# The Impact of Health on Wealth: Empirical Evidence

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**Abstract**

This paper empirically evaluates the impact of health on wealth among the adults between age 50 and 100 in the Unite States. Using the frailty index as a measure of health and carefully accounting for the dynamic relationship between frailty and wealth, I find that suffering one more health deficit leads, on average, to approximately 2.23 percent decline in the net worth of American households. The impact is significantly negative among the individuals over the age of 70, in poor health, in retirement, and without a college degree. The results are robust across several alternative definitions of wealth such as housing wealth, non-housing wealth, and financial wealth. I find that poor health has the largest impact on financial wealth and the smallest impact on housing wealth. The impact of wealth on frailty is insignificant.

JEL classification: D31, I140

Keywords: Health, Wealth

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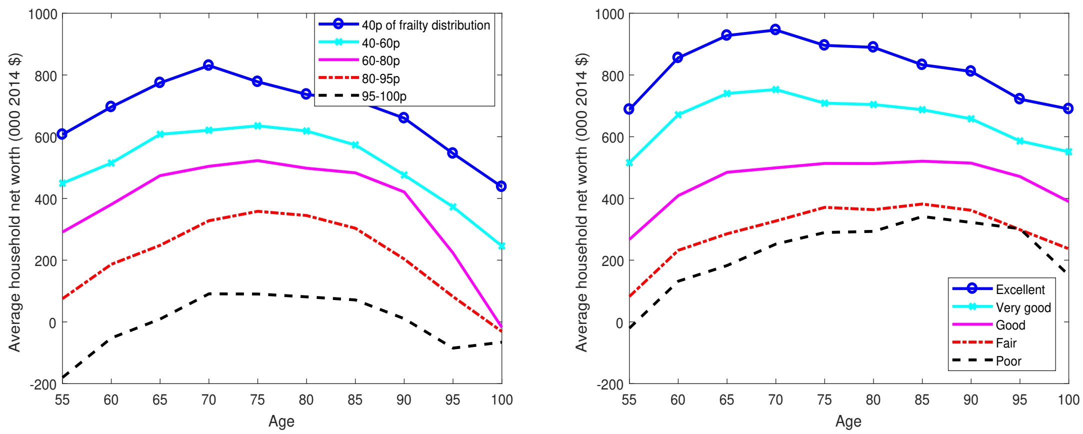
# 1 Introduction

The relationship between health and wealth has been an issue of increasing academic and policy interest. While there exists literature that studies the relationship between socioeconomic status and health, whether health affects wealth or wealth affects health is unclear. This paper contributes to the literature by examining the impact of health on wealth accounting for their dynamic relationship and arguing that within the age groups studied, the impact from health to wealth is significant while the impact from wealth to health appears insignificant. In doing so, the paper adopts a new measure of health, the frailty index, as in Hosseini, Kopecky, and Zhao (2022)[1]. Since frailty index is a continuous measure of health, it allows me to capture the effect of finer variations in health on wealth. Studies on the impact of health on wealth focus either only on the retirees (Wallace, Haveman, and Wolfe (2017), Wu (2003)) or use a narrow measure of health. The impact of health on wealth has been extensively studied in the quantitative macroeconomics literature (see Palumbo (1999), De Nardi, French, and Jones (2010), De Nardi, Pashchenko, and Porapakkarm (2017), Nakajima, Telyukova, et al. (2018), Kopecky and Koreshkova (2014), Zhao (2014), Zhao (2015) etc.). I document the empirical relationship between health and wealth using data from the Health and Retirement Study (HRS) covering nine waves of panel data (from 2000 to 2016)[2]. As shown in Figure 1, healthier individuals tend to be wealthier. A salient feature of the relationship between health and wealth is that healthier individuals tend to be wealthier across different measures of health. To illustrate this fact, I use two different measures of health and plot the average household wealth by age across health distribution ( see Figure 1). Wealth differences across the health distribution appear similar in both panels. Panel (a) of Figure 1plots the average wealth by age for five groups constructed based on frailty index. Panel (b) repeats this exercise using subjective rating of health available from the survey data [3]. It appears from Figure 1 that health and wealth are correlated. The objective of this paper is to identify which direction (from health to wealth or from wealth to health) the impact is significant and then quantify such impact.

1. Throughout the paper, I use health and frailty interchangeably. I will discuss in detail the construction of the frailty index in the next section. I will also define the concept of wealth in the next section.
2. Please see the next section for a detailed explanation of sample selection.
3. The use of subjective rating of health in panel (b) is only to illustrate the point that wealth differentials by health are independent of the measure of health I use. I do not use subjective health status in this analysis.




(a) (b)

Figure 1: Panel (a) average household net worth by frailty, panel (b) average household net worth by self-reported health status. These are averages for the five year age groups in 2014. For example, age 55 in the graph represents average for the age group 50-55. $40p$ refers to $0 - 40$ percent of the health distribution (healthiest 40 percent). Data source: Health and Retirement Study (HRS) 2000-2016.

This paper is related to a number of studies that have attempted to evaluate the empirical relationship between wealth and health. Smith (1999) uses PSID, HRS, and AHEAD data to assess the impact of health shocks on wealth. He concludes that health shocks reduce household wealth among the American elderly (age 70 or older). He further shows that the severity of health shock increases wealth loss. Smith (2004) assesses the connection between the socioeconomic status (measured by household income and household wealth) using PSID and the HRS data. He concludes that the effect of health on socioeconomic status is quantitatively important. While he finds that household wealth and individual health outcomes are unrelated, he shows that the impact of education on health outcomes is significant. Coile and Milligan (2009) argue that household wealth portfolio is affected by health shocks as individuals age. Using the HRS data, they show that households increase the proportion of wealth on liquid assets and reduce the proportion of wealth on assets such as real estate, vehicles, and businesses as they age. They argue that the effect of health shock is larger among individuals with physical or mental health limitations. Wallace et al. (2012) follow the retirees in the HRS data for a decade to assess how shocks the physical and mental health affects their annuitized net wealth during those years. They find that negative shocks to physical and mental health during early retirement have a significant effect. Since they focus on early retirees, they potentially miss larger effects of poor health during later ages. My analysis is based on the sample of individuals aged 50 and 100, which I believe is better suited not only to evaluate the average effect of health on wealth but also to understand how poor health affects retired and not-retired individuals differently. I find that poor health significantly negatively affects retirees and has no significant effect on non-retirees. In addition, the elderly (above age 70) are also significantly negatively affected by poor health.

A common feature of most of the studies on the relationship between health and wealth is that they ignore the dynamic relationship between health and wealth. One exception is Wallace, Haveman, and Wolfe (2017), which assesses the short-run and long-run effects of health shocks on the wealth of the married retiree couples using dynamic panel data methods (which I use in this paper). Wallace, Haveman, and Wolfe (2017) find that health shocks could lead to a significant wealth decline of the retirees in the long run (over a period of 10 years). I differ from their analysis in several ways. First, their emphasis is on assessing whether retirees have adequate assets during retirement, while I focus on the overall impact of health on wealth among retirees and working individuals. I estimate the average impact of suffering one more health deficit on wealth. My analysis uses more comprehensive data in the sense that it contains information on all individuals aged 50 or above, married or unmarried. The advantage is that it allows for the evaluation of the impact of health on wealth both before and after retirement, which could be important for policies. In fact, I find that poor health has a significant and negative effect on the wealth of the retirees and an insignificant effect on the wealth of individuals who have not retired. Second, I adopt a more comprehensive measure of health than Wallace, Haveman, and Wolfe (2017) as I use 36 different health conditions as opposed to their 21 conditions. Furthermore, Wallace, Haveman, and Wolfe (2017) rely only on the measures of physical health, while I use the measures of physical as well as cognitive health in the health index I use. A more comprehensive measure of health is important to accurately measure the average effect of one more health deficit on wealth. Third, their analysis is based on waves 2 through 10 of HRS data on just one cohort (the HRS cohort). The data I use is more comprehensive as I use data on all the cohorts included in the survey (more on this in the next section), which is crucial to evaluate the average impact of suffering from one more health deficit. Focusing only on married couples nearing retirement, Wu (2003) finds that shocks to the health of wife have a significant effect on household wealth while the effect of shocks to husband's health have an insignificant effect. Using a latent health index based on 28 different health conditions, Poterba, Venti, and Wise (2011) find that the evolution of assets is correlated with health status. They do not, however, estimate the impact of individual's health status on wealth.

The main contribution of the paper is to quantify the marginal impact of suffering one more health deficit (to be defined in the next section) on household wealth. Adoption of a comprehensive and continuous measure of health (the frailty index) is important for this purpose. The analysis shows that suffering one more health deficit leads to a 2.23 percent decline in total household net worth on average. This decline varies across different groups based on education, health, age, and retirement status. Results show that the impact of health on wealth among the non-retirees, those younger than age 70, those with a college degree, and those in the bottom 75 percent of the frailty distribution is insignificant. In contrast, the impact among the retirees, those aged 70 years or above, without a college degree, and in the top 25 percent of the frailty distribution is significantly negative. The impact varies by the type of wealth under consideration. For example, I find that the effect of frailty is largest(2.59%) on financial wealth and smallest (1.37%) on housing wealth. To my knowledge, there is no prior published work analyzing the impact of health on wealth accounting for the dynamic relationship between health, wealth, and other socioeconomic factors affecting both health and wealth. [4].

## 2 Data and summary statistics

I use wave 5 through 13 of the RAND HRS data for the analysis [5]. The HRS panel survey is run every two years. The data has detailed information on the health, income, wealth of respondents aged 50 years or older and their spouses of any age. Since the number of individuals below age 50 is small, I use data on individuals aged 50 to 100 years. I drop the first four waves of the data because the wealth data in the early waves of the HRS survey are inaccurate (Rohwedder, Haider, and Hurd (2006)). In addition, data on the secondary house is missing in wave 3. Starting the 2002 wave of the survey, the HRS took measures to improve the accuracy of wealth data (Hurd

4. Most of the related works are either focused only on one specific group (such as married, retired, or their combination) or are merely interested in evaluating how health and wealth evolve over time.

5. I use the RAND HRS Longitudinal File 2018 (V1), the latest available longitudinal file as of writing this paper, for the analysis.

et al. (2016)). This included, among other questions, asking respondents about the accuracy of the wealth numbers reported in the previous wave, allowing HRS to reduce erroneous variation in wealth data over time. As a result, wealth measures have improved. The first wave in the sample is 2000, and the last is 2016 (for a total of nine waves). I exclude the 2018 wave since imputations of some of the cognitive health indicators used in constructing the frailty index are unavailable in the current version of the data file[6]. The data file contains information about six cohorts based on their birth year: (1) The Asset and Health Dynamics Among the Oldest Old (AHEAD) cohort (born before 1924), (2) the Children of Depression (CODA) cohort (born 1924-1930), (3) the Health and Retirement Study (HRS) cohort (born 1931-1941), (4) the War Babies (WB) cohort (born 1942-1947), (5) the Early Baby Boomers (EBB) cohort (born 1948-1953), and (6) the Mid Baby Boomer (MBB) cohort (born 1954-1959). The EBB cohort entered the survey beginning the 2000 wave, and the MBB cohort entered the survey beginning the 2004 wave of the survey. All other cohorts were interviewed in all the waves the paper uses.

## 2.1 Measure of wealth

The HRS reports wealth at the household level. I use the concept of net worth (taken from the HRS data) as the measure of wealth. It is defined as follows:

Net worth = housing + vehicles + business + IRA + stocks + savings and checking deposits + certificate of deposits (CD) + bonds + other wealth − mortgage − home loan − other debt − other mortgages.

## 2.2 Frailty index

Following Hosseini, Kopecky, and Zhao (2022), I construct a frailty index to measure health[7]. The frailty index is a summary of the extent to which an individual suffers from health deficits. A health deficit is a condition that worsens health. It could be memory loss, high blood pressure, cancer, inability to carry out activities of daily living (ADL), or obesity. I take 36 different health

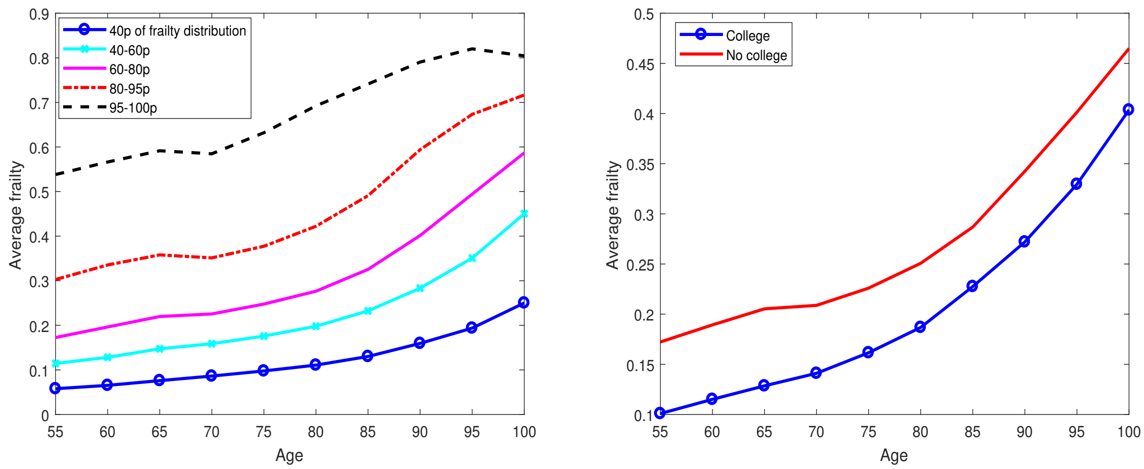
6. The indicators with missing imputations include immediate word recall, delayed word recall, serial 7s, backwards counting, and object naming variables.

7. See Hosseini, Kopecky, and Zhao (2022) for more details on this index.

conditions (deficits) from the HRS data to construct the frailty index as follows[8].

$$\text{Frailty index} = \frac{\text{Number of deficits present}}{\text{Total number of deficits considered}}.$$

For instance, an individual with 5 of the 36 deficits would have frailty index $= \frac{5}{36} = 0.14$. This objective measure of health is based on the 36 different health deficits, on which the data is available in the HRS data. As shown in Figure 2, the average frailty increases with age and decreases with education.




(a)

(b)

Figure 2: Panel (a): average frailty by frailty category, panel (b) average frailty by education level. (Data source: HRS 2000-2016)

Table 1 presents the descriptive statistics of the working sample. I drop the observations if household net worth or household net income is non-positive. Table 1 shows that healthier and better educated households have higher average net worth and income. The net worth and household income values are expressed in thousands of 2014 U.S. Dollars normalized by consumer price index available at the Federal Reserve Bank of St. Louis. Observe that the least frail 75 percent hold more than double the net worth the most frail 25 percent. There are similar differences in household income by across the frailty distribution. On the other hand, the most frail 25 percent are nearly thrice as frail as the least frail 75 percent. The standard deviation of frailty is also higher among the individuals in the most frail 25 percent group. The wealth and income differences are even larger by education. On average, the household net worth of college-educated individuals is

8. See Table 3 for the complete list of conditions included in frailty index.

about 2.8 times as high as those without a college degree. Individuals without a college degree have, on average, poorer health than those with a college degree.

Table 1: Summary statistics

| | Mean | S.D. | Observations |
|---|---|---|---|
| **Entire sample** | | | |
| Age | 68.52 | 10.41 | 145,446 |
| Frailty | 0.21 | 0.15 | 145,446 |
| Total household net worth (in 2014 '000$) | 568.41 | 1,609.82 | 145,446 |
| Total household income (in 2014 '000$) | 76.44 | 177.02 | 145,446 |
| **College education** | | | |
| Age | 66.86 | 10.15 | 32,634 |
| Frailty | 0.15 | 0.12 | 32,634 |
| Total household net worth | 1,125.11 | 2,783.33 | 32,634 |
| Total household income | 136.69 | 288.30 | 32,634 |
| **No college education** | | | |
| Age | 69.00 | 10.44 | 112,791 |
| Frailty | 0.22 | 0.15 | 112,791 |
| Total household net worth | 407.43 | 992.38 | 11,2791 |
| Total household income | 59.01 | 122.50 | 112,791 |
| **Age $< 70$** | | | |
| Age | 60.75 | 5.21 | 81,069 |
| Frailty | 0.17 | 0.13 | 81,069 |
| Total household net worth | 565.27 | 1,838.33 | 81,069 |
| Total household income | 94.48 | 220.24 | 81,069 |
| **Age $\geq 70$** | | | |
| Age | 78.30 | 6.27 | 64,377 |
| Frailty | 0.25 | 0.16 | 64,377 |
| Total household net worth | 572.36 | 1,264.63 | 64,377 |
| Total household income | 53.72 | 93.75 | 64,377 |
| **Top 25 percent of the frailty distribution** | | | |
| Age | 68.79 | 10.28 | 32,631 |
| Frailty | 0.41 | 0.14 | 32,631 |
| Total household net worth | 284.81 | 827.38 | 32,631 |
| Total household income | 46.64 | 76.35 | 32,631 |
| **Bottom 75 percent of the frailty distribution** | | | |
| Age | 68.44 | 10.45 | 112,815 |
| Frailty | 0.15 | 0.08 | 112,815 |
| Total household net worth | 650.44 | 1,764.40 | 112,815 |
| Total household income | 85.06 | 195.92 | 112,815 |

# 3 Empirical approach

Although there is evidence that the direction of the impact from health to wealth is more significant than the impact from wealth to health, other socio-economic factors such as education and parental status appear to be important for health outcomes (Smith (2004)). This is evident from Table 1, which shows that the household net worth of college-educated and healthier individuals is higher than that of unhealthy. The implication is that the endogeneity between wealth and health cannot be ruled out. In this paper, I aim to assess whether the impact of health on wealth is significant, accounting for such endogeneity. The empirical approach closely follows Hosseini, Kopecky, and Zhao (2021) except that I want to analyze the impact of health on wealth and not on earnings. Specifically, I run the following model.

$$w_{i,t} = a_i + \lambda_t + \beta h_{i,t} + \sum_{j=1}^{4} \alpha_j w_{i,t-j} + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t}. \tag{1}$$

In equation (1), $w_{i,t}$ is the log of individual $i's$ household wealth at time $t$. On the right-hand side, $a_i$ is the time-invariant individual fixed effect, which controls for the potential unobserved individual-specific heterogeneity. For example, it could include genetic endowment that affects both health as well as wealth or any potentially omitted variable. The time dummy, $\lambda_t$, is essential to account for the year-specific effects on wealth, although they may or may not affect an individual's health. For example, the average effect of the great recession on individual wealth in 2008 is accounted for by $\lambda_{2008}$. Health status is represented by $h_{i,t}$, which shows individual $i$'s frailty at time $t$. Larger the $h_{i,t}$, the poorer the health (the more frail the individual). $\mathbf{X}_{i,t}$ is a set of control variables including log total household income, marital status, family size, number of alive siblings, long term care insurance status, year dummies, and a cubic polynomial on age.

Family size and number of siblings are included in the model to account for the potential impact of family related factors on wealth or the impact of wealth on family size. In the regressions, I assume that the past shocks to wealth might have an effect on family size or the number of alive siblings. The number of siblings may also have an impact on inheritance, which is an important constituent of wealth. The inclusion of the long term care (LTC) insurance dummy is motivated by the finding in Lockwood (2018) that the possession of LTC insurance increases with wealth. One could argue that having LTC coverage could minimize potential wealth loss due to a bad health shock. For this reason, I treat LTC status as an endogenous variable. Another endogenous variable in the model is the total household income. The reason behind treating it as endogenous is that it includes labor as well as capital income. The inclusion of capital income means that current shocks to wealth could affect current income. For instance, owning a number of houses could increase the rent income, leading to higher total household income. In equation 1, $\epsilon_{i,t}$ is the random error term. I assume that

$$E(a_i) = E(\epsilon_{it}) = E(a_i \epsilon_{it}) = 0.$$

To estimate the coefficients, I use the dynamic panel data approach adopted by several papers in economics and finance. One such paper is Wintoki, Linck, and Netter (2012), which I follow closely. The dynamic panel data methods were introduced by Holtz-Eakin, Newey, and Rosen (1988) and further developed and popularized by the works of Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998). As outlined in Roodman (2009), the estimators developed in these papers are relevant to this paper for the following reasons: (1) HRS (2000-2016) is a small $T$, large $N$ data (only eight waves but a large number of individuals), (2) wealth (dependent variable) depends on its own past, (3) regressors such as health, or lagged value of wealth could be correlated with the past errors, (4) presence of unobserved (but presumably time-invariant) individual heterogeneity ($a_i$), (5) heteroskedasticity and auto-correlation within the individuals over time but not across the individuals, and (6) linear functional relationship (by assumption).

Estimation proceeds in two steps. In the first step, I create the following first-differenced equation by eliminating the time-invariant individual-specific effect $a_i$ from equation (1).

$$\Delta w_{i,t} = \beta \Delta h_{i,t} + \sum_{j=1}^{4} \alpha_j \Delta w_{i,t-j} + \gamma \Delta \mathbf{X}_{i,t} + \Delta \epsilon_{i,t} \tag{2}$$

$\beta$ thus estimated using equation (2) is called the "difference GMM estimator". The second step is to use the lagged values of wealth, health, and other control variables as their instruments to estimate the coefficients. For instrument validity, the following moment conditions must hold.

$$E(w_{i,t-s} \Delta \epsilon_{i,t}) = E(h_{i,t-s+3} \Delta \epsilon_{i,t}) = 0, \quad \text{for } s > 4 \tag{3}$$

While the first-differencing removes the time-invariant individual-specific unobserved heterogeneity, the difference GMM estimator uses the lagged levels as the instruments for the first-differenced variables. Arellano and Bover (1995) and Blundell and Bond (1998) point out that lagged levels are often poor instruments for the fist-differenced variables, especially when the variables in question are highly persistent. In that case, the difference GMM estimator is likely to be inefficient because first-differencing persistent variables such as wealth and health is likely to remove most of the variation. Blundell and Bond (1998) propose "system GMM estimator" to increase the efficiency of the difference GMM estimator. They suggest including the level equations in addition to the first-differenced equations (equation (2)) so that the estimators contain more "information". Specifically, system GMM doubles the observations by creating a $\Delta w_{i,t}$ for every $w_{i,t}$ and stacking them as follows.

$$\begin{bmatrix} \Delta w_{i,t} \\ w_{i,t} \end{bmatrix} = \beta \begin{bmatrix} \Delta f_{i,t} \\ f_{i,t} \end{bmatrix} + \alpha_j \sum_{j=1}^{4} \begin{bmatrix} \Delta w_{i,t-j} \\ w_{i,t-j} \end{bmatrix} + \gamma \begin{bmatrix} \Delta \mathbf{X}_{i,t} \\ \mathbf{X}_{i,t} \end{bmatrix} + \epsilon_{i,t} \tag{4}$$

Notice, however, that $\epsilon_{it}$ in equation (4) includes the unobserved heterogeneity $a_i$ present in equation (1). If $a_i$ is correlated with the regressors, and this correlation varies over time, it will lead to inconsistent estimates. First-differencing removes them out of the fixed effect equation. Therefore, $\bar{e_i}$ never appears in the error term. I still need to address the bias caused by $a_i$ remaining in the error term. To overcome this problem, I assume that the correlation between the regressors and the remaining $a_i$ is constant over time. It is a reasonable assumption given the small $T$ panel data. Consider, for instance, the impact of genetic endowment on health. While certain individuals may be healthier than others due to the genes they inherit from their parents, it is unlikely that the effect of genes on health will change in a few years. This assumption means that the following additional moment conditions hold.

$$E[\Delta w_{i,t-s}(a_i + \epsilon_{i,t})] = E[\Delta f_{i,t-s+3}(a_i + \epsilon_{i,t})] = 0, \quad \text{for } s > 4. \tag{5}$$

The moment conditions in equation (5) ensure that the unobserved heterogeneity present in the level equations do not correlate the past or current error terms to the differences ($\Delta w_{i,t-s}$, $\Delta f_{i,t-s}$, and $\Delta \mathbf{X}_{i,t}$) when I use levels as instruments in the equations in differences. In addition, if the above exogeneity assumptions are correct, then the following conditions must hold.

$$E[X_{it-s}\epsilon_{it}] = E[w_{it-s}\epsilon_{it}] = 0, \quad \text{for } s > 4. \tag{6}$$

While the current shocks to wealth could be correlated to health, one cannot rule out the possibility of dynamic endogeneity. That is, it is likely that the past health affects current wealth and past wealth also affects current health as well as current wealth. The potential presence of dynamic endogeneity further complicates the identification of the impact of health on wealth. As a solution to this problem, I include the first four lags of wealth as regressors. How do I determine how many lags to use? I follow the approach adopted by Wintoki, Linck, and Netter (2012) as their question has similar complications as the question my paper is attempting to address. Although they want to understand how the corporate board structure affects corporate performance, the relation between their dependent and independent variable is full of potential endogeneity concerns. My strategy, as in Wintoki, Linck, and Netter (2012), is to experiment with different lags of $w_{it}$ and choose the shortest lag that addresses the endogeneity problem. One could use the deepest possible lag to overcome endogeneity, but that increases the risk of weak IV problem. Choosing an appropriate number of lags involves adequately addressing both concerns.

To determine whether I have addressed endogeneity concerns, I use several tests suggested by Arellano and Bond (1991). A key assumption in my setup is that the current shocks to wealth are independent of the past wealth and the individual-specific characteristics beyond certain lags. This follows from the earlier discussion of why the number of lags of wealth used as regressors need to be chosen carefully. To test the validity of this assumption, Arellano and Bond (1991) suggest two tests. The first is the test of the second-order serial correlation, $AR(2)$ test. The idea behind this test is that if the model includes enough lags of wealth as regressors, then the past values of wealth (as well as the past values of other endogenous variables) beyond this lag must be exogenous to the current shocks to wealth. In other words, if I use the first 4 lags of wealth as regressors, then the 5 and deeper lags of wealth and other endogenous variables are their valid IVs. Based on the empirical specification, the residuals in the first difference will be correlated. That is, the null hypothesis that $AR(1)$ is zero will likely be rejected. To see why, note that in the first-differenced model,

$$\Delta w_{i,t} = \eta + \beta \Delta h_{i,t} + \sum_{j=1}^{4} \alpha_j \Delta w_{i,t-j} + \gamma \Delta \mathbf{X}_{i,t} + \Delta \epsilon_{i,t}, \tag{7}$$

where $\Delta\epsilon_{i,t} = \epsilon_{i,t} - \epsilon_{i,t-1}$. At $t-1$, $\Delta\epsilon_{i,t-1} = \epsilon_{i,t-1} - \epsilon_{i,t-2}$. Since $\epsilon_{i,t-1}$ is present in $\Delta\epsilon_{i,t}$ and $\Delta\epsilon_{i,t-1}$, the first-differenced residuals will most likely be serially correlated. If the model specification is correct, the residuals should not exhibit significant second order serial correlation, $AR(2)$. In the context of the model, this means that I should be unable to reject the null hypothesis that $AR(2)$ is zero. Arellano and Bond (1991) suggest a second test, called the Hansen test of over-identification. Its purpose is to test the joint validity of the set of instruments. Since the model uses several lags of control variables as their instruments, the system is over-identified. This means that the Hansen-test (Hansen J) can be used to test the null hypothesis that the instruments used in the model are jointly valid. If the instruments used in the model are valid, then I should be unable to reject the null hypothesis. In addition to these two tests, I also report the Difference-in-Hansen test to test the null that instruments used for the level equations are exogenous. Although passing all these tests cannot completely eliminate potential bias in the estimates (Wintoki, Linck, and Netter (2012)), the Hansen J test becomes more reliable as the sample size increases. A likely reason for the weak Hansen J test is instrument proliferation with the number of lags used. In the main models, the number of instruments remains around 40 with 32,880 observations. Note, however, that all the tests I described assume that the model is correctly specified.

### 3.1 How many lags of wealth to include as regressors?

To decide on how many lags of wealth variable to include as regressors, I run the OLS regression of log wealth on a set of control variables with different lags of wealth as regressors, similar to the approach adopted by Wintoki, Linck, and Netter (2012). Including enough lags is essential for the dynamic completeness of the model (Wintoki, Linck, and Netter (2012)).

It appears from the results in Table 12 that the first four lags are always significant for predicting current wealth level. Columns (5) and (6) show that as I include deeper lags, the significance of the lags after the fourth lag decreases. In column (5), the coefficient on the fifth lag becomes insignificant while the coefficient on the sixth lag is still significant. To understand whether the sixth lag is really important, I run the OLS with up to the seventh lags of wealth as regressors. With the seventh lags included, coefficients of both the fifth and the sixth lags become insignificant. The coefficients of later lags are smaller, indicating that deeper lags are a relatively weaker predictor of current wealth.

### 3.2 Accounting for the dynamic relationship between frailty and wealth

To highlight the importance of accounting for the dynamic relationship between frailty and past wealth, I run the following models[9].

- An OLS model, in which I ignore the dynamic relationship between wealth and frailty and the individual-specific unobserved heterogeneity. I call it the Static OLS model.
- A static fixed-effects model, in which I ignore the dynamic relationship between wealth and frailty but account for individual-specific unobserved heterogeneity.
- A dynamic OLS model, which takes into account the dynamic relationship between wealth and health but ignores the individual-specific unobserved heterogeneity. I call it the Static FE model.
- A dynamic fixed-effects model (system GMM), in which I account for the dynamic relationship between the dependent and independent variables and the time-invariant individual-specific unobserved heterogeneity.

The results are presented in Table 13. The effect of frailty on wealth is negative and significant in all the models. Notice, however, that the magnitude of the coefficient and the t-statistic (all based on robust, individual-clustered standard errors) are quite different across the specifications. In the static OLS model, I have accounted for the potential correlation of individual-specific errors over time by using cluster-robust errors. But there are two crucial shortcomings of this model. First, the static nature of the model means that it ignores the dynamic relation between wealth, frailty, and other explanatory variables. Table 12 has already shown that there is a significant dynamic relationship between health and wealth. The importance of dynamic relation is evident from the drastic decline in the magnitude of the frailty coefficient in the second column of Table 13 in the dynamic OLS model. Another evidence is observed in a sharp improvement in $R^2$ from the static OLS to the dynamic OLS model. This could also imply that current frailty is correlated with past wealth. Second, OLS ignores the individual-specific unobserved heterogeneity, which could be important for explaining the impact of frailty on wealth. The past wealth level may not fully

9. Here, I follow the approach adopted by Wintoki, Linck, and Netter (2012) to show the importance of dynamic relation between corporate performance and board structure.

capture such heterogeneity. To address these concerns, I account for the dynamic nature of the relationship as well as the potential role of unobserved heterogeneity by using system GMM to estimate the coefficients (column (4)). Observe that the coefficient declines sharply from static FE model to system GMM. This is because the static FE estimator is likely to be positively biased if frailty is negatively correlated to past wealth (since I ignore the dynamic nature of the relationship in the static FE model). The sharp decline in coefficient from the static OLS model to the dynamic OLS model shows that there is a negative correlation between frailty and past wealth.

I also report the result of the test for serial correlation on residual errors for the level equations. The AR(2) value is 0.630, implying that I cannot reject the null hypothesis of no second order serial correlation. I also test for over-identifying restrictions. The J-test has p-value of 0.772, implying that I cannot reject the null hypothesis that the instruments are valid. Finally, the Diff-in-Hansen test for exogeneity (under the null that the instruments used for the level equations are exogenous) with p-value of 0.332 shows that I cannot reject the null hypothesis that the subset of instruments used in the level equations are exogenous (Eichenbaum, Hansen, and Singleton (1988)).

# 4 Results

Table 2 presents the main results. Recall that this paper is interested in the marginal effect of frailty on wealth. The results show that frailty has a significantly negative impact on wealth. Recall that I used 36 different health deficits in the construction of the frailty index. The coefficient of frailty in column 1 of Table 2 shows that an additional deficit reduces household net worth by $\frac{(\exp(\beta)-1)}{36} = 2.23$ percentage points on average. The model passes all the tests essential to address potential endogeneity and IV validity issues. As explained earlier, the null of no first order serial correlation in the residual differences is rejected at 95 percent confidence level. This is to be expected due to the way first-differencing works. The results pass the AR(2) test, which is based on the null hypothesis that there is second order serial correlation on residual differences since I cannot reject the null. The results also pass the Hansen test of over-identification, meaning I cannot reject the null hypothesis that the set of instruments used in the equations in levels are jointly valid. I further run the difference-in-Hansen test of exogeneity of the instruments used for endogenous variables. Since I cannot reject the null hypothesis that the set of instruments are exogenous, it must be the case that the instruments are not endogenous. For all the results presented in Table 2 I use the lags 6-7 of endogenous variables and wealth as instruments. I run several experiments to determine which lags are most appropriate to address serial correlation and weak IV issue simultaneously (see Table 7, 8, 9, 10, and 11). I find that using fifth lag results into the rejection of the null of exogeneity of instruments. With lags 6-7, results pass all the three tests, which are reported.

Recall that in the main regression household income, frailty, and long term care insurance status are the endogenous variables along with the wealth. The number of siblings and family size are treated as predetermined variables as past shock to wealth could affect the current realizations of these variables. Finally, the year dummies, cubic polynomial in age, and marital status are treated as strictly exogenous variables and used only for the level equations. I collapse the instrument matrix to prevent quadratic increase in number of instruments with number of time periods.

### 4.1 Potential mechanisms

Given that the impact of frailty on wealth is significant and negative, we would want to know through what channels frailty may be affecting wealth. To that end, I estimate the effect of frailty among different groups. First, I consider two age groups: individuals younger than age 70 and those age 70 or older. In Table 2, I label them as "young" and "old", respectively. Column 2 shows that it is the old who face the severe wealth loss due to bad health. This is not surprising since frailty increases with age while the earning potential declines especially after retirement. In addition, most Americans live off their savings post retirement. The combination of these factors may explain the large and significant effect of frailty among the old. The impact is insignificant among the people younger than age 70. Observe that the results pass the AR(2) test, the Hansen test, and the difference-in-Hansen test.

Table 2: Effect of frailty on wealth

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| log(wealth$_{t-1}$) | 0.806*** | 0.809*** | 0.789*** | 0.796*** | 0.791*** |
| | (6.43) | (6.58) | (6.33) | (6.68) | (5.70) |
| log(wealth$_{t-2}$) | 0.174 | 0.221 | 0.162 | 0.178 | 0.355** |
| | (1.09) | (1.41) | (1.04) | (1.14) | (1.97) |
| log(wealth$_{t-3}$) | -0.204 | -0.247 | -0.207 | -0.236 | -0.331 |
| | (-0.88) | (-1.13) | (-0.94) | (-1.03) | (-1.42) |
| log(wealth$_{t-4}$) | 0.107 | 0.0963 | 0.116 | 0.138 | 0.0609 |
| | (0.74) | (0.71) | (0.81) | (0.94) | (0.44) |
| frailty$_t$ | -1.618*** | | | | |
| | (-4.37) | | | | |
| frailty$_t$ × young | | -0.954 | | | |
| | | (-1.52) | | | |
| frailty$_t$ × old | | -1.688*** | | | |
| | | (-4.57) | | | |
| frailty$_t$ × college | | | -0.813*** | | |
| | | | (-2.66) | | |
| frailty$_t$ × no college | | | -1.792*** | | |
| | | | (-4.70) | | |
| frailty$_t$ × good health | | | | -1.923 | |
| | | | | (-1.27) | |
| frailty$_t$ × bad health | | | | -1.695*** | |
| | | | | (-3.93) | |
| frailty$_t$ × retired | | | | | -1.425*** |
| | | | | | (-3.75) |
| frailty$_t$ × not retired | | | | | -1.890* |
| | | | | | (-1.82) |
| AR(1) test (p-value) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| AR(2) test (p-value) | 0.630 | 0.457 | 0.639 | 0.551 | 0.202 |
| Hansen test of over-identification (p-value) | 0.772 | 0.822 | 0.842 | 0.840 | 0.756 |
| Diff-in-Hansen test of exogeneity (p-value) | 0.332 | 0.684 | 0.453 | 0.216 | 0.277 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 45,336 | 45,336 | 45,336 | 45,336 | 45,336 |

$t$ statistics in parentheses; $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data. These are two-step GMM estimates with robust standard errors and forward orthogonal deviations (FOD) with collapsed instrument matrix. Regressions are run (using David Roodman's *xtabond2* Stata package for Dynamic Panel Data).

The second potential mechanism I consider is education. To evaluate the effect of frailty on wealth by education, I run the model with frailty interacted with the dummy for completed college education ("college") or no college education ("no college"). While the effect of frailty on wealth is significant and negative among both groups, the effect is much larger among those without a college degree. These results are intuitive because, as Table 1 shows, average frailty among the individuals without college degree is 0.22, while it is 0.15 among the college educated. Average wealth among the college educated is 2.8 times the average wealth among the people without a college degree. College educated have lower average frailty at any age from 50 through 100 (Figure 2). Column 3 of Table 2 shows that the impact among people without college degree is more than twice as much as the coefficient among those with a college degree.

The third mechanism I consider is the impact across the frailty distribution. For simplicity, I consider two groups: those with "good" health and those with "bad" health, defined as those in the first three quartiles of the frailty distribution and those in the fourth quartile, respectively. Column 4 of Table 2 shows that the impact is significant among the ones with bad health. The results indicate that bad health leads to wealth loss. The hypothesis that health affects wealth is further strengthened by this evidence.

I consider a fourth mechanism–retirement. It has been argued that health could affect retirees and non-retirees differently. The reason is that the retirees' do not earn regular wage to weather the financial repercussions of bad health shocks while non-retirees potentially do. The results appear consistent with this hypothesis. Although the effect of health on wealth among appears larger among the not retired, it is significant only at 90 percent confidence level. The results provide evidence that retirees face significant wealth loss due to poor health. Note that the results are also consistent with Hosseini, Kopecky, and Zhao (2021), who find that individuals with poorer education suffer larger earnings losses due to bad health.

## 4.2 Consistency of the estimates

Recall that the estimates rely on exploiting the dynamic relation between frailty and wealth available in dynamic panel data. An important feature of the specification is that it contains lagged values of dependent variable (wealth) as regressors. From equation (1), $\alpha_1$, $\alpha_2$, $\alpha_3$, and $\alpha_4$ are the coefficients on the lags of wealth. The OLS estimates of these coefficients are positively biased while the fixed-effects estimates of the coefficients are negatively biased (Nickell (1981), Arellano and Bond (1991), Bond (2002b)), leading to inconsistent estimators.

System GMM helps improve on reducing bias and thus consistently estimating the coefficients $\alpha_1$, $\alpha_2$, $\alpha_3$, and $\alpha_4$. In context of the model, this means that the sum of the coefficients on $\log(\text{wealth}_{t-1})$, $\log(\text{wealth}_{t-2})$, $\log(\text{wealth}_{t-3})$, and $\log(\text{wealth}_{t-4})$ using system GMM must lie between such sums while using OLS and FE estimators. The results of the regressions are presented in Table 14. The results pass this test, implying that the system GMM estimates are consistent.

### 4.3 Test for reverse causality

It is possible that the direction of causality runs from wealth to health. That is, not having enough wealth leads to poor health. To test this hypothesis, I run the following model using system GMM.

$$h_{i,t} = a_i + \lambda_t + \beta w_{i,t} + \sum_{j=1}^{4} \alpha_j h_{i,t-j} + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{8}$$

Equation (8) is different from equation (1) in that unlike in equation (1), the dependent variable in equation (8) is health. Here I want to assess whether the results above are driven by the impact of wealth on frailty rather than what I have argued in this paper. Table 15 shows that the results are not driven by reverse causality.

### 4.4 Alternative definitions of wealth

To check robustness of the results, I run the model using three alternative definitions of wealth: total non-housing net worth, total financial net worth (excluding housing), and total housing net worth. The results remain significant across the definitions although the level of significance and the magnitude of coefficients change. I present the results in Table 4, 5, and 6. While the results pass all the empirical tests reported, nearly all the results remain significant. Notice that the effect of bad health on financial wealth is significant across the education groups and retirement groups. The impact of frailty is the smallest on housing wealth across all groups. The model specification in the main model and across the three alternative definitions of wealth remains the same, except that I need to use deeper lags with the three alternative definitions for the results to pass the specification tests. For this reason, I report the “lags for IV”. Evidently, frailty has large and significant effect on all forms of wealth considered.

## 5 Conclusion

In this paper I document the empirical relationship between health and wealth. The paper’s main contribution is that it empirically evaluates the overall marginal impact of suffering from one more health deficit on household wealth. Analysis shows that suffering one more health deficit leads to a 2.23 percent reduction of household net worth. In particular, the individuals without college degree and the elderly suffer the biggest wealth loss due to poor health. Using dynamic panel data approach and a new measure of health (frailty index), I find that the impact of poor health among the retirees is significant, while it is insignificant among the non-retirees. This paper also contributes to the literature by rigorously accounting for the dynamic relationship between health, wealth, and other socioeconomic factors in the analysis of the impact of health on wealth. The results remain robust across several alternative definitions of wealth. Results show that the impact of bad health is largest on financial wealth and smallest on housing wealth. A number of empirical tests confirm the validity of the instruments used in the analysis. One of the limitations of this study is that the data includes only the individuals of age 50 to 100. Empirical evaluation of impact of health on wealth over the entire life-cycle is left for future research.

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# Appendix A: Health variables used in the frailty index

Table 3: Health deficits used in the construction of frailty index

| S.No. | Health variables | Score |
|---|---|---|
| | **Has the doctor ever told you that you have:** | |
| 1 | High blood pressure | $Yes = 1, No = 0$ |
| 2 | Diabetes | $Yes = 1, No = 0$ |
| 3 | Cancer or a malignant tumor of any kind except skin cancer | $Yes = 1, No = 0$ |
| 4 | Chronic lung disease except asthma such as chronic bronchitis or emphysema | $Yes = 1, No = 0$ |
| 5 | Heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems | $Yes = 1, No = 0$ |
| 6 | Stroke or transient ischemic attack (TIA) | $Yes = 1, No = 0$ |
| 7 | Emotional, nervous, or psychiatric problems | $Yes = 1, No = 0$ |
| 8 | Arthritis or rheumatism | $Yes = 1, No = 0$ |
| | **Do you have some difficulty with the following ADLs:** | |
| 9 | Bathing | $Yes = 1, No = 0$ |
| 10 | Dressing | $Yes = 1, No = 0$ |
| 11 | Eating | $Yes = 1, No = 0$ |
| 12 | Getting in/out of bed | $Yes = 1, No = 0$ |
| 13 | Walking across room | $Yes = 1, No = 0$ |
| 14 | using toilet | $Yes = 1, No = 0$ |
| | **Do you have some difficulty with the following IADLs:** | |
| 15 | Using a phone | $Yes = 1, No = 0$ |
| 16 | Managing money | $Yes = 1, No = 0$ |
| 17 | Taking medications | $Yes = 1, No = 0$ |
| 18 | Shopping for groceries | $Yes = 1, No = 0$ |
| 19 | Preparing a hot meal | $Yes = 1, No = 0$ |
| 20 | Walking several blocks | $Yes = 1, No = 0$ |
| 21 | Climbing one flat stair | $Yes = 1, No = 0$ |
| 22 | Sitting for two hours | $Yes = 1, No = 0$ |
| 23 | Getting up from chair | $Yes = 1, No = 0$ |
| 24 | Stooping/kneeling/crutching | $Yes = 1, No = 0$ |
| 25 | Pushing/pulling a large object | $Yes = 1, No = 0$ |
| 26 | Picking up a dime | $Yes = 1, No = 0$ |
| 27 | Lifting/carrying 10lbs | $Yes = 1, No = 0$ |
| 28 | Extending arms | $Yes = 1, No = 0$ |
| | **Cognitive health:** | |
| 29 | Immediate word recall | 0.1 for each word not recalled |
| 30 | Delayed word recall | 0.1 for each word not recalled |
| 31 | Serial 7 test | 0.2 for each word not recalled |
| 32 | Backward counting | Failed=1, $2^{nd}$ attempt =0.5, 1st attempt=0 |
| 33 | Identifying objects (four objects in total) | 0.25 for a wrong answer |
| 34 | Date naming (month, date, day, and year) | 0.25 for a wrong answer |
| 35 | Ever smoked? | $Yes = 1, No = 0$ |
| 36 | BMI $\geq$ 30 ? | $Yes = 1, No = 0$ |

## Appendix B: Effect of frailty on wealth using alternative definitions of wealth

Table 4: Effect of frailty on non-housing wealth

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| log(wealth$_{t-1}$) | 0.203 | 0.0197 | -0.0596 | 0.138 | 0.0970 |
| | (0.60) | (0.07) | (-0.21) | (0.48) | (0.45) |
| log(wealth$_{t-2}$) | 0.609$^{**}$ | 0.672$^{***}$ | 0.631$^{**}$ | 0.541$^{**}$ | 0.609$^{**}$ |
| | (2.10) | (2.77) | (2.57) | (1.98) | (2.48) |
| log(wealth$_{t-3}$) | -0.0664 | -0.0478 | 0.0183 | -0.0108 | 0.117 |
| | (-0.26) | (-0.22) | (0.07) | (-0.04) | (0.58) |
| log(wealth$_{t-4}$) | 0.282 | 0.261 | 0.341 | 0.267 | 0.0928 |
| | (1.31) | (1.54) | (1.60) | (1.25) | (0.46) |
| frailty | -2.452$^{***}$ | | | | |
| | (-2.85) | | | | |
| frailty$_t$ × young | | 1.600 | | | |
| | | (0.92) | | | |
| frailty$_t$ × old | | -1.789$^{**}$ | | | |
| | | (-2.35) | | | |
| frailty$_t$ × college | | | -0.823 | | |
| | | | (-0.91) | | |
| frailty$_t$ × no college | | | -3.319$^{***}$ | | |
| | | | (-3.46) | | |
| frailty$_t$ × good health | | | | -3.299 | |
| | | | | (-1.05) | |
| frailty$_t$ × bad health | | | | -2.588$^{***}$ | |
| | | | | (-2.77) | |
| frailty$_t$ × retired | | | | | -2.338$^{***}$ |
| | | | | | (-3.53) |
| frailty$_t$ × not retired | | | | | -3.554 |
| | | | | | (-1.43) |
| AR(1) test (p-value) | 0.293 | 0.267 | 0.353 | 0.267 | 0.318 |
| AR(2) test (p-value) | 0.229 | 0.110 | 0.184 | 0.236 | 0.091 |
| Hansen test of over-identification (p-value) | 0.594 | 0.256 | 0.848 | 0.464 | 0.172 |
| Diff-in-Hansen test of exogeneity (p-value) | 0.346 | 0.075 | 0.554 | 0.218 | 0.143 |
| Lags for IV | 7-8 | 7-8 | 7-8 | 7-8 | 7-8 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 40,448 | 40,448 | 40,448 | 40,448 | 40,448 |

$t$ statistics in parentheses; $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data. These are two-step GMM estimates with robust standard errors and forward orthogonal deviations (FOD) with collapsed instrument matrix. Regressions are run (using David Roodman's *xtabond*2 Stata package for Dynamic Panel Data).

Table 5: Effect of frailty on financial wealth

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| log(wealth$_{t-1}$) | 0.616$^{***}$ | 0.652$^{***}$ | 0.546$^{***}$ | 0.636$^{***}$ | 0.560$^{***}$ |
| | (3.58) | (3.49) | (2.91) | (3.53) | (2.84) |
| log(wealth$_{t-2}$) | 0.156 | 0.148 | 0.0344 | 0.0658 | 0.193 |
| | (0.67) | (0.57) | (0.15) | (0.29) | (0.76) |
| log(wealth$_{t-3}$) | -0.154 | -0.378 | -0.122 | -0.168 | -0.254 |
| | (-0.70) | (-1.51) | (-0.59) | (-0.76) | (-1.05) |
| log(wealth$_{t-4}$) | 0.324$^{*}$ | 0.413$^{**}$ | 0.304$^{*}$ | 0.263 | 0.340$^{*}$ |
| | (1.79) | (2.01) | (1.77) | (1.52) | (1.70) |
| frailty | -2.680$^{***}$ | | | | |
| | (-4.04) | | | | |
| frailty × young | | -0.503 | | | |
| | | (-0.31) | | | |
| frailty × old | | -2.496$^{***}$ | | | |
| | | (-3.38) | | | |
| frailty × college | | | -3.274$^{***}$ | | |
| | | | (-5.02) | | |
| frailty × no college | | | -2.885$^{***}$ | | |
| | | | (-3.61) | | |
| frailty × good health | | | | -4.953 | |
| | | | | (-1.45) | |
| frailty × bad health | | | | -2.872$^{***}$ | |
| | | | | (-3.20) | |
| frailty × retired | | | | | -2.369$^{***}$ |
| | | | | | (-2.96) |
| frailty × not retired | | | | | -6.695$^{**}$ |
| | | | | | (-1.98) |
| AR(1) test (p-value) | 0.002 | 0.002 | 0.002 | 0.001 | 0.001 |
| AR(2) test (p-value) | 0.637 | 0.393 | 0.865 | 0.738 | 0.476 |
| Hansen test of over-identification (p-value) | 0.847 | 0.386 | 0.436 | 0.630 | 0.828 |
| Diff-in-Hansen test of exogeneity (p-value) | 0.548 | 0.081 | 0.120 | 0.179 | 0.444 |
| Lags for IV | 7-8 | 7-8 | 7-8 | 7-8 | 7-8 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 29,239 | 29,239 | 29,239 | 29,239 | 29,239 |

$t$ statistics in parentheses; $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data. These are two-step GMM estimates with robust standard errors and forward orthogonal deviations (FOD) with collapsed instrument matrix. Regressions are run (using David Roodman's *xtabond2* Stata package for Dynamic Panel Data).

Table 6: Effect of frailty on housing wealth

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| log(wealth$_{t-1}$) | -0.00525 | 0.0472 | 0.00445 | 0.0179 | 0.151 |
| | (-0.03) | (0.24) | (0.03) | (0.10) | (0.79) |
| log(wealth$_{t-2}$) | 0.366 | 0.385 | 0.358 | 0.428$^{*}$ | 0.357$^{*}$ |
| | (1.62) | (1.63) | (1.63) | (1.90) | (1.71) |
| log(wealth$_{t-3}$) | 0.349 | 0.314 | 0.367 | 0.239 | 0.160 |
| | (1.40) | (1.20) | (1.52) | (1.00) | (0.83) |
| log(wealth$_{t-4}$) | 0.232$^{**}$ | 0.207$^{*}$ | 0.235$^{**}$ | 0.265$^{**}$ | 0.202$^{*}$ |
| | (2.15) | (1.91) | (2.19) | (2.23) | (1.88) |
| frailty | -0.677$^{**}$ | | | | |
| | (-2.26) | | | | |
| frailty $\times$ young | | 0.0873 | | | |
| | | (0.22) | | | |
| frailty $\times$ old | | -0.761$^{***}$ | | | |
| | | (-2.70) | | | |
| frailty $\times$ college | | | -1.124$^{***}$ | | |
| | | | (-3.05) | | |
| frailty $\times$ no college | | | -0.648$^{**}$ | | |
| | | | (-2.07) | | |
| frailty $\times$ good health | | | | -2.563 | |
| | | | | (-1.09) | |
| frailty $\times$ bad health | | | | -1.097$^{*}$ | |
| | | | | (-1.74) | |
| frailty $\times$ retired | | | | | -1.029$^{***}$ |
| | | | | | (-3.27) |
| frailty $\times$ not retired | | | | | -2.059$^{**}$ |
| | | | | | (-1.98) |
| AR(1) test (p-value) | 0.738 | 0.630 | 0.730 | 0.543 | 0.235 |
| AR(2) test (p-value) | 0.292 | 0.326 | 0.301 | 0.246 | 0.334 |
| Hansen test of over-identification (p-value) | 0.177 | 0.428 | 0.245 | 0.226 | 0.458 |
| Diff-in-Hansen test of exogeneity (p-value) | 0.074 | 0.146 | 0.137 | 0.134 | 0.130 |
| Lags for IV | 8 | 8 | 8 | 8 | 8 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 39,842 | 39,842 | 39,842 | 39,842 | 39,842 |

$t$ statistics in parentheses; $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data. These are two-step GMM estimates with robust standard errors and forward orthogonal deviations (FOD) with collapsed instrument matrix. Regressions are run (using David Roodman's *xtabond2* Stata package for Dynamic Panel Data).

## Appendix C: Experiment with different IV lags

Since the first four lags of wealth are used as independent variables in the model specification, I can only choose the instruments from lag 5 or deeper. In this section, I experiment with different lags and choose the lags that best satisfy the trade-off between the endogeneity problem and the weak IV problem. If I use deeper lags, the IVs may lose explanatory power (weak IV problem) while the potential correlation between the error and regressors is reduced, strengthening the exogeneity of IVs at the expense of their strength. On the other hand, if I use recent lags, I could address the weak IV problem at the expense of greater endogeneity. In Table 7, I observe that using lag 5-6 and 5-7 leads to one or another problem. With both lags, endogeneity seems to be the major problem. For example, when using lags 5-6, I pass the AR(2) test but fail the Diff-in-Hansen test of exogeneity of instruments. The problem persists even when using the lags 5-7. It appears that fifth lag is problematic. This forces us to use deeper lags as instruments. Using lag 6-7, the results pass the AR(2) test, Hansen test of over-identification, and the Diff-in-Hansen test of exogeneity of instruments.

Table 7: Experiment with different IV lags for the main model

| | 5-6 | 6-7 | 5-7 |
|---|---|---|---|
| log(wealth$_{t-1}$) | 0.861*** | 0.806*** | 0.895*** |
| | (6.90) | (6.43) | (7.23) |
| log(wealth$_{t-2}$) | 0.0588 | 0.174 | 0.0514 |
| | (0.34) | (1.09) | (0.30) |
| log(wealth$_{t-3}$) | -0.140 | -0.204 | -0.122 |
| | (-0.79) | (-0.88) | (-0.67) |
| log(wealth$_{t-4}$) | 0.0679 | 0.107 | 0.0553 |
| | (1.58) | (0.74) | (1.27) |
| frailty | -1.087*** | -1.618*** | -1.080*** |
| | (-4.02) | (-4.37) | (-3.96) |
| AR(1) test (p-value) | 0.000 | 0.000 | 0.000 |
| AR(2) test (p-value) | 0.969 | 0.630 | 0.893 |
| Hansen test of over-identification (p-value) | 0.181 | 0.772 | 0.195 |
| Diff-in-Hansen test of exogeneity (p-value) | 0.009 | 0.332 | 0.004 |
| Controls | Yes | Yes | Yes |
| Observations | 45,336 | 45,336 | 45,336 |

$t$ statistics in parentheses; $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data. These are two-step GMM estimates with robust standard errors and forward orthogonal deviations (FOD) with collapsed instrument matrix. Regressions are run (using David Roodman's *xtabond*2 Stata package for Dynamic Panel Data).

Table 8: Experiment with different IV lags, by age group

| | 5-6 | 6-7 | 5-7 |
|---|---|---|---|
| $\log(\text{wealth}_{t-1})$ | 0.930*** | 0.809*** | 0.961*** |
| | (7.52) | (6.58) | (7.89) |
| $\log(\text{wealth}_{t-2})$ | 0.0326 | 0.221 | 0.0353 |
| | (0.21) | (1.41) | (0.23) |
| $\log(\text{wealth}_{t-3})$ | -0.200 | -0.247 | -0.196 |
| | (-1.19) | (-1.13) | (-1.16) |
| $\log(\text{wealth}_{t-4})$ | 0.0802* | 0.0963 | 0.0704 |
| | (1.80) | (0.71) | (1.55) |
| frailty $\times$ young | -0.208 | -0.954 | -0.178 |
| | (-0.40) | (-1.52) | (-0.36) |
| frailty $\times$ old | -1.111*** | -1.688*** | -1.096*** |
| | (-4.21) | (-4.57) | (-4.10) |
| AR(1) test (p-value) | 0.000 | 0.000 | 0.000 |
| AR(2) test (p-value) | 0.962 | 0.457 | 0.981 |
| Hansen test of over-identification (p-value) | 0.305 | 0.822 | 0.332 |
| Diff-in-Hansen test of exogeneity (p-value) | 0.018 | 0.684 | 0.015 |
| Controls | Yes | Yes | Yes |
| Observations | 45,336 | 45,336 | 45,336 |

$t$ statistics in parentheses; $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data. These are two-step GMM estimates with robust standard errors and forward orthogonal deviations (FOD) with collapsed instrument matrix. Regressions are run (using David Roodman's *xtabond2* Stata package for Dynamic Panel Data).

Table 9: Experiment with different IV lags, by education

| | 5-6 | 6-7 | 5-7 |
|---|---|---|---|
| log(wealth$_{t-1}$) | 0.861*** | 0.789*** | 0.897*** |
| | (6.86) | (6.33) | (7.29) |
| log(wealth$_{t-2}$) | 0.0537 | 0.162 | 0.0387 |
| | (0.31) | (1.04) | (0.23) |
| log(wealth$_{t-3}$) | -0.142 | -0.207 | -0.119 |
| | (-0.79) | (-0.94) | (-0.64) |
| log(wealth$_{t-4}$) | 0.0724 | 0.116 | 0.0582 |
| | (1.64) | (0.81) | (1.32) |
| frailty × college | -1.098*** | -0.813*** | -1.039*** |
| | (-3.47) | (-2.66) | (-3.30) |
| frailty × no college | -1.183*** | -1.792*** | -1.175*** |
| | (-4.18) | (-4.70) | (-4.14) |
| AR(1) test (p-value) | 0.000 | 0.000 | 0.000 |
| AR(2) test (p-value) | 0.960 | 0.639 | 0.855 |
| Hansen test of over-identification (p-value) | 0.231 | 0.842 | 0.287 |
| Diff-in-Hansen test of exogeneity (p-value) | 0.020 | 0.453 | 0.012 |
| Controls | Yes | Yes | Yes |
| Observations | 45,336 | 45,336 | 45,336 |

$t$ statistics in parentheses; $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data. These are two-step GMM estimates with robust standard errors and forward orthogonal deviations (FOD) with collapsed instrument matrix. Regressions are run (using David Roodman's *xtabond2* Stata package for Dynamic Panel Data).

Table 10: Experiment with different IV lags, by health

| | 5-6 | 6-7 | 5-7 |
|---|---|---|---|
| log(wealth$_{t-1}$) | 0.834$^{***}$ | 0.796$^{***}$ | 0.867$^{***}$ |
| | (7.12) | (6.68) | (7.46) |
| log(wealth$_{t-2}$) | -0.0136 | 0.178 | -0.000446 |
| | (-0.08) | (1.14) | (-0.00) |
| log(wealth$_{t-3}$) | -0.0771 | -0.236 | -0.0759 |
| | (-0.47) | (-1.03) | (-0.45) |
| log(wealth$_{t-4}$) | 0.0702$^{*}$ | 0.138 | 0.0577 |
| | (1.65) | (0.94) | (1.34) |
| frailty $\times$ good health | 0.260 | -1.923 | 0.171 |
| | (0.25) | (-1.27) | (0.17) |
| frailty $\times$ bad health | -0.856$^{**}$ | -1.695$^{***}$ | -0.868$^{***}$ |
| | (-2.57) | (-3.93) | (-2.60) |
| AR(1) test (p-value) | 0.000 | 0.000 | 0.000 |
| AR(2) test (p-value) | 0.663 | 0.551 | 0.674 |
| Hansen test of over-identification (p-value) | 0.221 | 0.840 | 0.249 |
| Diff-in-Hansen test of exogeneity (p-value) | 0.014 | 0.216 | 0.006 |
| Controls | Yes | Yes | Yes |
| Observations | 45,336 | 45,336 | 45,336 |

$t$ statistics in parentheses; $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data. These are two-step GMM estimates with robust standard errors and forward orthogonal deviations (FOD) with collapsed instrument matrix. Regressions are run (using David Roodman's *xtabond*2 Stata package for Dynamic Panel Data).

Table 11: Experiment with different IV lags, by retirement status

| | 5-6 | 6-7 | 5-7 |
|---|---|---|---|
| log(wealth$_{t-1}$) | 0.931*** | 0.791*** | 0.952*** |
| | (6.76) | (5.70) | (6.91) |
| log(wealth$_{t-2}$) | 0.0921 | 0.355** | 0.102 |
| | (0.53) | (1.97) | (0.57) |
| log(wealth$_{t-3}$) | -0.147 | -0.331 | -0.153 |
| | (-0.88) | (-1.42) | (-0.89) |
| log(wealth$_{t-4}$) | 0.0429 | 0.0609 | 0.0393 |
| | (0.99) | (0.44) | (0.89) |
| frailty × retired | -0.972*** | -1.425*** | -0.996*** |
| | (-3.04) | (-3.75) | (-3.06) |
| frailty × not retired | -0.237 | -1.890* | -0.174 |
| | (-0.35) | (-1.82) | (-0.25) |
| AR(1) test (p-value) | 0.000 | 0.000 | 0.000 |
| AR(2) test (p-value) | 0.973 | 0.202 | 0.945 |
| Hansen test of over-identification (p-value) | 0.251 | 0.756 | 0.410 |
| Diff-in-Hansen test of exogeneity (p-value) | 0.015 | 0.277 | 0.024 |
| Control | Yes | Yes | Yes |
| Observations | 45,336 | 45,336 | 45,336 |

$t$ statistics in parentheses; $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data. These are two-step GMM estimates with robust standard errors and forward orthogonal deviations (FOD) with collapsed instrument matrix. Regressions are run (using David Roodman's *xtabond*2 Stata package for Dynamic Panel Data).

## Appendix D: How many lags of wealth to include as regressors?

Table 12: How many lags of wealth to use as regressors?

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| log(wealth$_{t-1}$) | 0.609*** | 0.576*** | 0.556*** | 0.558*** | 0.565*** | 0.527*** | 0.564*** | |
| | (175.21) | (136.26) | (111.53) | (93.69) | (75.92) | (51.91) | (36.85) | |
| log(wealth$_{t-2}$) | 0.261*** | 0.179*** | 0.169*** | 0.167*** | 0.178*** | 0.180*** | 0.108*** | |
| | (74.44) | (36.40) | (28.59) | (23.91) | (20.09) | (14.92) | (6.02) | |
| log(wealth$_{t-3}$) | | 0.141*** | 0.106*** | 0.0862*** | 0.0785*** | 0.0968*** | 0.0954*** | |
| | | (32.53) | (17.66) | (11.89) | (8.71) | (7.62) | (4.84) | |
| log(wealth$_{t-4}$) | | | 0.0780*** | 0.0619*** | 0.0526*** | 0.0637*** | 0.0580** | |
| | | | (14.75) | (8.47) | (5.66) | (5.06) | (2.88) | |
| log(wealth$_{t-5}$) | | | | 0.0445*** | 0.0126 | 0.00944 | 0.00448 | 0.441*** |
| | | | | (6.95) | (1.37) | (0.73) | (0.23) | (22.00) |
| log(wealth$_{t-6}$) | | | | | 0.0415*** | 0.0458*** | 0.0725*** | 0.179*** |
| | | | | | (5.18) | (3.57) | (3.65) | (7.35) |
| log(wealth$_{t-7}$) | | | | | | -0.00765 | -0.0147 | 0.101*** |
| | | | | | | (-0.69) | (-0.75) | (4.17) |
| log(wealth$_{t-8}$) | | | | | | | 0.00930 | 0.113*** |
| | | | | | | | (0.57) | (5.54) |
| frailty | -0.576*** | -0.517*** | -0.475*** | -0.418*** | -0.401*** | -0.405*** | -0.472*** | -1.032*** |
| | (-26.04) | (-21.00) | (-17.17) | (-13.27) | (-10.54) | (-8.09) | (-6.34) | (-10.50) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 84,997 | 63,277 | 45,336 | 32,149 | 21,255 | 11,996 | 5,286 | 5,845 |

$t$ statistics in parentheses; $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

## Appendix E: Accounting for the dynamic relationship between health and wealth

Table 13: Comparison of static OLS, FE, and the dynamic model

| | Static OLS | Dynamic OLS | Static FE | System GMM |
|---|---|---|---|---|
| frailty | -2.610*** | -0.549*** | -0.784*** | -1.618*** |
| | (-40.92) | (-14.24) | (-14.16) | (-4.37) |
| $\log(\text{wealth}_{t-1})$ | | 0.555*** | | 0.806*** |
| | | (59.69) | | (6.43) |
| $\log(\text{wealth}_{t-2})$ | | 0.177*** | | 0.174 |
| | | (17.52) | | (1.09) |
| $\log(\text{wealth}_{t-3})$ | | 0.0998*** | | -0.204 |
| | | (10.86) | | (-0.88) |
| $\log(\text{wealth}_{t-4})$ | | 0.081*** | | 0.107 |
| | | (10.53) | | (0.74) |
| AR(1) test (p-value) | | | | 0.000 |
| AR(2) test (p-value) | | | | 0.630 |
| Hansen test for over-identification (p-value) | | | | 0.772 |
| Diff-in-Hansen test for exogeneity (p-value) | | | | 0.332 |
| $R^2$ | 0.33 | 0.77 | | |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 142,531 | 49,957 | 142,531 | 45,336 |

$t$ statistics in parentheses; $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data. These are two-step GMM estimates with robust standard errors and forward orthogonal deviations (FOD) with collapsed instrument matrix. Regressions are run (using David Roodman's *xtabond2* Stata package for Dynamic Panel Data).

# Appendix F: Consistency of the estimates

Table 14: Comparison of OLS, FE, and System GMM

| | OLS | FE | System GMM |
|---|---|---|---|
| log(wealth$_{t-1}$) | 0.555*** | -0.0104 | 0.806*** |
| | (59.69) | (-0.84) | (6.43) |
| log(wealth$_{t-2}$) | 0.177*** | -0.0897*** | 0.174 |
| | (17.52) | (-8.70) | (1.09) |
| log(wealth$_{t-3}$) | 0.0998*** | -0.0632*** | -0.204 |
| | (10.86) | (-6.63) | (-0.88) |
| log(wealth$_{t-4}$) | 0.0811*** | -0.0457*** | 0.107 |
| | (10.53) | (-4.95) | (0.74) |
| frailty | -0.549*** | -0.517*** | -1.618*** |
| | (-14.24) | (-6.16) | (-4.37) |
| AR(1) test (p-value) | | | 0.000 |
| AR(2) test (p-value) | | | 0.630 |
| Hansen test of over-identification (p-value) | | | 0.772 |
| Diff-in-Hansen test of exogeneity (p-value) | | | 0.332 |
| Controls | Yes | Yes | Yes |
| Observations | 49,957 | 49,957 | 45,336 |

$t$ statistics in parentheses; $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data.

## Appendix G: Reverse causality test

Table 15: Effect of wealth on frailty

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $\text{frailty}_{t-1}$ | 1.636*** | 0.914*** | 1.600*** | 0.748*** | 1.504*** |
| | (5.11) | (3.23) | (5.18) | (2.82) | (4.92) |
| $\text{frailty}_{t-2}$ | -0.326 | 0.378 | -0.176 | 0.365 | -0.0178 |
| | (-0.49) | (0.75) | (-0.30) | (1.02) | (-0.03) |
| $\text{frailty}_{t-3}$ | 0.0691 | 0.746** | -0.153 | -0.142 | 0.181 |
| | (0.12) | (2.26) | (-0.32) | (-0.53) | (0.38) |
| $\text{frailty}_{t-4}$ | -0.342 | -0.804** | -0.224 | -0.303 | -0.565 |
| | (-0.67) | (-2.12) | (-0.46) | (-1.18) | (-1.20) |
| $\log(\text{wealth}_t)$ | -0.00530 | | | | |
| | (-0.33) | | | | |
| $\log(\text{wealth}_t) \times$ young | | 0.0113 | | | |
| | | (0.99) | | | |
| $\log(\text{wealth}_t) \times$ old | | 0.0199 | | | |
| | | (1.51) | | | |
| $\log(\text{wealth}_t) \times$ college | | | -0.00422 | | |
| | | | (-0.28) | | |
| $\log(\text{wealth}_t) \times$ no college | | | -0.00448 | | |
| | | | (-0.31) | | |
| $\log(\text{wealth}_t) \times$ good health | | | | -0.00393 | |
| | | | | (-0.42) | |
| $\log(\text{wealth}_t) \times$ bad health | | | | 0.0134 | |
| | | | | (1.21) | |
| $\log(\text{wealth}_t) \times$ retired | | | | | -0.000821 |
| | | | | | (-0.10) |
| $\log(\text{wealth}_t) \times$ not retired | | | | | 0.00221 |
| | | | | | (0.28) |
| AR(1) test (p-value) | 0.043 | 0.009 | 0.035 | 0.047 | 0.043 |
| AR(2) test (p-value) | 0.471 | 0.440 | 0.681 | 0.456 | 0.484 |
| Hansen test of over-identification (p-value) | 0.131 | 0.095 | 0.113 | 0.328 | 0.298 |
| Diff-in-Hansen test of exogeneity (p-value) | 0.106 | 0.152 | 0.170 | 0.356 | 0.265 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 45,336 | 45,336 | 45,336 | 45,336 | 45,336 |

$t$ statistics in parentheses; $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Control variables include total household income, marital status, number of alive siblings, family size, year dummies, cubic polynomial in age, and a dummy for long term care insurance status. Individuals younger/older than 70 are 'young/old'. Those in the first three quartiles/top quartile are in 'good/bad' health. Retirement status is self-reported in the HRS data. These are two-step GMM estimates with robust standard errors and forward orthogonal deviations (FOD) with collapsed instrument matrix. Regressions are run (using David Roodman's *xtabond2* Stata package for Dynamic Panel Data).