causes an increase in wages for frail individuals at all ages. Note that, this implies that the wage (labor productivity) channel accounts for the largest portion of the decline in the variance of log lifetime earnings for younger workers. But its effect is dominated by the SSDI channel by age 75.

The impact of the disutility channel on the decline in the variance of log lifetime earnings is less than half the impact of the labor productivity channel. Moreover, the medical expenditure channel has almost no effect.

There are two offsetting effects of using the average frailty profile to determine each individual's mortality. First, it increases the life expectancy of frail individuals which increases their labor supply. With a higher life expectancy, these individuals discount the future less heavily which increases their return from working and accumulating wealth. This first effect

Table 9: Effects of frailty heterogeneity by education group on SSDI enrollment, Participation, and receipt of means-tested transfers (impact of different channels)

	Benchmark	NFH in model	NFH in SSDI	NFH in Disutility	NFH in Labor prod.	NFH in Med. Exp.	NFH in Mortality
			SSDI Enrollment (% of 25 to 65 year olds)				
All	4.07	0.07	0.10	3.22	3.06	4.08	4.35
HSD	8.38	0.09	0.16	6.95	5.79	8.40	9.05
HSG	4.92	0.08	0.12	3.89	3.69	4.93	5.24
CG	0.84	0.04	0.05	0.57	0.82	0.84	0.88
			Participation Rate (% of 25 to 65 year olds)				
ALL	90.84	94.81	91.80	92.03	92.15	90.86	90.57
HSD	84.14	92.70	85.05	86.05	87.93	84.15	83.69
HSG	89.40	94.12	90.53	90.83	90.92	89.43	89.11
CG	96.13	96.99	96.74	96.57	96.15	96.14	95.99
			Means Tested Program Claims (%)				
ALL	2.41	2.30	4.16	2.24	2.07	2.35	2.39
HSD	4.06	3.28	8.75	3.78	2.86	3.97	4.03
HSG	2.75	2.65	4.85	2.52	2.39	2.68	2.70
CG	1.14	1.24	1.22	1.13	1.15	1.15	1.17

Note: Top panel shows the fraction of 25 to 65 year old on SSDI in benchmark and each counterfactual. Middle panel is labor force participation. Bottom panel is the fraction who receive means-tested transfers. HSD: high school dropout, HSG: high school graduate, CG: college graduate. NFH: no frailty heterogeneity. NFH in SSDI: probability of SSDI acceptance is the same for all individuals at same age, NFH in Labor Prod.: there is no heterogeneous effect of frailty on wage, NFH in Disutility: there is no heterogeneous effect of frailty on disutility from work, NFH in Med. Exp.: no heterogeous effect of frailty on out of pocket medical expenditures, NFH in Mortality: no heterogeneous effect of frailty on mortality.

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. As a result, relative to the benchmark, there are more poor individuals in each age group. This second effect works to increase lifetime earnings inequality. The impact of the second effect grows with age due to the nature of mortality risk. The impact of the first effect grows smaller with age as more individuals retire. Thus, the first effect dominates at younger ages and the second one at older ages.

Table 9 shows the fraction of 25 to 65 year old workers who are on SSDI (top panel), labor force participation (middle panel), and share of people who receive means-tested transfers (bottom panel) for benchmark economy, No-Frailty-Heterogeneity economy and the five counterfactual economies described above. Looking at the first two columns, the effect of frailty heterogeneity in SSDI enrollment is almost uniform and large across education groups. However, the increase in labor force participation is concentrated among high school dropouts and to a lesser extent high school graduates. The rise in participation among college graduates is very small. Moreover, eliminating heterogeneity in frailty has small effect on receiving means-tested transfers.

Table 10: Aggregate Effect of Inequality in Frailty

	NFH in model	NFH in SSDI	NFH in Disutility	NFH in Labor prod.	NFH in Med. Exp.	NFH in Mortality
	% change relative to benchmark					
GDP	3.36	1.41	1.16	0.85	0.00	−1.22
Consumption	2.51	0.82	1.27	0.37	−0.10	−1.40
Capital	3.36	1.41	1.16	0.85	0.00	−1.22
Labor input	3.36	1.41	1.16	0.85	0.00	−1.22
Hours	4.35	1.50	1.62	1.05	0.01	−1.04
GDP per Hour	−0.94	−0.09	−0.45	−0.20	−0.01	−0.18

Note: Each column shows the difference in aggregate measure between the respective counterfactual and benchmark. NFH: no frailty heterogeneity. NFH in SSDI: probability of SSDI acceptance is the same for all individuals at same age, NFH in Labor Prod.: there is no heterogeneous effect of frailty on wage, NFH in Disutility: there is no heterogeneous effect of frailty on disutility from work, NFH in Med. Exp.: no heterogeous effect of frailty on out of pocket medical expenditures, NFH in Mortality: no heterogeneous effect of frailty on mortality.

The third to seventh columns show that the effect of No-Frailty-Heterogeneity on SSDI enrollment is entirely driven by SSDI channel. This is, of course expected. However, the effect on participation is likely a combination of all five channels.

Finally, as the bottom panel shows, the effect on means-tested program receipt is due to balance of two opposing forces. On one hand, SSDI channel pushes young frail workers out of labor force and on the means-tested program. On the other hand, labor productivity channel and disutility channel provide more work incentive at older ages and move workers away from mean-tested programs.

Figures 12, 13, and 14, show participation, SSDI enrollment and mean-tested transfer recipient by frailty group and age for benchmark economy, No-Frailty-Heterogeneity economy, and each of the five counterfactual economies we described. Note first, that all the effects are concentrated in the top 30 percentiles of frailty with very little difference in the bottom 70 percent between benchmark and any of the counterfactuals. Also, the effects are most pronounced at top 10 percent and top 5 percent of frailty. This highlight, once again, why it is important to use frailty as a measure of health status and be able to focus on the impact of health status at on a fine scale.

Figure 12 clearly shows that shutting down SSDI channel reduces participation at younger ages specially at top 10 percentile of frailty (panels (d) and (e)). On the other hand it increases participation at older ages, specially for those in 70th to 95th percentile of frailty (panels (c) and (d)). Shutting down disutility channel and wage channel increase participation at all ages.

Figure 13 shows, once again, that the effect on SSDI enrollment is entirely driven by SSDI channel. There is however small effect from disutiliy channel and labor productivity channel for those in top 10 percentile of frailty (panels (d) and (e)).

Finally 14 shows that shutting down SSDI channel significantly increase fraction who receive means-tested transfers among young and very frail individuals (panel e)). These are individuals who don't have incentive to accumulate earnings credit to raise their SSDI benefit, and yet, they are too frail to work. Therefore, they go on means-tested programs. On the other hand, older frail workers have accumulated wealth and are not eligible for these programs. Therefore, as panel (e) shows, the share of means-tested program recipients is very close to benchmark at older ages.

To sum up these findings, inequality in health is an important source of lifetime earnings inequality. The impacts of health inequality on lifetime earnings inequality are concentrated in the bottom of the earnings distribution. The important channels through with health inequality works to increase lifetime earnings inequality are the SSDI channel and the labor productivity (wage) channel. The labor productivity channel increases health inequality at all ages because negative health shocks only affect the productivity of less-educated workers. The SSDI channel initially works to reduce lifetime earnings inequality by incentivizing frail young individuals to work to receive higher DI benefits when older. However, by age 75, the DI channel is the most important channel through which health inequality generates lifetime earnings inequality. This is because the dominate effect of SSDI is that is induces older frail working-age individuals to exit the labor force to apply for and collect SSDI benefits.

5.2 Aggregate effects

We report the aggregate implications of each of the counterfactuals in Table 10. Each column shows the change in GDP per capita, aggregate consumption, aggregate capital, aggregate labor services, aggregate hours, and labor productivity (GDP per hours) for each of our counterfactual economies relative to benchmark. The first column shows that removing all inequality in frailty raises GDP per capita by 3.36 percent and aggregate consumption by 2.51 percent. It also increases hours worked by 4.35 percent. This is expected in light of the previous discussions. Removing inequality in frailty mainly increases participation of workers at the bottom of income/wage distribution. Since these are on average the less productive workers, the resulting GDP per hours falls by 0.94 percent.

Columns 2 through 6 show that the main driver of the GDP impact is the SSDI channel, while removing frailty heterogeneity in disutility has the largest impact on consumption and hours. This is due to the fact that removing only the SSDI channel has opposite effects on labor supply at young and old ages. Moreover, while it reduces the aggregate disability benefit, it increases the fraction of individuals who are eligible for the means-tested welfare transfers. These opposing effects aggregate to a smaller impact on consumption and hours from the SSDI channel (relative to the impact of the disutility channel), even-though it is significantly more important in terms of affecting individual labor supply and income inequality.

Finally, removing frailty inequality in mortality increases survival and tilts the age distribution of the model towards older (mostly retired) individuals. For this reason it has a negative impact on all aggregate measures.

5.3 Alternative measures of income

Our findings show that inequality in frailty can have a significant impact on lifetime earnings inequality. The impact mainly operates through the effect of poor health on labor productivity of workers and their chances of becoming SSDI beneficiaries. Removing health inequality

Table 11: Variance of log lifetime disposable income.

	Var. log lifetime disposable income			
	age 45	age 55	age 65	age 75
Benchmark	0.30	0.32	0.33	0.31
No frailty heterogeneity	0.28	0.29	0.29	0.27
% change relative to benchmark	-6.30	-10.79	-11.55	-12.81
Removing only frailty shocks	0.29	0.30	0.31	0.29
% change relative to benchmark	-0.72	-5.40	-6.94	-5.93
Removing only frailty fixed effect	0.28	0.31	0.32	0.30
% change relative to benchmark	-4.01	-2.94	-2.98	-2.06

Note: Each row shows the percentage change in variance of log lifetime earnings relative to benchmark. NFH: no frailty heterogeneity. NFH in SSDI: probability of SSDI acceptance is the same for all individuals at same age, NFH in Labor Prod.: there is no heterogeneous effect of frailty on wage, NFH in Disutility: there is no heterogeneous effect of frailty on disutility from work, NFH in Med. Exp.: no heterogeous effect of frailty on out of pocket medical expenditures, NFH in Mortality: no heterogeneous effect of frailty on mortality. Disposable income is the sum of labor earnings and any transfer net of any tax.

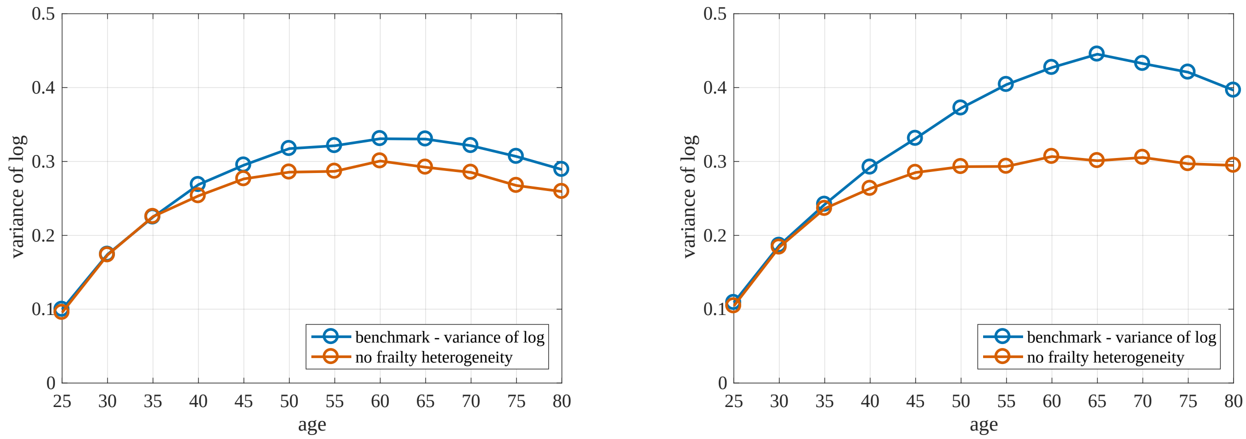
has two effects. On the one hand it increases income, on the other hand it increases taxes and reduces transfers for these workers. Here, we report the impact of frailty heterogeneity on inequality in lifetime disposable income. For this purpose we compute disposable income as the sum of labor earnings and transfers net of all taxes.[34]

Table 11 shows the variance of log lifetime disposable income for the benchmark economy with no frailty heterogeneity, the economy with only individual fixed effect heterogeneity (and no shock), and the economy with only frailty shocks (and no fixed effect heterogeneity). First, note that removing all frailty heterogeneity reduces the variance of log lifetime disposable income by 6.3 percent (at age 45) to 12.8 percent (at age 75). Comparing this to the numbers in Table 7, the decline in the dispersion of lifetime disposable income is less than half the decline in the dispersion of lifetime earnings. This can be seen more clearly in Figure 11. Also, as is the case for the variance of log lifetime earnings, most of the decline in the variance of log lifetime disposable income at older ages is driven by the removal of transitory and permanent shocks.

6 Conclusion

We documented empirically that declines in health reduce labor productivity and the probability of labor force participation. The effects are concentrated in less educated individuals and those already in poor health. These findings suggest that health inequality may be an important source of lifetime earnings inequality. Using a structural model, we quantified that 29% of the variation in lifetime earnings at age 75 is due to the fact that individuals in the United States face risky and heterogeneous lifecycle health profiles. The impact of

[34] We have done all the calculations with an alternative definition that includes capital income. The results are very similar.



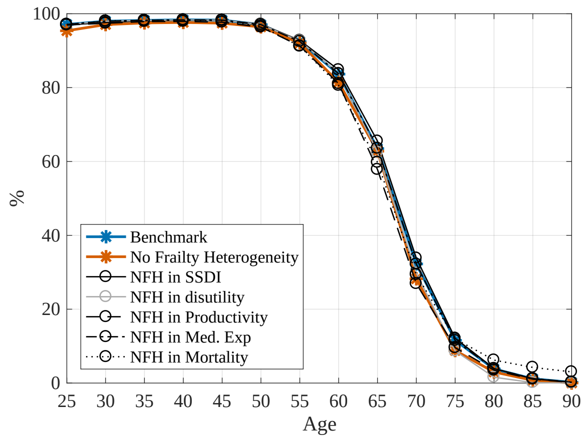
(a) Variance of log lifetime disposable income

(b) Variance of log lifetime earnings

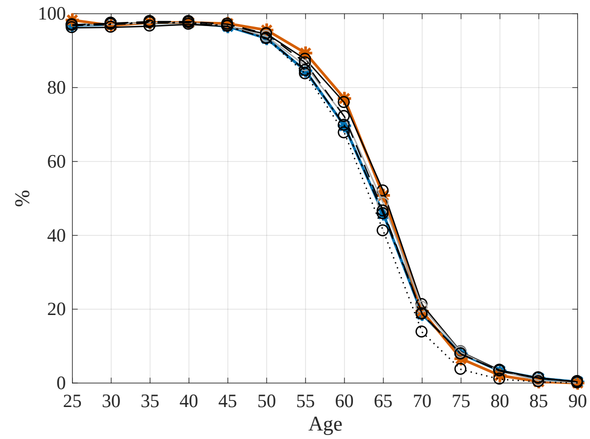
Figure 11: Panel (a) is variance of log lifetime disposable (defined as sum of earnings and transfers net of taxes). Panel (b) is variance of log lifetime earnings. Blue line is benchmark. Red line is the economy with no frailty heterogeneity.

health on lifetime earnings is largest at the bottom of the lifetime earnings distribution. This is because poor health has a large impact on the participation of lower productivity individuals.

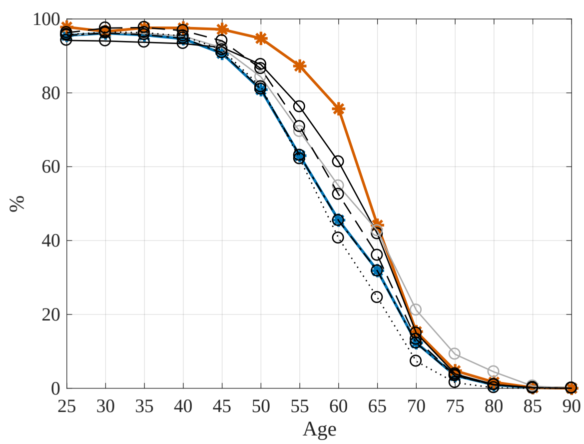
In a decomposition exercise, we show that impact of poor health on wages and access to social security disability benefits are the most important factors for our results. In other words, we find that the primary reason why poor health individuals have low lifetime earnings is because they have a high likelihood of obtaining social security disability benefits or that they have lower wages. Interestingly, we find that disutility effects of working while in poor health play a relatively small role. Our results support the view that the labor force participation rates of individuals in poor health are highly sensitive to the structure and scale of the social security disability program.



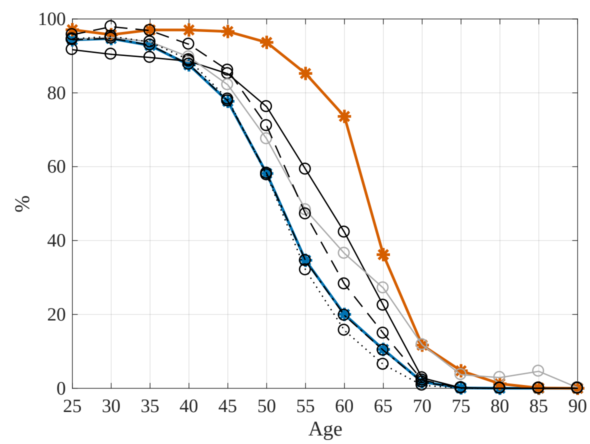
(a) Bottom half



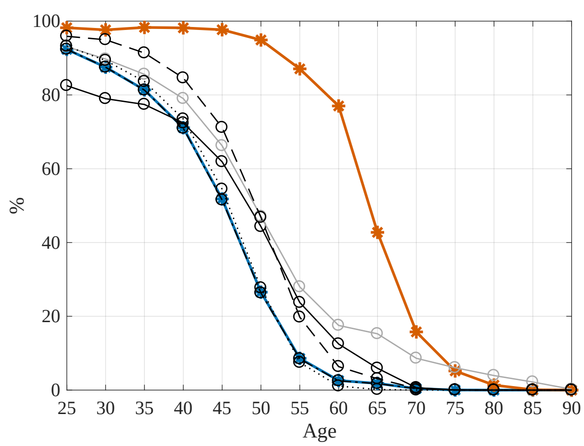
(b) 50th to 70th percentile



(c) 70th to 90th percentile

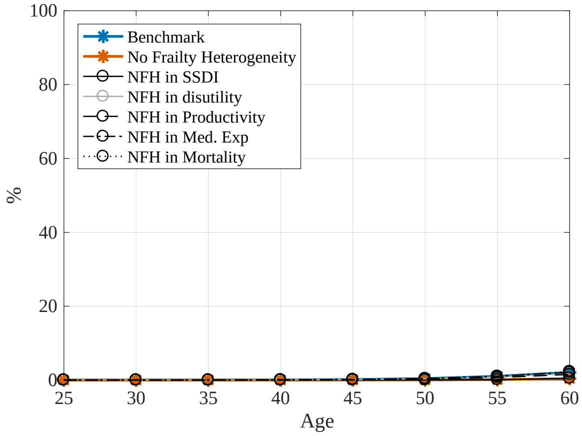


(d) 90th to 95th percentile

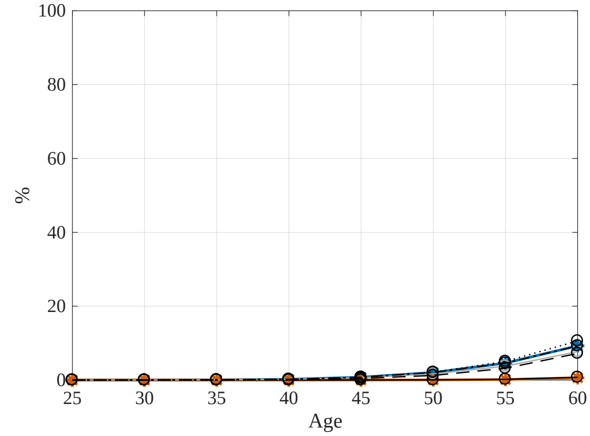


(e) 95th and above

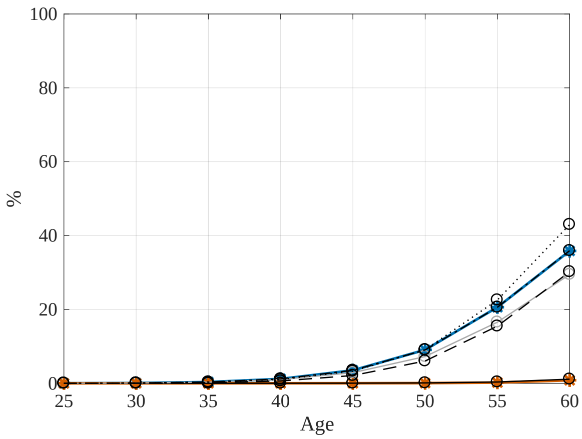
Figure 12: Labor force participation by age and frailty quantiles: comparison between benchmark, No-Frailty-Heterogeneity and all other counterfactuals. Each line plots labor force participation by age for benchmark (blue), No-Frailty-Heterogeneity (red) and all other counterfactuals (black and grey).



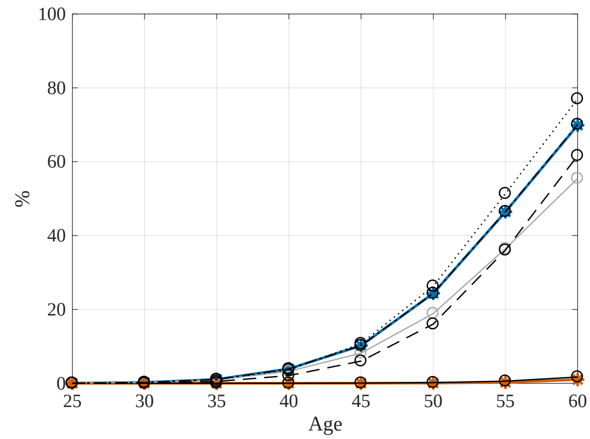
(a) Bottom half



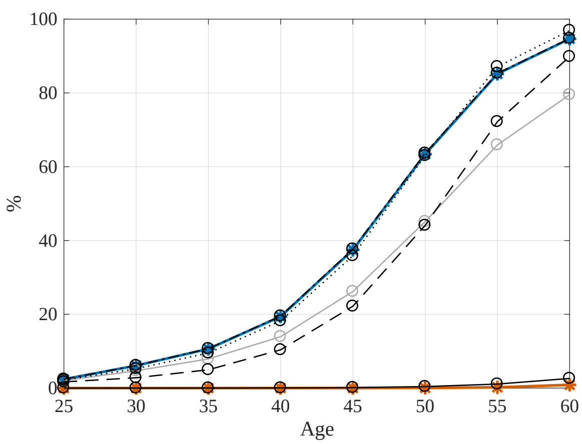
(b) 50th to 70th percentile



(c) 70th to 90th percentile

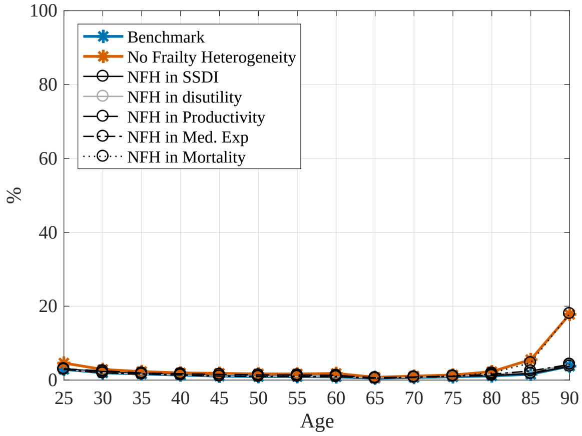


(d) 90th to 95th percentile

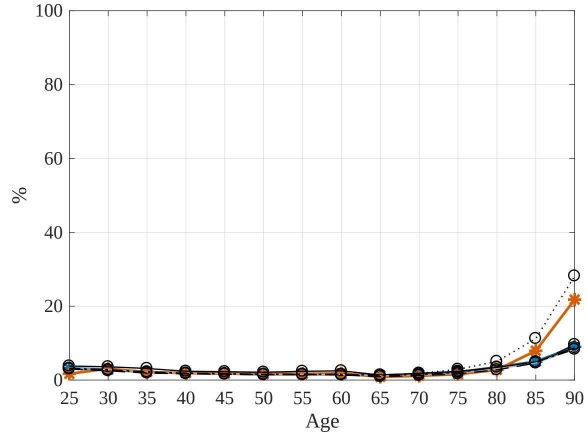


(e) 95th and above

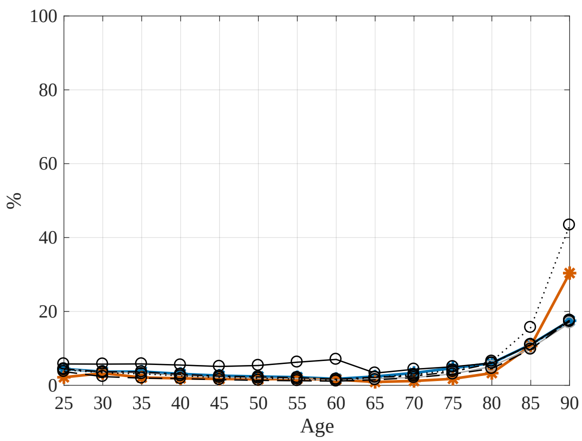
Figure 13: SSDI enrollment by age and frailty quantiles: comparison between benchmark, No-Frailty-Heterogeneity and all other counterfactuals. Each line plots fraction who is SSDI beneficiary by age for benchmark (blue), No-Frailty-Heterogeneity (red) and all other counterfactuals (black and grey).



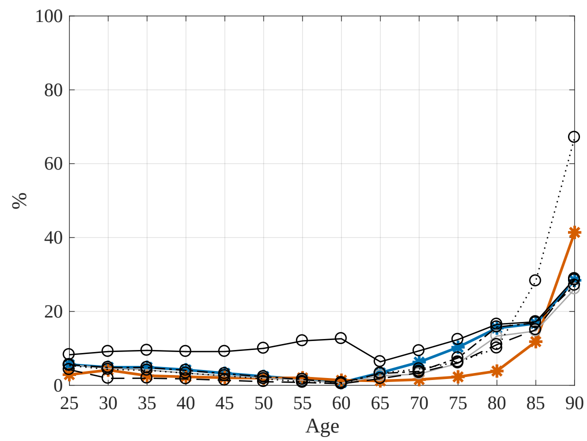
(a) Bottom half



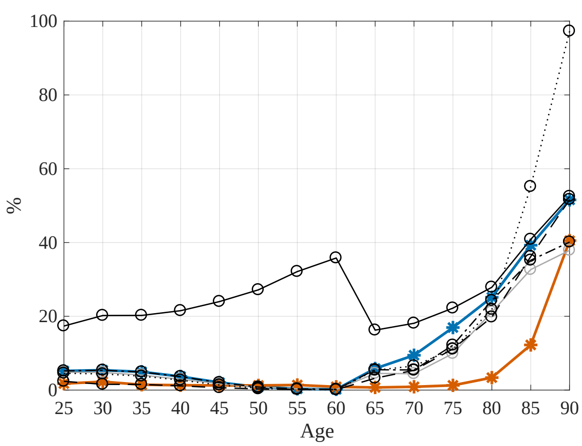
(b) 50th to 70th percentile



(c) 70th to 90th percentile



(d) 90th to 95th percentile



(e) 95th and above

Figure 14: fraction who receive means-tested transfers by age and frailty quantiles: comparison between benchmark, No-Frailty-Heterogeneity and all other counterfactuals. Each line plots fraction who receive means-testes transfers by age for benchmark (blue), No-Frailty-Heterogeneity (red) and all other counterfactuals (black and grey).

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Appendix

A Data Description

A.1 PSID

We use 2003–2017 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. PSID only collects detailed health information for household heads and spouses. A good description of the PSID household head definition is in Heathcote et al. (2010). The base sample consists of 22,143 individuals (10,600 men, 11,543 women).

Table 12 lists the 27 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 13 reports summary statistics on the PSID sample used for the dynamic panel estimations. The sample consists of household heads and spouses aged 25 to 74. All individuals in the sample are in at least 3 consecutive waves of the PSID over the 2003–2017 sample period. Annual earnings are total annual labor earnings (including wages and salaries, bonuses, overtime tips, commissions, professional practice or trade, any additional job income, and any miscellaneous labor income). Annual hours are the total annual work hours for all jobs, including overtime. Hourly wage a PSID constructed variable that is constructed using annual earnings and annual hours. It is adjusted by PSID for outliers.

A.1.1 Health and Retirement Survey

The HRS is a biennial longitudinal survey of Americans over age 50. Aside from spouses of respondents, the HRS does not survey individuals under the age of 51. We use the HRS waves spanning the period 1998 to 2014. Our sample consists of 205,711 observations of 36,032 individuals (15,860 men and 20,172 women). We construct a frailty index for HRS respondents in the same way as for PSID respondents. The lifecycle dynamics of frailty in the HRS and PSID samples are very similar even though the HRS contains a larger number of deficit variables (36 versus 27). See Hosseini et al. (2019) for additional details.

A.1.2 Medical Expenditure Panel Survey

The MEPS consists of a collection of rotating two-year panels. We use MEPS data from the 2000 to 2016 period. Our sample consists of respondents aged 25 to 84 years. We do not include individuals aged 85 years or older because, starting in 2001, MEPS top codes

Table 12: 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 ever smoked	Yes=1, No=0

age at 85. The base sample contains 345,022 observations on 191,165 individuals (88,389 men and 102,776 women). The frailty index is constructed in the same way as for PSID and HRS respondents as has similar lifecycle dynamics. See Hosseini et al. (2019) for additional details.

B Dynamic Panel Analysis: More Results (incomplete)

In Section 2.2 we use a dynamic GMM panel estimator to estimate the impact of frailty on earnings, hours and wages. In this appendix we present additional results regarding validity of instruments, causality and further diagnostics.

Table 13: Summary statistics on our dynamic panel PSID sample

	2002	2004	2006	2008	2010	2012	2014	2016	Pooled 2002-2016
Panel A: Mean (median) [standard deviation] of sample characteristics									
Age	40.75	41.2	41.73	42.36	42.97	43.77	45.64	47.53	42.65
	(41)	(42)	(42)	(42)	(42)	(42)	(44)	(46)	(42)
	[11.11]	[11.77]	[12.33]	[12.85]	[13.34]	[13.7]	[13.7]	[13.69]	[12.72]
Frailty	0.08	0.09	0.10	0.10	0.11	0.11	0.12	0.13	0.11
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.10)	(0.10)	(0.07)
	[0.09]	[0.09]	[0.1]	[0.1]	[0.11]	[0.11]	[0.12]	[0.12]	[0.11]
Annual Earnings	\$39,913.5	\$39,951.17	\$39,779.58	\$39,670.04	\$36,294.58	\$36,659.7	\$36,554.79	\$38,088.25	\$38,526.71
	(30,944.81)	(30,446.27)	(30,277.88)	(29,730.3)	(26,121.94)	(25,100)	(26,256.93)	(27,860.24)	(29,174.36)
	[73,161.16]	[68,148.32]	[65,088.35]	[77,401.9]	[58,809.46]	[92,687.86]	[70,310.25]	[56,168.13]	[68,482.15]
Annual Hours	1,698.71	1,675.51	1,647.33	1,550.34	1,466.27	1,492.25	1,495.81	1,482.53	1,590.6
	(1,960)	(1,960)	(1,944)	(1,880)	(1,820)	(1,856)	(1,872)	(1,888)	(1,920)
	[965.19]	[990.17]	[989.62]	[949.76]	[1,011.75]	[1,030.75]	[1,051.32]	[1,064.97]	[999.24]
Hourly Wage	\$22.84	\$23.27	\$23.03	\$24.38	\$24.01	\$23.27	\$23.67	\$25.27	\$23.50
	(17.84)	(17.94)	(17.74)	(18.96)	(18.09)	(17.56)	(18.04)	(18.89)	(18.06)
	[25.85]	[28.3]	[23.46]	[27.15]	[26.59]	[25.73]	[23.07]	[26.81]	[25.37]
Panel B: Fraction of sample by characteristics									
Male	0.45	0.45	0.45	0.45	0.45	0.45	0.44	0.44	0.45
High School Dropouts (HSD)	13.47	13.31	13.06	13.02	13.04	13.04	13.12	12.86	13.21
High School Graduates (HS)	55.62	55.06	54.56	54.33	53.97	53.47	53.49	53.42	54.51
College Graduates (CL)	30.91	31.63	32.39	32.66	32.99	33.48	33.39	33.72	32.28
$+\Delta$ Frailty	-	0.28	0.32	0.3	0.28	0.28	0.27	0.27	0.29
$-\Delta$ Frailty	-	0.13	0.13	0.13	0.13	0.13	0.14	0.14	0.13
Observations (N)	9,665	10,100	10,647	11,174	11,536	11,663	10,809	10,206	85,800
# of Individuals (n)									14,269
Average # of Years Observed (T)									6.01

Note: Means are reported; median values are reported in parentheses; standard deviations are reported in brackets.

Table 14: Full Set of Diagnostic Tests for Table 2

	Everyone				Workers			
	(1)	(2) By Educ	(3) By Health	(4) By Age	(5)	(6) By Educ	(7) By Health	(8) By Age
AR(1) test (p-value)	0.455	0.319	0.497	0.104	0.030	0.010	0.021	0.008
AR(2) test (p-value)	0.380	0.474	0.298	0.949	0.130	0.082	0.138	0.160
Hansen test (p-value)	0.796	0.132	0.826	0.752	0.434	0.826	0.543	0.465
Diff-in-Hansen test (p-value)	0.652	0.360	0.827	0.464	0.255	0.484	0.259	0.214
Diff-in-Hansen test (p-value), Y-lag set	0.796	0.516	0.960	0.479	0.434	0.388	0.283	0.249
Starting IV Lag t-k (k=)	4	4	4	4	5	5	5	5
Ending IV Lag t-k (k=)	5	5	5	5	6	6	6	6

Notes: Each column shows the full set of diagnostic tests and instruments used for the regression results in Table 2.

B.1 Additional diagnostic tests and checks for instrument robustness

Table 14 presents the full set of results from the diagnostic tests run on the dynamic panel regressions with dependent variable log earnings in Table 2. In particular, in Table 14 the diff-in-Hansen test for the y-lag explanatory variables only is included. The table also shows the lags used in the estimation. Notice that, as expected, in most runs we reject the null of no AR(1) correlation in the error terms. However, we fail to reject the null in all the other tests for all the specifications.

B.2 Comparison with OLS and Fixed Effect estimator

For purposes of comparison, we estimate Equation (1) in Section 2.2 using OLS and fixed effect estimators, and compare the results to our system GMM estimates. The results are presented in Tables 15, 16, 17 and 18 for the overall effect, the effect by education, by health, and by age group, respectively. The three panels in the table show results for earnings, hours, and wages, respectively.

Table 15: Comparison with OLS and Fixed Effect Estimator, Average Frailty Effect

		Everyone			Workers	
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM
Panel A. Earnings Regressions						
log(earnings$_{t-1}$)	0.564***	0.206***	0.283	0.555***	0.098***	1.474***
	(0.006)	(0.004)	(0.364)	(0.013)	(0.006)	(0.509)
log(earnings$_{t-2}$)	0.188***	-0.021***	0.396	0.240***	-0.031***	-0.640
	(0.006)	(0.005)	(0.298)	(0.012)	(0.006)	(0.454)
frailty$_t$	-4.973***	-8.818***	-5.374***	-0.519***	-0.471***	-0.978**
	(0.138)	(0.235)	(1.653)	(0.044)	(0.084)	(0.447)
Observations	64,965	64,965	64,965	34,274	34,274	34,274
R^2	0.580	0.432		0.601	0.080	
Panel B. Hours Regressions						
log(hours$_{t-1}$)	0.554***	0.200***	0.399	0.332***	-0.027***	0.003
	(0.006)	(0.004)	(0.322)	(0.008)	(0.006)	(0.345)
log(hours$_{t-2}$)	0.180***	-0.028***	0.263	0.157***	-0.090***	0.304
	(0.006)	(0.004)	(0.257)	(0.007)	(0.006)	(0.218)
frailty$_t$	-3.626***	-6.655***	-3.887***	-0.175***	-0.442***	0.070
	(0.100)	(0.172)	(1.188)	(0.028)	(0.056)	(0.246)
Observations	64,965	64,965	64,965	34,274	34,274	34,274
R^2	0.556	0.400		0.234	0.001	
Panel C. Wage Regressions						
log(wage$_{t-1}$)				0.525***	0.067***	0.212
				(0.010)	(0.006)	(0.541)
log(wage$_{t-2}$)				0.288***	-0.028***	0.532
				(0.009)	(0.006)	(0.489)
frailty$_t$				-0.378***	-0.028	-0.623**
				(0.037)	(0.073)	(0.263)
Observations				34,170	34,170	34,170
R^2				0.592	0.056	

Notes: Panel A (top) shows regression results for the effect of frailty on earnings. Panel B (middle) shows regression results for the effect of frailty on hours. Panel C (bottom) shows regression results for the effect of frailty on wages. All regressions include controls (marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, time dummies, and cubic polynomial in age). 'F.E.' is fixed effect (within groups) estimation. 'Good Health' is a value of frailty at or below 75th percentile frailty in the sample. 'Bad Health' is a value of frailty above the 75th percentile. 'Young/Old' are individuals younger/older than 45 years of age. Standard errors on in parenthesis. R^2 is adjusted R-squared for OLS, and overall R-squared for FE. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

We would like to point out couple of observations. It is well known that the OLS estimates of the coefficient on lagged values of the left-hand-side variable have an upward bias. Moreover, as Nickell (1981), Arellano and Bond (1991), and Bond (2002b) have shown, the estimates acquired via a fixed effects estimator have downward bias. Therefore, an unbiased estimate should lie between the OLS and FE estimates. As Bond (2002b) argues, if multiple lags of the left-hand-side variable are included on the right-hand-side, the sum of the coefficients on these variables must satisfy this condition. In other words, a necessary condition for the dynamic panel estimates to be unbiased is that the sum of the estimated values of α_1 and α_2 in Equation (1) are smaller than the corresponding sum of OLS estimates, but larger than those from the fixed effect estimation. We cannot statistically reject this condition in any of our estimations. Therefore, our regressions pass this consistency test.

Note, also that in Tables 15 through 18 the OLS estimation shows significant effect of frailty on hours even for those who continuously work. This is likely due to the fact that in these OLS estimations individuals fixed effects are ignored. The fixed effects are included in the FE estimation but this estimator is biased. However, as we argued before, GMM estimation that satisfy the identifying conditions discussed in Blundell and Bond (2000) and Arellano and Bond (1991) is unbiased.

B.3 IV Robustness

B.4 Reverse causality

So far in this analysis we argued that there is a causal effect from frailty to earnings, hours, and wages. However, one could imagine that past earnings could also affect current frailty (health status). To examine this proposition we estimate the following regression

$$f_{i,t} \quad = \quad b_i + \lambda_t + \gamma y_{i,t-1} + \alpha_1 f_{i,t-1} + \alpha_2 f_{i,t-2} + \alpha_2 f_{i,t-3} + \beta \boldsymbol{X}_{i.t} + \varepsilon_{i,t} \tag{20}$$

using system GMM estimation procedure outlined in Section 2.2. The results for impact of past earnings in frailty are presented in Table 23. Note that, for all alternative specifications, the diagnostics tests are passed. In other words, the error terms are not second order autoregressive. Moreover, the Hansen-Sargan tests indicate that null hypothesis of valid instruments cannot be rejected. Note that, in almost all cases, there is no significant effect from past earning on frailty. The only exception is the specification in which past earnings are interacted with health status. However, even in this case the effect is very small and borderline insignificant.

C Additional information about the structural model

C.1 Recursive competitive equilibrium

In this section we provide the definition of equilibrium we employ in the structural model economy. Let $\{\mu^E(x, i_s), \mu^N(x, n_a), \mu^D(x, n_d), \mu^R(x)\}$ represent the time-invariant measures of individuals. We assume that these 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.

Given a fiscal policy $\{G, Tr(\cdot), SS(\cdot), T(\cdot)\}$, a *stationary recursive competitive equilibrium* is a set of value functions $\{V^E(x,i_s), V^N(x,n_a), V^D(x,n_d), V^R(x)\}$, households' consumption decisions $\{c^E(x,i_s), c^N(x,n_a), c^D(x,n_d), c^R(x)\}$, saving decisions $\{a^E(x,i_s), a^N(x,n_a), a^D(x,n_d), a^R(x)\}$, labor force participation decisions $I_E(x,i_s)$ and $I_N(x,n_a)$; prices of labor and capital $\{w,r\}$; and time-invariant measures of households $\{\mu^E(x,i_s), \mu^N(x,n_a), \mu^D(x,n_d), \mu^R(x)\}$ such that:

1. Given the fiscal policy and prices, households' decision rules solve households' decision problems in equations (6), (8), (10), (12), (13), (15), and (16).

2. Rental rate r is exogenously given and the wage is given by equation (18).

3. Aggregate labor and capital input satisfy:

$$N = \sum_{\{x,i_s\}} \eta(x)\,\mu^E(x,i_s),$$
$$r = (1-\tau_K)\left(\alpha A (K/N)^{\alpha-1} - \delta\right).$$

4. The government's budget constraint holds

$$\sum_{\{x,i_s\}} T(w\eta(x))\,\mu^E(x,i_s) + \tau_K\left(\alpha A (K/N)^{\alpha-1} - \delta\right) = G + \sum_{\{x,n_d\}} \left(\mu^D(x,n_d) + \mu^R(x)\right) SS(\bar{e}) + \sum_{\{x,i_s,n_d\}} \left(\mu^E(x,i_s) + \mu^D(x,n_d) + \mu^R(x)\right) Tr(x)$$

5. The measures $\{\mu^E(x,i_s), \mu^N(x,n_a), \mu^D(x,n_d), \mu^R(x)\}$ are stationary

   (a) Employed:

$$\mu^E(x',0) = \frac{I_E(x',0)}{1+\nu} \sum_{\{x,i_s\}} (1-\sigma)\,p(j,f)\,\pi^e(\epsilon'|x)\,\pi^f(f'|x)\,\mathbf{1}_{a'=a^E(x,i_s)}\mu^E(x,i_s)$$
$$\mu^E(x',1) = \frac{I_E(x',1)}{1+\nu} \sum_{\{x,i_s\}} \sigma p(x)\,\pi^e(\epsilon'|x)\,\pi^f(f'|x)\,\mathbf{1}_{a'=a^E(x,i_s)}\mu^E(x,i_s) + \frac{1}{1+\nu} \sum_{\{x,n_a\}} (1-\theta(f,n_a))\,p(x)\,\pi^e(\epsilon'|x)\,\pi^f(f'|x)\,\mathbf{1}_{a'=a^N(x,n_a)} I_N(x',n_a+1)\,\mu^N(x,n_a)$$

(b) Non-employed:

$$\mu^N(x',0) = \frac{1-I_E(x',0)}{1+\nu}\sum_{\{x,i_s\}}(1-\sigma)\,p\,(x)\,\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^E(x,i_s)}\mu^E\,(x,i_s)$$
$$+\frac{1-I_E(x',1)}{1+\nu}\sum_{\{x,i_s\}}\sigma p\,(x)\,\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^E(x,i_s)}\mu^E\,(x,i_s)$$
$$\mu^N(x',n_a+1) = \frac{1-I_N(x',n_a+1)}{1+\nu}\sum_{\{x,n_a\}}p\,(x)\,(1-\theta\,(f,n_a))\,\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^N(x,n_a)}\mu^N\,(x,n_a)$$

(c) DI beneficiary:

$$\mu^D(x',0) = \frac{1}{1+\nu}\sum_{\{x,n_a\}}\theta\,(f,n_a)\,p(x)\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^N(x,i_s)}\mu^N\,(x,n_a)$$
$$\mu^D(x',n_d+1) = \frac{1}{1+\nu}\sum_{\{x\}}p(x)\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^D(x,n_d)}\mu^D\,(x,n_d)$$

(d) Retiree:
for $j = R-1$

$$\mu^R(x') = \frac{1}{1+\nu}\sum_{\{x,n_d\}}p(x)\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^D(x,i_s)}\mu^D\,(x,n_d)$$
$$+\frac{1-I_E(x',1)}{1+\nu}\sum_{\{x,i_s\}}(1-\sigma)\,p\,(x)\,\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^E(x,i_s)}\mu^E\,(x,i_s)$$
$$+\frac{1-I_E(x',0)}{1+\nu}\sum_{\{x,i_s\}}\sigma p\,(x)\,\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^E(x,i_s)}\mu^E\,(x,i_s)$$
$$+\frac{1}{1+\nu}\sum_{\{x,n_a\}}p\,(x)\,\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^N(x,i_s)}\left(1-I_N\left(x',n_a+1\right)\right)\mu^N\,(x,n_a)$$

for $j > R-1$

$$\mu^R(x') = \frac{1}{1+\nu}\sum_{\{x\}}p\,(x)\,\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^R(x)}\mu^R\,(x)$$
$$+\frac{1-I_E(x',1)}{1+\nu}\sum_{\{x,i_s\}}(1-\sigma)\,p\,(x)\,\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^E(x,i_s)}\mu^E\,(x,i_s)$$
$$+\frac{1-I_E(x',0)}{1+\nu}\sum_{\{x,i_s\}}\sigma p\,(x)\,\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^E(x,i_s)}\mu^E\,(x,i_s)$$
$$+\frac{1}{1+\nu}\sum_{\{x,n_a\}}p\,(x)\,\pi^e\left(\epsilon'|x\right)\pi^f\left(f'|x\right)\mathbf{1}_{a'=a^N(x,i_s)}\left(1-I_N\left(x',n_a+1\right)\right)\mu^N\,(x,n_a)$$

D Additional Estimation Results

This section includes results of the estimations outlined in Section 4. We use the results in these tables as input to our model.

E More on estimation of wage process

E.1 Comparing to Low and Pistaferri (2015)

Low and Pistaferri (2015) estimate the effect of *disability status* on wage. They use PSID to define three disability groups $d = 0, 1, 2$. Group $d = 0$ are those with no work limitations, group $d = 2$ are those with severe work limitations, and group $d = 1$ are the rest. In order to compare our estimation with theirs, we first calculation mean frailty for each of the disability groups defined above in our sample. Using these mean frailties we can calculate our counterpart fo the effect of disability groups on wages. These estimations are reported in Table 30b. Note that our estimation imply stronger impact of work limitation on wages both for workers with some limitations ($d = 1$) and for those with severe limitations ($d = 2$). It is worth pointing out that Low and Pistaferri (2015) only include non-college educated workers in their sample whereas we included college educated as well as high school dropouts and high school graduates. The numbers reported in Table 30b are average effect among all education groups.

Table 16: Comparison with OLS and Fixed Effect Estimator, Frailty Effects by Education

	Everyone			Workers		
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM
Panel A. Earnings Regressions						
log(earnings$_{t-1}$)	0.560***	0.206***	0.370	0.544***	0.097***	1.371***
	(0.006)	(0.004)	(0.319)	(0.013)	(0.006)	(0.400)
log(earnings$_{t-2}$)	0.183***	-0.022***	0.318	0.233***	-0.031***	-0.569
	(0.006)	(0.005)	(0.259)	(0.011)	(0.006)	(0.356)
frailty$_t$ × HSD	-6.143***	-8.533***	-6.269***	-1.340***	-0.742***	-1.846**
	(0.213)	(0.526)	(1.777)	(0.111)	(0.254)	(0.807)
frailty$_t$ × HS	-5.215***	-9.586***	-5.591***	-0.762***	-0.712***	-1.239***
	(0.155)	(0.289)	(1.574)	(0.052)	(0.107)	(0.460)
frailty$_t$ × CL	-3.003***	-6.900***	-2.519*	0.053	-0.014	-0.558
	(0.209)	(0.457)	(1.402)	(0.053)	(0.132)	(0.484)
Observations	64,965	64,965	64,965	34,274	34,274	34,274
R^2	0.581	0.435		0.605	0.089	
Panel B. Hours Regressions						
log(hours$_{t-1}$)	0.550***	0.200***	0.383	0.331***	-0.027***	0.074
	(0.006)	(0.004)	(0.319)	(0.008)	(0.006)	(0.313)
log(hours$_{t-2}$)	0.176***	-0.028***	0.269	0.156***	-0.091***	0.168
	(0.006)	(0.004)	(0.253)	(0.007)	(0.006)	(0.221)
frailty$_t$ × HSD	-4.433***	-6.526***	-4.770***	-0.403***	-0.942***	-0.533
	(0.157)	(0.385)	(1.320)	(0.078)	(0.169)	(0.356)
frailty$_t$ × HS	-3.732***	-7.241***	-4.303***	-0.189***	-0.440***	-0.033
	(0.112)	(0.211)	(1.224)	(0.032)	(0.071)	(0.281)
frailty$_t$ × CL	-2.380***	-5.119***	-2.219**	-0.092***	-0.311***	0.248
	(0.150)	(0.334)	(1.118)	(0.035)	(0.088)	(0.254)
Observations	64,965	64,965	64,965	34,274	34,274	34,274
R^2	0.557	0.402		0.234	0.001	
Panel C. Wage Regressions						
log(wage$_{t-1}$)				0.514***	0.067***	0.122
				(0.010)	(0.006)	(0.368)
log(wage$_{t-2}$)				0.279***	-0.029***	0.600*
				(0.009)	(0.006)	(0.328)
frailty$_t$ × HSD				-1.040***	0.191	-1.854***
				(0.102)	(0.222)	(0.616)
frailty$_t$ × HS				-0.602***	-0.268***	-0.889***
				(0.043)	(0.094)	(0.307)
frailty$_t$ × CL				0.123***	0.298***	-0.216
				(0.046)	(0.116)	(0.309)
Observations				34,170	34,170	34,170
R^2				0.596	0.063	

Notes: Panel A (B) [C] shows regression results for the effect of frailty on earnings (hours) [wages]. All regressions include controls (marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, time dummies, and a quadratic in age). 'FE' is fixed effect (within groups) estimation. Standard errors are in parenthesis. R^2 is adjusted R-squared for OLS, and overall R-squared for FE. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 17: Comparison with OLS and Fixed Effect Estimator, Frailty Effects by Health Status

	Everyone			Workers		
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM
Panel A. Earnings Regressions						
log(earnings$_{t-1}$)	0.564***	0.206***	0.220	0.555***	0.097***	1.293***
	(0.006)	(0.004)	(0.362)	(0.013)	(0.006)	(0.410)
log(earnings$_{t-2}$)	0.188***	-0.021***	0.444	0.240***	-0.031***	-0.498
	(0.006)	(0.005)	(0.297)	(0.012)	(0.006)	(0.377)
frailty$_t$ × Good Health	-3.076***	-6.816***	-1.930	-0.610***	-0.230*	-1.765
	(0.305)	(0.499)	(4.816)	(0.082)	(0.135)	(1.775)
frailty$_t$ × Bad Health	-4.818***	-8.607***	-5.207***	-0.522***	-0.446***	-0.963**
	(0.137)	(0.239)	(1.745)	(0.044)	(0.085)	(0.469)
Observations	64,965	64,965	64,965	34,274	34,274	34,274
R^2	0.580	0.433		0.601	0.079	
Panel B. Hours Regressions						
log(hours$_{t-1}$)	0.553***	0.200***	0.386	0.332***	-0.027***	0.040
	(0.006)	(0.004)	(0.317)	(0.008)	(0.006)	(0.311)
log(hours$_{t-2}$)	0.180***	-0.028***	0.272	0.157***	-0.091***	0.282
	(0.006)	(0.004)	(0.253)	(0.007)	(0.006)	(0.219)
frailty$_t$ × Good Health	-1.957***	-5.137***	-2.216	-0.046	-0.292***	-0.060
	(0.222)	(0.365)	(3.455)	(0.049)	(0.090)	(0.910)
frailty$_t$ × Bad Health	-3.491***	-6.494***	-3.707***	-0.171***	-0.426***	0.026
	(0.099)	(0.175)	(1.242)	(0.028)	(0.056)	(0.258)
Observations	64,965	64,965	64,965	34,274	34,274	34,274
R^2	0.556	0.402		0.234	0.001	
Panel C. Wage Regressions						
log(wage$_{t-1}$)				0.525***	0.067***	0.303
				(0.010)	(0.006)	(0.449)
log(wage$_{t-2}$)				0.288***	-0.028***	0.461
				(0.009)	(0.006)	(0.419)
frailty$_t$ × Good Health				-0.561***	0.061	0.348
				(0.071)	(0.118)	(1.685)
frailty$_t$ × Bad Health				-0.384***	-0.019	-0.581*
				(0.037)	(0.074)	(0.332)
Observations				34,170	34,170	34,170
R^2				0.592	0.055	

Notes: Panel A (B) [C] shows regression results for the effect of frailty on earnings (hours) [wages]. All regressions include controls (marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, time dummies, and a quadratic in age). 'Good Health' is a value of frailty at or below the 75th percentile. 'Bad Health' is a value of frailty above the 75th percentile. 'FE' is fixed effect (within groups) estimation. Standard errors are in parenthesis. R^2 is adjusted R-squared for OLS, and overall R-squared for FE. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 18: Comparison with OLS and Fixed Effect Estimator, Frailty Effects by Age Group

	Everyone			Workers		
	OLS	FE	SYS-GMM	OLS	FE	SYS-GMM
Panel A. Earnings Regressions						
$\log(\text{earnings}_{t-1})$	0.564***	0.206***	0.628**	0.555***	0.098***	1.127***
	(0.006)	(0.004)	(0.291)	(0.013)	(0.006)	(0.302)
$\log(\text{earnings}_{t-2})$	0.188***	-0.021***	0.115	0.241***	-0.031***	-0.308
	(0.006)	(0.005)	(0.239)	(0.012)	(0.006)	(0.273)
$\text{frailty}_t \times$ Young	-4.870***	-8.547***	-4.992***	-0.660***	-0.483***	-1.650**
	(0.202)	(0.297)	(1.784)	(0.061)	(0.099)	(0.673)
$\text{frailty}_t \times$ Old	-5.034***	-8.943***	-4.030***	-0.376***	-0.463***	-0.293
	(0.161)	(0.249)	(1.317)	(0.054)	(0.091)	(0.365)
Observations	64,965	64,965	64,965	34,274	34,274	34,274
R^2	0.580	0.433		0.601	0.080	
Panel B. Hours Regressions						
$\log(\text{hours}_{t-1})$	0.554***	0.200***	0.669***	0.332***	-0.027***	0.382
	(0.006)	(0.004)	(0.257)	(0.008)	(0.006)	(0.318)
$\log(\text{hours}_{t-2})$	0.180***	-0.028***	0.048	0.157***	-0.090***	0.254
	(0.006)	(0.004)	(0.206)	(0.007)	(0.006)	(0.246)
$\text{frailty}_t \times$ Young	-3.457***	-6.411***	-3.564***	-0.200***	-0.484***	-0.286
	(0.149)	(0.217)	(1.325)	(0.039)	(0.066)	(0.387)
$\text{frailty}_t \times$ Old	-3.726***	-6.767***	-3.131***	-0.151***	-0.414***	0.144
	(0.116)	(0.182)	(0.936)	(0.036)	(0.060)	(0.259)
Observations	64,965	64,965	64,965	34,274	34,274	34,274
R^2	0.556	0.401		0.234	0.001	
Panel C. Wage Regressions						
$\log(\text{wage}_{t-1})$				0.525***	0.067***	0.511
				(0.010)	(0.006)	(0.399)
$\log(\text{wage}_{t-2})$				0.289***	-0.029***	0.272
				(0.009)	(0.006)	(0.359)
$\text{frailty}_t \times$ Young				-0.481***	0.028	-1.106**
				(0.050)	(0.086)	(0.463)
$\text{frailty}_t \times$ Old				-0.274***	-0.064	-0.414
				(0.045)	(0.079)	(0.295)
Observations				34,170	34,170	34,170
R^2				0.592	0.055	

Notes: Panel A (B) [C] shows regression results for the effect of frailty on earnings (hours) [wages]. All regressions include controls (marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, time dummies, and a quadratic in age). 'Young/Old' are individuals younger/older than 45 years of age. 'FE' is fixed effect (within groups) estimation. Standard errors are in parenthesis. R^2 is adjusted R-squared for OLS, and overall R-squared for FE. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 19: Comparison With Different IV Lags, Average Frailty Effect

	Everyone			Workers		
IV Lags	3-4	4-5	5-6	3-4	4-5	5-6
Number of Instruments	20	20	20	20	20	20
Panel A. Earnings Regressions						
log(earnings$_{t-1}$)	0.689***	0.283	0.013	0.367***	-0.235	1.474***
	(0.105)	(0.364)	(0.545)	(0.120)	(0.446)	(0.509)
log(earnings$_{t-2}$)	0.046	0.396	0.684	0.089**	0.833**	-0.640
	(0.044)	(0.298)	(0.439)	(0.041)	(0.346)	(0.454)
frailty$_t$	-4.462***	-5.374***	-5.415**	-0.606**	-0.251	-0.978**
	(1.498)	(1.653)	(2.584)	(0.238)	(0.390)	(0.447)
AR(2) test (p-value)	0.115	0.380	0.233	0.494	0.051	0.130
Hansen test (p-value)	0.060	0.796	0.465	0.475	0.063	0.434
Diff-in-Hansen test (p-value)	0.063	0.652	0.440	0.297	0.027	0.255
Diff-in-Hansen test (p-value), Y-lag set	0.060	0.796	0.465	0.475	0.063	0.434
Panel B. Hours Regressions						
log(hours$_{t-1}$)	0.669***	0.399	0.292	-0.275	-0.208	0.003
	(0.119)	(0.322)	(0.387)	(0.379)	(0.288)	(0.345)
log(hours$_{t-2}$)	0.046	0.263	0.459	0.117**	0.448**	0.304
	(0.048)	(0.257)	(0.293)	(0.058)	(0.192)	(0.218)
frailty$_t$	-3.366***	-3.887***	-3.068*	-0.563***	-0.091	0.070
	(1.195)	(1.188)	(1.642)	(0.206)	(0.233)	(0.246)
AR(2) test (p-value)	0.158	0.596	0.302	0.219	0.060	0.273
Hansen test (p-value)	0.068	0.971	0.433	0.141	0.133	0.060
Diff-in-Hansen test (p-value)	0.073	0.944	0.450	0.453	0.083	0.080
Diff-in-Hansen test (p-value), Y-lag set	0.068	0.971	0.433	0.141	0.230	0.060
Panel C. Wage Regressions						
log(wage$_{t-1}$)				0.605***	0.603	0.212
				(0.086)	(0.865)	(0.541)
log(wage$_{t-2}$)				0.041	0.184	0.532
				(0.027)	(0.742)	(0.489)
frailty$_t$				-0.167	-0.302	-0.623**
				(0.197)	(0.266)	(0.263)
AR(2) test (p-value)				0.042	0.958	0.454
Hansen test (p-value)				0.335	0.056	0.085
Diff-in-Hansen test (p-value)				0.187	0.024	0.044
Diff-in-Hansen test (p-value), Y-lag set				0.335	0.056	0.085

Notes: Panel A (B) [C] shows regression results for the effect of frailty on earnings (hours) [wages]. All regressions include controls (marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, time dummies, and a quadratic in age). Standard errors are in parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 20: Comparison With Different IV Lags, Frailty Effects by Education

	Everyone			Workers		
IV Lags	3-4	4-5	5-6	3-4	4-5	5-6
Number of Instruments	26	26	26	26	26	26
Panel A. Earnings Regressions						
log(earnings$_{t-1}$)	0.676***	0.370	0.055	0.410***	0.077	1.371***
	(0.110)	(0.319)	(0.264)	(0.112)	(0.290)	(0.400)
log(earnings$_{t-2}$)	0.050	0.318	0.632***	0.070*	0.580**	-0.569
	(0.046)	(0.259)	(0.210)	(0.038)	(0.229)	(0.356)
frailty$_t$ × HSD	-5.133***	-6.269***	-5.772***	-1.561***	-1.359**	-1.846**
	(1.809)	(1.777)	(2.050)	(0.540)	(0.692)	(0.807)
frailty$_t$ × HS	-5.009***	-5.591***	-6.532***	-1.137***	-0.577	-1.239***
	(1.610)	(1.574)	(1.876)	(0.294)	(0.364)	(0.460)
frailty$_t$ × CL	-3.237**	-2.519*	-3.125*	0.379	0.526	-0.558
	(1.313)	(1.402)	(1.743)	(0.252)	(0.402)	(0.484)
AR(2) test (p-value)	0.156	0.474	0.024	0.760	0.052	0.082
Hansen test (p-value)	0.022	0.132	0.116	0.681	0.050	0.826
Diff-in-Hansen test (p-value)	0.015	0.360	0.151	0.323	0.008	0.484
Diff-in-Hansen test (p-value), Y-lag set	0.053	0.516	0.516	0.219	0.005	0.388
Panel B. Hours Regressions						
log(hours$_{t-1}$)	0.657***	0.383	0.216	-0.366	-0.192	0.074
	(0.123)	(0.319)	(0.253)	(0.383)	(0.280)	(0.313)
log(hours$_{t-2}$)	0.049	0.269	0.495***	0.130**	0.433**	0.168
	(0.050)	(0.253)	(0.189)	(0.058)	(0.186)	(0.221)
frailty$_t$ × HSD	-3.795***	-4.770***	-3.609**	-0.726*	-0.121	-0.533
	(1.412)	(1.320)	(1.580)	(0.380)	(0.342)	(0.356)
frailty$_t$ × HS	-3.749***	-4.303***	-4.232***	-0.749***	-0.076	-0.033
	(1.256)	(1.224)	(1.422)	(0.248)	(0.255)	(0.281)
frailty$_t$ × CL	-2.473**	-2.219**	-2.058	-0.334	-0.092	0.248
	(1.061)	(1.118)	(1.314)	(0.206)	(0.249)	(0.254)
AR(2) test (p-value)	0.196	0.569	0.071	0.149	0.062	0.572
Hansen test (p-value)	0.090	0.317	0.053	0.515	0.384	0.166
Diff-in-Hansen test (p-value)	0.050	0.597	0.108	0.618	0.582	0.062
Diff-in-Hansen test (p-value), Y-lag set	0.105	0.730	0.283	0.430	0.230	0.019
Panel C. Wage Regressions						
log(wage$_{t-1}$)				0.598***	0.564	0.122
				(0.087)	(0.481)	(0.368)
log(wage$_{t-2}$)				0.040	0.203	0.600*
				(0.027)	(0.409)	(0.328)
frailty$_t$ × HSD				-0.792*	-1.104**	-1.854***
				(0.410)	(0.547)	(0.616)
frailty$_t$ × HS				-0.516**	-0.566**	-0.889***
				(0.234)	(0.244)	(0.307)
frailty$_t$ × CL				0.356	0.239	-0.216
				(0.241)	(0.356)	(0.309)
AR(2) test (p-value)				0.044	0.884	0.189
Hansen test (p-value)				0.446	0.104	0.374
Diff-in-Hansen test (p-value)				0.198	0.059	0.145
Diff-in-Hansen test (p-value), Y-lag set				0.181	0.038	0.097

Notes: Panel A (B) [C] shows regression results for the effect of frailty on earnings (hours) [wages]. All regressions include controls (marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, time dummies, and a quadratic in age). Standard errors are in parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 21: Comparison With Different IV Lags, Frailty Effects by Health Status

	Everyone			Workers		
IV Lags	3-4	4-5	5-6	3-4	4-5	5-6
Number of Instruments	23	23	23	23	23	23
Panel A. Earnings Regressions						
log(earnings$_{t-1}$)	0.799***	0.220	0.009	0.409***	-0.088	1.293***
	(0.106)	(0.362)	(0.492)	(0.114)	(0.387)	(0.410)
log(earnings$_{t-2}$)	0.001	0.444	0.695*	0.077*	0.734**	-0.498
	(0.045)	(0.297)	(0.396)	(0.039)	(0.304)	(0.377)
frailty$_t$ × Good Health	-4.191	-1.930	-4.126	0.220	1.049	-1.765
	(3.587)	(4.816)	(7.067)	(0.763)	(1.326)	(1.775)
frailty$_t$ × Bad Health	-2.963*	-5.207***	-4.941*	-0.621**	-0.191	-0.963**
	(1.570)	(1.745)	(2.665)	(0.255)	(0.408)	(0.469)
AR(2) test (p-value)	0.010	0.298	0.178	0.685	0.055	0.138
Hansen test (p-value)	0.014	0.826	0.544	0.345	0.067	0.543
Diff-in-Hansen test (p-value)	0.007	0.827	0.400	0.162	0.017	0.259
Diff-in-Hansen test (p-value), Y-lag set	0.004	0.960	0.451	0.262	0.019	0.283
Panel B. Hours Regressions						
log(hours$_{t-1}$)	0.819***	0.386	0.258	-0.274	-0.085	0.040
	(0.118)	(0.317)	(0.391)	(0.372)	(0.236)	(0.311)
log(hours$_{t-2}$)	-0.014	0.272	0.493*	0.118**	0.383**	0.282
	(0.049)	(0.253)	(0.296)	(0.057)	(0.160)	(0.219)
frailty$_t$ × Good Health	-2.545	-2.216	-2.880	0.434	-0.262	-0.060
	(2.717)	(3.455)	(4.901)	(0.535)	(0.773)	(0.910)
frailty$_t$ × Bad Health	-1.883	-3.707***	-2.900	-0.504**	-0.140	0.026
	(1.236)	(1.242)	(1.845)	(0.205)	(0.239)	(0.258)
AR(2) test (p-value)	0.007	0.565	0.259	0.208	0.064	0.312
Hansen test (p-value)	0.013	0.838	0.478	0.114	0.251	0.174
Diff-in-Hansen test (p-value)	0.007	0.713	0.340	0.250	0.235	0.108
Diff-in-Hansen test (p-value), Y-lag set	0.005	0.838	0.250	0.228	0.187	0.063
Panel C. Wage Regressions						
log(wage$_{t-1}$)				0.593***	0.151	0.303
				(0.087)	(0.410)	(0.449)
log(wage$_{t-2}$)				0.045	0.581*	0.461
				(0.027)	(0.351)	(0.419)
frailty$_t$ × Good Health				-0.007	1.661*	0.348
				(0.649)	(0.986)	(1.685)
frailty$_t$ × Bad Health				-0.229	-0.053	-0.581*
				(0.212)	(0.292)	(0.332)
AR(2) test (p-value)				0.059	0.244	0.474
Hansen test (p-value)				0.262	0.210	0.207
Diff-in-Hansen test (p-value)				0.600	0.168	0.082
Diff-in-Hansen test (p-value), Y-lag set				0.465	0.137	0.098

Notes: Panel A (B) [C] shows regression results for the effect of frailty on earnings (hours) [wages]. All regressions include controls (marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, time dummies, and a quadratic in age). 'Good Health' is a value of frailty at or below the 75th percentile. 'Bad Health' is a value of frailty above the 75th percentile. Standard errors are in parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 22: Comparison With Different IV Lags, Frailty Effects by Age Group

	Everyone			Workers		
IV Lags	3-4	4-5	5-6	3-4	4-5	5-6
Number of Instruments	23	23	23	23	23	23
Panel A. Earnings Regressions						
log(earnings$_{t-1}$)	0.754***	0.628**	0.356	0.334**	0.288	1.127***
	(0.105)	(0.291)	(0.403)	(0.130)	(0.218)	(0.302)
log(earnings$_{t-2}$)	0.019	0.115	0.408	0.099**	0.440**	-0.308
	(0.045)	(0.239)	(0.328)	(0.043)	(0.176)	(0.273)
frailty$_t$ × Young	-5.068***	-4.992***	-4.360*	-0.545	-0.346	-1.650**
	(1.631)	(1.784)	(2.649)	(0.341)	(0.465)	(0.673)
frailty$_t$ × Old	-3.265**	-4.030***	-4.238**	-0.861***	-0.472*	-0.293
	(1.422)	(1.317)	(1.802)	(0.232)	(0.262)	(0.365)
AR(2) test (p-value)	0.029	0.949	0.435	0.383	0.078	0.160
Hansen test (p-value)	0.342	0.752	0.414	0.163	0.000	0.465
Diff-in-Hansen test (p-value)	0.286	0.464	0.389	0.314	0.000	0.214
Diff-in-Hansen test (p-value), Y-lag set	0.204	0.479	0.195	0.766	0.000	0.249
Panel B. Hours Regressions						
log(hours$_{t-1}$)	0.739***	0.669***	0.467	0.281	0.245	0.382
	(0.115)	(0.257)	(0.286)	(0.231)	(0.310)	(0.318)
log(hours$_{t-2}$)	0.017	0.048	0.325	0.035	0.208	0.254
	(0.047)	(0.206)	(0.221)	(0.037)	(0.211)	(0.246)
frailty$_t$ × Young	-3.640***	-3.564***	-2.511	-0.648***	-0.149	-0.286
	(1.286)	(1.325)	(1.871)	(0.235)	(0.321)	(0.387)
frailty$_t$ × Old	-2.537**	-3.131***	-2.623**	-0.518***	-0.210	0.144
	(1.087)	(0.936)	(1.121)	(0.141)	(0.198)	(0.259)
AR(2) test (p-value)	0.039	0.706	0.438	0.741	0.642	0.642
Hansen test (p-value)	0.251	0.811	0.609	0.024	0.006	0.051
Diff-in-Hansen test (p-value)	0.185	0.545	0.485	0.007	0.002	0.037
Diff-in-Hansen test (p-value), Y-lag set	0.108	0.557	0.373	0.014	0.002	0.069
Panel C. Wage Regressions						
log(wage$_{t-1}$)				0.524***	0.306	0.511
				(0.096)	(0.382)	(0.399)
log(wage$_{t-2}$)				0.063**	0.434	0.272
				(0.029)	(0.325)	(0.359)
frailty$_t$ × Young				-0.022	-0.227	-1.106**
				(0.295)	(0.379)	(0.463)
frailty$_t$ × Old				-0.304*	-0.328	-0.414
				(0.174)	(0.211)	(0.295)
AR(2) test (p-value)				0.298	0.398	0.734
Hansen test (p-value)				0.202	0.024	0.170
Diff-in-Hansen test (p-value)				0.317	0.031	0.104
Diff-in-Hansen test (p-value), Y-lag set				0.147	0.036	0.065

Notes: Panel A (B) [C] shows regression results for the effect of frailty on earnings (hours) [wages]. All regressions include controls (marital status, marital status interacted with gender, number of kids, number of kids interacted with gender, time dummies, and a quadratic in age). 'Young/Old' are individuals younger/older than 45 years of age. Standard errors are in parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 23: Effect of Earnings on Frailty

	Everyone				Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
frailty_{t-1}	0.445	0.334	-0.152	-0.456	-0.182	0.712*	0.302	-0.190
	(0.463)	(0.435)	(0.528)	(0.400)	(0.566)	(0.416)	(0.737)	(0.498)
frailty_{t-2}	0.602	0.661	1.124**	1.446***	1.316**	0.405	0.820	1.321**
	(0.447)	(0.443)	(0.495)	(0.404)	(0.596)	(0.451)	(0.741)	(0.529)
$\log(\text{earnings}_t)$	0.004*				-0.004			
	(0.002)				(0.007)			
$\log(\text{earnings}_t)$ × HSD		0.003				0.001		
		(0.002)				(0.002)		
$\log(\text{earnings}_t)$ × HS		-0.008				-0.019		
		(0.039)				(0.073)		
$\log(\text{earnings}_t)$ × CL		0.000				-0.000		
		(0.001)				(0.001)		
$\log(\text{earnings}_t)$ × Good Health			0.000				0.000	
			(0.003)				(0.008)	
$\log(\text{earnings}_t)$ × Bad Health			0.002				0.000	
			(0.002)				(0.008)	
$\log(\text{earnings}_t)$ × Young				-0.000				-0.004
				(0.001)				(0.007)
$\log(\text{earnings}_t)$ × Old				-0.000				-0.003
				(0.002)				(0.007)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	50,844	50,844	50,844	50,844	27,444	27,444	27,444	27,444
AR(1) test (p-value)	0.531	0.573	0.501	0.001	0.260	0.388	0.763	0.188
AR(2) test (p-value)	0.333	0.260	0.061	0.002	0.060	0.570	0.380	0.032
Hansen test (p-value)	0.269	0.842	0.621	0.129	0.440	0.430	0.747	0.848
Diff-in-Hansen test (p-value)	0.450	0.852	0.894	0.132	0.656	0.225	0.805	0.818
Diff-in-Hansen test (p-value), Y-lag set	.	0.990	0.723	0.223	.	0.245	0.814	0.788
Starting IV Lag t-k (k=)	6	6	6	6	6	6	6	6
Ending IV Lag t-k (k=)	8	8	8	8	8	8	8	8

Notes: Regression results for the effect of past earnings on frailty. 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 frailty at or below the 75th percentile. 'Bad Health' is frailty above the 75th percentile. 'Young/Old' are individuals younger/older than 45 years of age. 'High/Low Earnings' are top/bottom half of earnings distribution. Standard errors on parenthesis. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table 24: Estimation of mortality rates

	Probit regression for mortality rate
frailty	3.213***
	(0.122)
frailty^2	-1.676***
	(0.164)
age	-0.017**
	(0.006)
age^2	0.0004***
	(0.00004)
education (years)	-0.0026
	(0.0017)
male	0.297***
	(0.0121)
married	-0.0987***
	(0.0124)
constant	-3.357***
	(0.2346)
year fixed effects	included
Observations	167,851
Pseudo R^2	0.191

Note: Standard errors on parenthesis. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 25: Estimating labor productivity profiles. Step 1: Exclusion Restriction Regression.

	Exclusion Restriction Regression
frailty × HSD	-0.891
	(6.251)
frailty × HSG	-0.874
	(6.251)
frailty × CG	-0.535
	(6.250)
age	0.038***
	(0.003)
age^2	-0.0003***
	(0.00002)
exclusion restrictions	total of 436 combinations
joint p-value	0.000

Note: The right hand side variable is employment (1 if employed, 0 otherwise). Standard errors on parenthesis. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 26: Estimating labor productivity profiles. Step 2: bias correction.

	without bias correction	with bias correction
log(wage_$t-1$)	1.044***	1.034***
	(0.298)	(0.295)
log(wage_$t-2$)	-0.263	-0.262
	(0.270)	(0.262)
$\text{frailty}_t \times$ HSD	-1.128**	-1.201**
	(0.453)	(0.469)
$\text{frailty}_t \times$ HS	-0.662***	-0.741***
	(0.235)	(0.251)
$\text{frailty}_t \times$ CL	0.052	0.025
	(0.119)	(0.119)
selection term		0.076**
		(0.035)
Observations	23,874	23,755
AR(2) test (p-value)	0.182	0.163
Hansen test (p-value)	0.107	0.096
Diff-in-Hansen test (p-value)	0.307	0.417

Note: The right hand side variable is is log wage. Selection term is the coefficient on predicted fixed effects from regression in step 1. Standard errors on parenthesis. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 27: Estimation of wage process after bias correction and removal of frailty effect

(a) Estimation results for deterministic component of wage (net of frailty effect).

	Non-college	Col Graduates
age	0.0535	0.181
	(0.0194)	(0.0323)
age^2	-0.0005	-0.0027
	(0.0004)	(0.0007)
age^3	5.25e-7	1.19e-5
	(3.0e-6)	(4.9e-6)
constant	1.830	-0.0334
	(0.286)	(0.4808)

(b) Estimation results for For stochastic component of wage.

	Non-college	Col Graduates
var. of transitory shock	0.0824	0.1033
	(0.0115)	(0.0180)
var. of permanent shock	0.0165	0.0181
	(0.0049)	(0.0070)
var. of fixed effect	0.0920	0.0636
	(0.0145)	(0.0291)
persistence	0.9218	0.9805
	(0.0231)	(0.0125)

Table 28: Estimation of frailty process

(a) First Stage: deterministic component

	coefficients (×100)
age	-0.030
	(0.013)
age^2	0.003
	(0.000)
years of school	-0.630
	(0.014)
male	-1.371
	(0.069)
married	-3.157
	(0.077)
constant	12.87
	(0.379)
Year fixed effect	included
Observations	81659
R^2	0.25

	HS Dropout	HS Graduates	Col Graduates
ρ	0.994	0.998	1.000
	(0.002)	(0.001)	(0.002)
$\sigma_\alpha^2 \times 10^4$	17.175	10.198	3.744
	(5.549)	(1.471)	(0.848)
$\sigma_u^2 \times 10^4$	3.152	5.149	1.626
	(0.916)	(0.399)	(0.223)
$\delta_{\varepsilon,0} \times 10^4$	4.161	3.082	2.019
	(0.609)	(0.209)	(0.119)
$\delta_{\varepsilon,1} \times 10^4$	0.264	0.187	0.051
	(0.041)	(0.018)	(0.011)

(b) Second stage: Stochastic component

Table 29: Estimation of out of pocket medical expenditures

	Estimation of log of out of pocket medical expenditures								
	High School Dropouts			High School Graduates			College Graduates		
	on medicare	working	not working	on medicare	working	not working	on medicare	working	not working
age	0.19	-0.23	0.42	-0.08	-0.03	-0.05	0.47	-0.11	-0.75
	(0.10)	(0.09)	(0.22)	(0.07)	(0.06)	(0.16)	(0.16)	(0.08)	(0.30)
age^2	-0.0024	0.00577	-0.00948	0.00238	0.00166	0.00165	-0.00717	0.00339	0.0163
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
age^3	0.0000114	-0.0000391	0.0000749	-0.0000149	-0.0000115	-0.00000646	0.0000359	-0.0000235	-0.000104
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
frailty	21.1	29.15	26.66	15.12	25.01	23.07	12.32	19.89	21.68
	(0.87)	(0.84)	(1.40)	(0.71)	(0.52)	(1.24)	(0.90)	(0.72)	(2.28)
$frailty^2$	-49.27	-71.78	-62.71	-35.9	-66.46	-55.72	-32.42	-49.45	-62.04
	(2.77)	(4.76)	(4.87)	(2.41)	(3.05)	(4.83)	(3.34)	(4.63)	(9.30)
$frailty^3$	35.86	55.31	47.43	27.32	54.53	42.95	26.16	37.55	51.05
	(2.45)	(6.36)	(4.56)	(2.27)	(4.28)	(5.03)	(3.33)	(6.77)	(9.67)
constant	-2.138	3.876	-5.45	3.535	1.525	1.232	-5.263	3.977	12.97
	(1.90)	(1.27)	(3.01)	(1.30)	(0.78)	(2.28)	(3.15)	(1.04)	(4.20)
Obs.	7160	17232	3068	10941	46641	5138	5182	24998	1456
R^2	0.162	0.205	0.312	0.113	0.181	0.278	0.0694	0.142	0.259

Table 30: Comparing estimated effect of frailty/disability with Low and Pistaferri (2015)

(a) Mean frailty for each work limitation group

	no work limitation ($d = 0$)	some work limitation ($d = 1$)	severe work limitation ($d = 2$)
mean frailty	0.068	0.177	0.285

(b) Estimated effect of work limitations on log wage

	Low and Pistaferri (2015)	Our estimation
$d = 1$	-0.057	-0.110
$d = 2$	-0.177	-0.219