Health Status, Wealth, and Portfolio Choice: Causality or Heterogeneity?

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Abstract

This paper explores the causal links between health and household assets holding and portfolio choices, using a unique longitudinal data set to control for unobserved individual characteristics that may drive the correlations. Our analysis focuses on comparing the estimates from panel-data methods and the OLS results. The OLS results first present a strong cross-sectional correlation between health and various types of assets, as well as between health and risky assets share. These correlations are highly robust to different health measures and remain evident when we instead use lagged health status. In contrast, after individual heterogeneity is controlled for, the health effect virtually disappears for all asset classes, highlighting the dominating role of heterogeneity on the cross-sectional health-wealth nexus. The impact of heterogeneity on the health-portfolio correlation, however, is relatively limited, as the correlation remains strong in the fixed-effects model, at least for two health indexes used in the analyses. Finally, further examinations suggest that our empirical results cannot be reconciled by measurement errors – a common threat to strategies that compares the OLS method and the fixed-effects method.

Key words: Health, Portfolio Choice, Heterogeneity, Causality

EFM classification codes: 760, 370

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1. Introduction

The 1990s witnessed a remarkable growth in household wealth in many high-income and mid-income countries alike. In the US context, for example, per capita household wealth increased by 43.7% from 1989 to 2001, while financial wealth increased even more drastically, by 51.1%, in the same period (Wolff, 2004). As these assets constitute considerable resources in financial markets, discussions contemplating to understand households' decisions on savings and portfolio choices have become prominent. In the past years, a large body of literature has examined various factors that affect household wealth and investors' portfolio choices.

A recent development of this literature has focused on how health status is associated with wealth accumulation as well as portfolio choices of the household. For example, both using the US Health and Retirement Study (HRS), Rosen and Wu (2003) and Berkowitz and Qiu (2005) find a positive cross-sectional correlation between health and risky portfolio choice, despite the two studies employ different health measures in their examinations.[2] Berkowitz and Qiu (2005) additionally find that health deterioration leads to declines in financial assets holding. Further, using multiple health measures drawn from the HRS, Coile and Milligan (2006) document the sharp declines in various assets after retirement. Their primary finding suggests that health shocks play an

[2] Rosen and Wu (2003) employ the self-reported health status (SRHS) as the sole health measure. The SRHS refers to a self-assessment of health on a 1 to 5 scale, with 1 representing excellent health and 5 representing poor health. The results show that better SRHS is associated with both total wealth and financial assets holding and portfolio choices of the household. Berkowitz and Qiu (2005) use an indicator of newly-developed severe health conditions, including a heart problem, stroke, cancer or malignant tumor, lung disease and diabetes. Their OLS results first present a stronger health effect on financial assets than on non-financial assets. Also, the health effect on financial portfolio choice becomes insignificant after controlling for financial wealth of household. Accordingly, they conclude that negative health shocks cast significantly negative effects on financial wealth, and consequently make the household restructure their financial assets holdings.

important role in those declines of assets. Nonetheless, while their results present a negative effect of chronic health shocks on risky assets holding[3], they find no such an effect on the *share* of risky assets out of total assets.

While these studies have all presented evidence suggesting that negative health shocks are associated with less accumulated wealth as well as less risk-taking financial managements, the causality is less clearly identified. For the health-wealth nexus, as argued by Meer et al. (2003), it is plausible that the causality runs in the both directions, or that there exists unobserved individual characteristics that drive the correlation. An example of such characteristics, as taken in Hurd and Kapteyn (2003), is the subjective time rate of discount across people that would plausibly cause variations in health investment and assets holding, leading to both cross-sectional and intertemporal correlations between the two. For the health-portfolio correlation, the reverse causality flow (through health to risky portfolio choices) might be a secondary concern. But, as highlighted by Rosen and Wu (2003), the heterogeneity issue remains as a primary challenge in identifying the causal link between health and household portfolio choices.

In contrast to a large body of studies that have explored the causality direction between health and wealth (Ettner, 1996; Smith, 1999; Hurd and Kapteyn, 2003; Meer et al., 2003; Adams et al, 2003), much less has been done to assess the extent to which the health-wealth nexus is driven by heterogeneity, and only little has been done to explore the health-portfolio correlation. One exceptional example that addresses the latter case is Rosen and Wu (2003), who control for individual characteristics including risk attitude, planning horizon, bequest motive, and entitlement to health insurance in a regression of risky asset holding on health status. Their estimates suggest that the estimated health

[3] In their paper, assets that are categorized into the group of risky assets include IRAs, stocks, and bonds.

effect is robust to specifications with or without these characteristics being controlled for. This method, however, cannot entirely rule out the possibility that other unobservable factors, such as time preference and innate ability, would still induce the cross-sectional correlation, thus leading to an over- or understatement of the health-portfolio causality.

The specific focus of this study, therefore, is to evaluate the effect of heterogeneity on cross-sectional health-wealth and health-portfolio correlations. Using a unique longitudinal data set that traces respondents for a relatively long period of time and thus allows for broad variations in health status, we are able to tackle the heterogeneity issue by tracing the dynamics of corresponding changes in wealth management. Particularly, to assess the impact of heterogeneity, our analyses focus on comparing the OLS estimates and the results from the fixed-effects (FE) model. The key hypothesis here is that these two methods should present similar estimates of health effects on portfolio choices if heterogeneity bears no significant influence on the OLS estimates.

One possible threat to this strategy refers to measurement errors on health status, which may unevenly bias the OLS and FE estimates, leading to unreliable comparisons between the two results. For instance, when we find a smaller FE health-portfolio estimate than the OLS counterpart, it is difficult to distinguish whether it is because OLS effects are biased up due to heterogeneity or FE estimates are biased down as a result of measurement errors in health. To assess the possible attenuation bias, we examine whether a health measure brings about a same gap between OLS and FE health estimates in regressions using different dependent variables, including various assets classes and portfolio choices. This examination is informative because if measurement errors are the main reason biasing the FE estimates more than the OLS estimates, this should evenly happen to all the regressions. Accordingly, checking the gaps between the OLS and FE estimates across regressions using the same health index provides a window to check whether measurement errors seriously damage the identification strategy.

Our empirical work produces multiple interesting outcomes. First, consistent with the general findings of previous studies, our OLS results suggest a significantly positive cross-sectional correlation between health and the levels of total assets, financial assets, non-financial assets, share of financial assets, and share of risky assets[4]. These correlations are highly robust to all the four health indexes, and remain strong when we use lagged health measures. Second, in sharp contrast to the OLS results, the correlations between health and *levels* of different wealth types all disappear in the FE model. This highlights the possibility that both the cross-sectional and the intertemporal health-wealth correlations are driven by heterogeneity. Third, while the health effects on the risky assets *share* and the probability of holding risky assets also disappears in FE results for two health measures – CCs and WRLs[5], it remains statistically significant for the other two health measures – PFs and HASH, and the estimated health effects are somewhat close to the corresponding OLS estimates. These results suggest a limited impact of measurement errors on the gaps between the OLS results and the FE estimates, highlighting the role of heterogeneity.

Overall, our results show a considerable effect of heterogeneity on cross-sectional health-wealth nexus, but the effect appears to be less obvious on the correlation between health and risky assets holding. Further, measurement errors might not be a primary

[4] In this paper, we categorize equities and bonds as risky assets.
[5] We will explain all these health measure in more details in the next section about data.

concern for comparing the results of health-wealth and health-risky asset holding from OLS model and the FE model.

The rest of the paper is organized as follows. In the next section, we describe the data set and explain the key variables retrieved from it. Using the data, we then graphically demonstrate the unconditional correlations between health and wealth/portfolio choice in Section 3. In Section 4, we construct the identification strategies, followed by the corresponding regression results in Section 5. Finally, Section 6 concludes this paper.

2. Data

The reference of this paper is mainly drawn from wave 1 and wave 2 of the US *New Beneficiary Survey* (NBS) conducted in 1982 and 1991, respectively. The NBS surveyed new recipients of social security benefits and his/her spouse. Information collected in the NBS contains demographic characteristics, health status, labour supply, and income of individuals, and various assets of households.

The NBS is a nationally representative household survey using samples randomly selected from the Social Security Administration's Master Beneficiary Record. The representative samples are all new Social Security beneficiaries who received their first retired-worker, disabled-worker, wife's, or widow's cash benefit from mid-1980 to mid-1981. Also, the NBS contains a representative sampling of persons aged 65 and over who were entitled to Medicare benefits but who had not yet received Social Security cash benefits as of July 1982.[6]

There are two unique advantages of using the NBS to examine the health-wealth nexus. First, the two waves of the survey spans over nine years, allowing room for variations in both health and assets over time. Second, the questionnaires concerning the subjects of health and various assets are highly consistent in these two waves. While more questions are imposed in the 1991 survey, the 1982 questionnaires regarding health and wealth remain unchanged in the second wave. The consistency in questionnaire designs is of substantial importance for applying panel-data methods.

To make our results more comparable to findings from previous work, in this paper we focus the health-wealth analysis on individuals who are 60-year-old or over, though our results appear to be robust to more extensive samples that also incorporate younger individuals. While the data sample used in this paper is different from the Health and Retirement Study (HRS) which is often exploited in previous study, the two samples are largely comparable. Particularly, as presented later in this paper, the OLS results from the NBS sample suggested a similar cross-sectional pattern of health-wealth or health-portfolio correlations to the OLS results from previous studies using the HRS sample.

2.1 Measurement of assets

[6] The NBS separately sampled from strata of retired-worker men aged 62, aged 63-64, aged 65, and aged 66 or older, and from strata of retired-worker women aged 62, aged 63-64, aged 65, and aged 66 or older. The NBS separately sampled strata of disabled-worker men and of disabled-worker women. The NBS also separately sampled from strata of women first receiving cash benefits solely as wives, as widows, as divorced wives, and as surviving divorced wives. In addition, insured workers entitled to Medicare but not receiving benefits by July, 1982, were eligible for sample selection.

In this study, we follow the conventional categorizations of assets in literature and focus on the total assets, financial assets, non-financial assets, and risky assets. First, total assets are comprised of two components – financial and non-financial assets. The non-financial assets refer to current values of real estates (home residence, lands, and other properties) and business assets (ownership of businesses, professional practices, and farms). As for the financial assets, we adopt a four-way classification scheme, which include safe assets (checking and saving accounts, money market funds, CDs, government savings bonds and T-bills), bonds (corporate and municipal and foreign bonds and bond funds), risky assets (stocks and mutual funds), and retirement accounts (individual retirement account and Keogh accounts). In addition to the *levels* of assets, we further explore health effects on (1) share of financial assets within total assets, (2) share of risk assets within financial assets, (3) share of risk assets of total assets, (4) the probability of risky assets holding.

2.2 Measurement of health status

In this study, we use four health measures so as to capture different aspects of health status and health changes. These measures include physical function limitations (PFs), chronic conditions (CCs), history of heart attack and stroke (Hearthis) and limitations on work ability (worklimit).

The PFs indicates an individual's ability to carry out a list of various activities. In the context of NBS, there are six questions measuring the degree of difficulty to walk for a quarter mile, to stoop, crouch, or kneel, to stand or sit for a long time, or to lift or carry a weight of 25 pounds. For each question, respondents are required to assess the degree of difficulty in the corresponding physical function on scale from 1 (no difficulty) to 4 (completely unable to do). In principle, PFs provides a relatively objective measure of health, compared to the self-reported health status (SRHS)[7] that is often used in health economics literature. Further, PFs capture functional difficulties in a monotonic (increasing) way, so it improves upon the Body Mass Index that presents a "U-shaped" relationship with health outcomes, like mortality (See Costa 1996, 1998). However, PFs have their own limitations, and the major one is that they neglect health risk of people who have chronicle diseases, like diabetes, but do not have obvious limitations on physical functions.

To reduce the multi-dimensional responses to six questions into one single measure, we apply the following formula to quantify these functions and obtain a numerical value:

$$PF_i = 1 - \frac{\sum_{j=1}^{6} (pf_j^i - 1)}{24} \tag{1}$$

where pf_j^i refers to the value of individual *i*'s response to question *j*. It is important to note that equation (1) limits the value of index PF_i between 0 and 1, with 0 indicating the greatest limitation in these functions in a general sense.

Similar to the PFs, the Chronic Conditions (CCs) also involves multiple indicators as responses to five different questions asking about health conditions on nervous system,[8] paralysis, lung and respiratory system,[9] digestive system,[10] and malignant

[7] Usually, interviewers obtain SRHS by asking, "Right now, how would you describe your health compared to that of other people of your age." Responses are then coded on a scale of one (excellent) to four or five (poor).
[8] Such as multiple sclerosis, cerebral palsy, epilepsy, or any other condition affecting the nervous system.
[9] Respiratory conditions refer to asthma, emphysema or any other condition affecting the lungs or respiratory system, including work-related respiratory conditions such as silicosis or pneumoconiosis.

tumors or growth. One benefit of the CCs as a health measure is that new onsets of chronic conditions are expected to have long-term impacts on individual health, presumably leading to more serious shocks on income in the future compared to temporary health conditions. However, in the context of the NBS, a disadvantage of CCs is that respondents are required to answer only "yes or no" to each of the five questions. Therefore, for those who report having a certain chronic condition, we do not have information to distinguish those with only minor conditions from the very frail ones. Again, to reduce the dimensions of five dichotomous variables to one sole variable, we apply the following formula which is similar to equation 1:

$$CC_i = 1 - \frac{\sum_{j=1}^{5} (cc_j^i - 1)}{5} \tag{2}$$

The third health measure used in this paper is heart attack or stroke history (HASH) – a dichotomous variable that indicates people who have experienced heart attack or stroke at least once before the survey. In general, the HASH has an advantage over the CCs as it describes more acute health shocks than most chronic conditions in a general sense. But as a dichotomous variable, the HASH shares a similar limitation with CCs – for those who report no experience of heart attack or stroke, we do not have any further information to distinguish their health status.

The last health measure we employed is based on a series of questions about self-assessed health limitations that keep respondents from working or restrict their hours worked (work-related health limitations, WRLs).[11] On the positive side, WRLs capture

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[10] Including gallbladder, stomach, kidney or liver trouble, diabetes, and any other condition affecting digestive system.

[11] The WRLs involve questions regarding health conditions that (1) limit work to pay; (2) limit work at home; and (3) keep from working in general.

the ability to work, so they are in principle highly correlated with income variations. As for the cons, a potentially serious concern about WRLs is that, as pointed out by Bound et al. (1999), one's labour supply may determines his/her sense of health. For example, one may justify his/her absence in labour participation by reporting poor health. As a result, instead of reflecting limitations of underlying latent health, WRLs actually reflect labour market outcomes. This brings up noises in measuring health in terms of WRLs, leading to conventional attenuation bias. Following the same way to simplify the multi-dimensions of PFs and CCs, we generate the single-variable index of WRLs by applying a formula analogous to Equation (1).

3. Graphical Analysis

In this section, we present graphically the unconditional health-wealth and health-portfolio nexus, using both 1982 and 1991 data from the NBS. In these graphic analyses, we separate male and female beneficiaries, although the results based on data pooling both genders demonstrate highly similar patterns of health-wealth and health-portfolio relationship.

Insert Figure 1 here.

Figure 1 illustrates the unconditional relationship between health and assets and assets shares of the male respondents. The upper panel in Figure 1 displays the correlation between the PFs and (a) total assets, (b) financial assets, (c) non-financial assets, (d) risky assets, (e) ratio of financial assets to total assets, and (f) ratio of risky assets to financial assets. In each cell, the x-axis of the graph refers to the index of the

PFs, on scale of 0 to 1, which is imputed using Equation (1). The y-axis represents the corresponding levels of various assets levels or assets shares. The fitted lines are graphed by carrying out a locally weighted regression of y variable on x variable,[12] using assets and health in 1982 (solid line), assets and health in 1991 (bar line), and assets in 1991 and health in 1982 (dotted line) separately. We start with the graph for total assets, where the positive slope of the fitted lines suggests that better physical conditions are associated with higher total wealth accumulation.[13] For year 1982 (solid line), the average level of total assets of people reporting no limitations on physical functions (a value of 1 in PFs) is over $150,000, which is three times larger than the level for individuals reporting extreme difficulties (a value of 0 in PFs). The gap is fairly substantial, especially compared to the mean value of assets for this group – around 130,000. Further, there are two features that are worth a discussion. First, this positive correlation is robust to the 1991 fitted line (bar line), using health and assets in 1991. This suggests that the cross-sectional health-assets nexus is fairly time-persistent for people over 60, despite around 35 percent of observations dropped out of sample from wave 1 to wave 2. Second, the correlation between the PFs and total assets remains robust using assets in 1991 and the PFs measured in 1982. However, this does not necessarily validate the causality that poor health hinders subsequent assets accumulation, as the intertemporal correlation could also be driven by heterogeneity, say individual preference, which could be invariant over a fairly long period of lifetime.

Moving to graph (b) and (c) in the upper panel, the positive relationships between PFs and assets (as well as assets shares) remain evident for both financial assets and non-

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[12] Practically, this is implemented by using the "lowess" command in STATA with bandwidth of 1.
[13] The two curves are virtually overlapped, suggesting a highly similar patter of the health-wealth correlation over the two survey years.

financial assets, as shown in graph (b) and (c). These suggest that healthier individuals tend to hold more financial assets as well as non-financial assets, both leading to a positive correlation of health and total assets displayed in graph (a). Further, graph (d) also presents a positive relationship between risky assets and the PFs. Combined with the three lines in graph (f) that all show a positive correlation between the PFs and the proportion of risky assets among financial assets, it appears that healthier individuals are more likely to have riskier portfolio holdings.

The middle and bottom panels tell much the same story about the correlations between assets (and assets) shares and the other two health indexes – CCs and WRLs, respectively. Using either health measure, the positive correlation remains strong virtually for all the assets levels assets shares, and for both years 1982 and 1991 (using contemporary health or lagged health). The consistency in the patterns of health-wealth correlation across different health indexes enhances our confidence in the legitimacy of these health measures.

Insert Figure 2 here.

To take a preliminary look at the correlation of health and assets after individual heterogeneity is netted out, in Figure 2 we plot changes in health against changes in assets (and assets shares) at the individual level from 1982 to 1991. The key issue of interest here is that, if health and assets (or risky assets holding) are causally linked, we should observe that deterioration in health goes along with a reduced amount of assets (or less risky assets holding). However, the graphs in Figure 2 do not support such a hypothesis of causality. Instead, the positive correlations that are commonly detested in Figure 1 when various health indexes and assets (or assets share) are employed all disappear in Figure 2. Although the comparison between Figure 1 and Figure 2 is based on unconditional plotting without controlling for other factors, the abrupt difference between the cross-sectional correlation and the first-difference correlation of health and assets implies the possibility that unobserved individual characteristics may play an important role in driving the cross-sectional correlations.

4. Empirical Strategies

4.1 The OLS vs. the fixed effects model

To estimate the health effect on household wealth holding or household risky portfolio choice, a common methodology used in previous studies is to estimate the OLS model specified as follows:

$$W_{it} = \beta_0 + \beta_1 \cdot h_{it} + \gamma \cdot X_{it} + \lambda \cdot Z_{it} + \varepsilon_{it} \tag{3}$$

where W_{it} refers to the level of an asset type or the share of risky assets held by household *i* at time *t*; h_{it} denotes health status of individuals at time *t*; X_{it} are individual characteristics including age, education, and ethnic background; Z_{it} refer to household characters such as demographic composition, number of children, and household location; finally, ε_{it} represents the error term that includes all unobservable factors. The primary assumption for the legitimacy of this specification is that ε_{it} is uncorrelated with any covariates in the regression. Thus, the coefficient of health measure, β_1, can be validly interpreted as the marginal effect of current health status on W_{it}. Accordingly, a positive estimate of β_1 implies that a negative health shock leads to less holding of W_{it}.

This key assumption, however, does not hold if unobservable factors are correlated with h_{it}, X_{it}, or Z_{it}. Some unobservable individual characteristics fall into this category. For example, in the portfolio context, an individual with higher innate ability may be more capable of investing in risky assets (if they are the dependent variable), while he/she is likely to learn more knowledge about keeping healthy. As the innate ability is not controlled for in the regression, it biases β_1 upward and leads to an overstatement of the health effect. Another example is variation in unobserved optimism across individuals, also causing a spurious correlation between health and risky assets share since people who are more optimistic tend to take more risks while they have a higher propensity to under-assess health problems.

To address this heterogeneity bias, we assume that ε_{it} in Equation (3) is composed of two elements – v_i and u_{it}. The individual specific component, denoted by v_i, is time-independent and is assumed to be correlated with the covariates in Equation (3). Other unobservable factors in the error term, denoted by u_{it}, are considered uncorrelated with any regressors. Accordingly, Equation (3) can be restated as:

$$W_{it} = \beta_0 + \beta_1 \cdot h_{it} + \gamma \cdot X_{it} + \lambda \cdot Z_{it} + v_i + u_{it} \tag{4}$$

which highlights the bias of OLS estimates from equation (3) as v_i is assumed to be correlated with regressors.

It is important to note that replacing the regressors with lagged variables ($h_{i,t-k}$, $X_{i,t-k}$, or $Z_{i,t-k}$) might not correct the bias, as it is likely that the unobserved variations in individuals' taste can be formed early in life, producing both cross-sectional and intertemporal correlations between the regressors and the unobserved characteristics.

One way to address the unobserved characteristics is to restructure the specification by taking the first difference of Equation (4). Equation (4) then reduces to:

$$W_{it} - W_{it-1} = \beta_1 \cdot (h_{it} - h_{it-1}) + \gamma \cdot (X_{it} - X_{it-1}) + \lambda \cdot (Z_{it} - Z_{it-1}) + (u_{it} - u_{it-1}) \qquad (5)$$

where the time-invariant component of the original error term, v_i, is differenced out. The new errors, $u_{it} - u_{it-1}$, are no longer correlated with regressors. Applying OLS to Equation (5), therefore, will not lead to a biased estimate of β_1.

The regression analysis in this paper focuses on comparing the fixed-effects (FE) results based on Equation (5) and the OLS results from Equation (3). This comparison provides a chance to investigate the effect of unobserved characteristics on cross-sectional health-wealth or health-portfolio correlations. If the effect of heterogeneity is substantial, we should observe a significant difference between results from these two models.

4.2 Attenuation bias

While Equation (5) fixes the endogeneity problem due to unobserved individual characteristics, it might introduce other concerns. One potential problem is the attenuation bias brought about by poor measurement of health status. If health indexes are poorly-measured, the estimate of health effect will be biased toward zero. While the attenuation bias applies to both Equation (3) and Equation (5), the problem might, though not necessarily, be more serious in Equation (5) as the measurement errors could be enlarged by taking the first difference of the originally poorly-measured health. To illustrate this, assuming that the unobserved *true* health is h^*, and $h^* = h + m$, where h and m refer to a measure of health and measurement errors, respectively. Accordingly, OLS estimate of β_1 from Equation (3) is inconsistent since

$$\text{plim } \hat{\beta}_1 = \beta_1 \left(\frac{\sigma_{h^*}^2}{\sigma_{h^*}^2 + \sigma_m^2} \right), \tag{6}$$

where $\sigma_{h^*}^2$ and σ_m^2 represent the variance of h and the variance of m, respectively. Note that the degree of inconsistency depends on the value of σ_m^2 relative to the value of $\sigma_{h^*}^2$. Intuitively, a large σ_m^2 implies that substantial noises are imposed into the regression along with the health measure. The noises then reduce the correlation between the true health and W_{it}, leading to an attenuated estimate of β_1.

Similarly, the counterpart description of the probability limit of $\hat{\beta}_1$ from Equation (5) is

$$\text{plim } \tilde{\beta}_1 = \beta_1 \left(\frac{\sigma_{\Delta h^*}^2}{\sigma_{\Delta h^*}^2 + \sigma_{\Delta m}^2} \right) \tag{7}$$

where Δh^* and Δm refers to changes in health and measurement errors from 1982 to 1991, respectively, and $\sigma_{\Delta h^*}^2$ and $\sigma_{\Delta m}^2$ are the corresponding variances. Again, similar to Equation (6), the extent of attenuation is determined by the values of $\sigma_{\Delta h^*}^2$ and $\sigma_{\Delta m}^2$. Compared to equation (6), whether the attenuation bias in $\tilde{\beta}_1$ is larger than that in β_1 is generally ambiguous. But there is room for this possibility, especially when $\sigma_{\Delta h^*}^2$ is small and $\sigma_{\Delta m}^2$ is large. This possibility makes it complex to compare the FE results and the

OLS results, as detailed in the preceding section. For example, when we find a smaller FE estimate of health effect than the estimated OLS effect, it is difficult to distinguish whether it is because OLS estimate is biased up due to heterogeneity, or it is because FE estimate is biased down as a result of greater measurement errors in health after taking the first difference.

To evaluate the possible attenuation bias, we conduct the following examination. Regarding a single health index, we run regressions of various assets classes and asset shares, using both the OLS and the FE models. We then calculate the gap within each pair of OLS estimate and FE estimate for all the regressions. If measurement errors are the main reason biasing the FE estimates more than the OLS estimates, this should evenly happen to all the regressions using the same health index. Therefore, the gap should be the same across all pairs of OLS and FE estimates.

5. Empirical results

Our primary objective is to investigate whether cross-sectional or intertemporal correlation between health and wealth and between health and portfolio is driven by the third factors. We focus on comparing the OLS model, which falls short in controlling for unobserved individual characteristics, with the FE model where these characteristics are practically netted out.

When applying Equation (3) and (5) described in Section 4, the control variables we employ are largely comparable to those used in previous studies. They include age, age squared, gender, marital status, years of schooling, ethnicity, household size, household demographic composition. Also, we control for entitlement of health insurance,[14] which is considered crucial in determining risk attitude. We also impose number of children into the regressions, as it obviously affects bequest motive. Finally, for regressions of financial assets share or risky assets share, we also impose total assets as a regressor. For expositional clarity, we will not repeat most of the obvious caveats with every table, but they must be born in mind.

Insert Table 1 here.

Table 1 summarizes the descriptive statistics of the samples in 1982 and 1991 separately. Between the two waves of survey, about one third of observations dropped out of the sample. Among these attriters, close to 70% were due to death. As a result, there is a concern about non-random selectivity that would lead to an over- or under-estimated health-wealth nexus for the panel-balanced sample, especially in light of the possibility that less healthy respondents in 1982 are more likely to be subject to attrition. To weight this problem, we start with comparing column 1 and column 2 in Table 1 where we display the statistics of the whole sample and panel-balanced observations, respectively. It turns out that the panel-balanced sample has higher levels of average total assets, financial assets, and non-financial assets than held by the whole 1982 observations, but all by a fairly narrow margin. Also, the two groups share a highly similar health status in 1982, in terms of all four health indexes used in this paper. Similarly, we find only slight differences in all the demographic characteristics between these two samples. Combined, these comparison results suggest that the attrited observations are highly similar to those remained in the 1991 wave.

[14] These include Medicare, Medicaid, CHAMPUS, VA, military health care, or other health insurance programs.

Moving to the statistics of the 1992 sample displayed in the last column, which are all deflated by CPI. Compared to the statistics nine years before, the average value of total assets is reduced from around 136 thousand dollars to around 115 thousand dollars. In contrast, the average level of financial assets increases from 47.5 to 50.5 thousand dollars, raising the share of financial assets from 35% to 42%. As part of the boost in the financial assets, risky assets increase dramatically from 10.9 to 16.7 thousand dollars. Further, we also find that observations are less healthy in 1991 than nine years before, most obviously in terms of the History of Heart Attacks or Stroke (HHAS) and Work-related Conditions (WRLs).

5.1 Cross-sectional results – using the Physical Functions as an example

In this section, we apply the OLS regression model as specified in Equation (3) to the whole 1982 sample, the panel-balanced observations in 1982, and the full 1991 sample, separately. In these regressions, we employ total assets as the dependent variable and the PFs as the health index. The results are summarized in Table 2.

Insert Table 2 here.

The first column demonstrates the OLS estimates of Equation (3) based on the full sample from the 1982 wave. The estimated coefficient of the PFs is 36.3, which is significantly different from zero. Under that assumption that the causality flow has been through health to wealth, the coefficient can be interpreted as the estimated marginal effect of the PFs on household total assets. As the index PFs has been normalized on a scale of 0 to 1, the coefficient of 36.3 thousand dollars refers to the “marginal effect” of a change in PFs from the extreme difficulties to no limitations in these functions. Compared to the sample mean value of total assets (around 130 thousand dollars), this effect is rather substantial. This positive effect remains strong when we implement the same estimation based on the 1982 panel-balanced observations, and the estimated coefficient, 33.6 thousand dollars, is pretty close to the estimate using the full 1982 sample. The resemblance between these two OLS estimates corroborates the comparison of the statistics between the 1982 full sample and the panel-balanced sample in Table 1, again highlighting the similarities shared by the two samples.

The significantly positive coefficient of the PFs is robust to the estimation using data from the 1991 survey. As shown in the last column, the estimated "effect" is 52.5 thousand dollars, which is even stronger than that estimated using observations from the 1982 survey. This positive relationship between total assets and health has been extensively observed by previous studies[15].

Estimates of other covariates also present sensible correlations with total assets. First, the age effect on accumulated wealth is negative, and is convex as the coefficient of the squared term is significantly positive. The decreasing pattern of total assets is consistent with the results from Coeli and Milligan (2006), who find that older US households decrease their ownership of most asset classes as they age. Second, the coefficient of years of schooling suggests a considerable effect of education on wealth accumulation. Taking 1982 full sample as an example, the effect is 14.5 thousand dollars per year of schooling, roughly accounting for 11 percent of the average total assets held. Third, the ethnicity appears to be an important determinant of the relationship of total assets and PFs. Throughout all three columns, the estimated coefficient is higher for the

[15] For a survey of this literature, please refer to Goldman (2001).

white than for the American natives, the Asian and Pacific Islanders, and further higher than the Black. Again, this outcome echoes the findings of a large body of empirical research, such as Blau and Graham (1990); Wolff (1998); and Hurst et al. (1998), which all identify evident racial differences in household wealth accumulation, as while households hold a lot more assets than held by minority households.

5.2 Comprehensive comparisons

We now turn to a more comprehensive regression analysis on the effects of the four health measures on various asset categories and assets shares. The primary goal of this analysis is to measure the extent to which the cross-sectional health-wealth and health-portfolio correlations are driven by unobserved individual characteristics. Thus, we focus on comparing the OLS results with the FE estimates based on models specified by Equation (3) and (5), respectively. The rationale behind these comparisons is that if heterogeneity does not matter, estimates from the OLS model and the FE model should present a similar pattern of the assets-health and health-portfolio correlations. Following this, we also address a potential threat to this legitimacy – the possible measurement errors that could lead to a more serious attenuation bias on the FE estimates than on the OLS ones.

Insert Table 3 here.

Table 3 summarizes the regression results from these two models. For expositional simplicity, we only report the coefficients of health variables, while coefficients of all other covariates are ignored. Coefficients in Table 3 are categorized into six different panels. From the top, these panels summarize coefficients of the four health indexes in regressions of different asset classes and assets shares using OLS based on (1) 1982 full sample; (2) 1982 panel-balanced sample; (3) 1991 observations; (4) 1991 assets (or assets share) and lagged health measures in 1982; (5) the FE model, and (6) the random-effects model.

OLS results

In the top panel of Table 3, we demonstrate the estimated coefficients of health indexes from regressions of various types of assets and shares of assets. The coefficients in the first column refer to estimates of the PFs using solely the 1982 sample. The first coefficient suggests that an improvement from 0 to 1 in PFs is associated in an increase of $36,273 in total assets, which is quite evenly broken down to an increase of $17,272 in financial assets and a rise of $19,001 in non-financial assets. Also, these two coefficients are both significantly positive. While these two estimates are relatively similar, they imply two diverse percentage changes as the average level of non-financial assets is almost twice the average value of financial assets.[16] Going down this column, a more interesting result is presented by the next two estimates, which are marginal effects imputed from coefficients of Tobit regression with threshold at zero value of risky assets, and from Probit estimation based on holding positive amount of risky assets. The Tobit estimate is $21,730, a strikingly high estimate, especially compared to the mean value of risky assets held by this sample – around $9,800. As for the Probit estimate, a value of

[16] To be specific, the two estimates correspond to a 38 percent change in financial assets and a 22 percent change in non-financial assets, respectively.

0.102 implies that a change in PFs from 0 to 1 is related to an incline of 10.2 percent in the probability that an individual would hold positive amount of risky assets.

Moving downward, the next three coefficients were estimated using regressions of three different assets shares. They are share of financial assets in total assets, share of risky assets in financial assets, and share of risky assets in total assets. The outcomes show significant estimates of the PFs in all the three regressions, suggesting that an improvement in PFs is associated with higher share of financial assets, as well as higher share of risky assets (either of financial assets or of total assets). These OLS results well line up with the findings from previous studies that explore the health effect on portfolio using cross-sectional approaches, especially well with Berkowitz and Qiu (2005) who find that impairment in health reduces financial assets and consequently decreases risky assets holding. Finally, it is worth to highlight the magnitude of the estimated health coefficient on the risky assets share in financial assets. The estimate is 2.7%, which almost as high as half of the average proportion of risky assets holding – 6%.

Moving to the second column, the estimates present a very similar pattern of significance as shown in the first column. The only exception is that the coefficient of financial assets share is positive, but not statistically significant. Compared to the estimated coefficients of PFs, estimates of the CCs suggest much larger changes in all asset classes and in risky assets shares associated with a change in CCs from 0 (extreme conditions) to 1 (no chronic conditions). Further, the pattern is much the same for WRLs, as described in column (4), where estimates are relatively similar to those of PFs in column (1), and all estimates are also significantly positive. The pattern is somewhat different for the HASH, however, as it appears that changes in health are only associated with higher risky assets holding, either in terms of asset levels or shares, while the correlation with non-financial assets is less obvious.

Analogous to our earlier discussion on Table 2 which shows little difference between results based on 1982 full sample and those based on panel-balanced observations, we can only discern limited differences between estimates in the top panel and those in the middle panel, which are obtained using the panel-balanced sample in 1982. While all the t values are virtually smaller, presumably due to larger variances caused by fewer observations, most coefficient estimates are rather close to those in the top panel. The results underline the similarity between these two samples, implying that the attrition might not seriously bias the estimates when only panel-balanced sample is exploited. One striking difference between these two sets of estimates is that the Probit estimates in the middle panel are three to five times larger than the counterparts in the top panel. Taking the coefficient of the PFs as an example, the estimate is 50.8%, roughly five times larger than the corresponding estimate in the upper panel. However, while this implies that the panel-balanced observations, compared to the attriters, are far more likely to hold risky assets as a result of a health improvement, there is no as clear sign that they will hold *more* risky assets – the Tobit estimates in both panels are relatively similar in magnitude.

The bottom panel summarizes the same estimates based on the 1991 data. As shown in the top panel, the strong health-wealth and health-portfolio correlations remain evident. While most estimates are similar to those based on 1982 sample, either in magnitude or in statistical significance, the coefficients of financial assets share reduces dramatically and they become insignificant (and some even negative) for all the four health indexes. It suggests that, from 1982 to 1991, the respondents' holding of financial assets turn less responsive toward health shocks. While this is an interesting phenomenon, the reason for this shift is unclear and it demands further examination to shed more light on this behavioral change.

OLS results using lagged health

In addition to the contemporary variables, we also use lagged variables in the regression. To do so, we regress levels or shares of 1991 assets on health indexes calibrated from the 1982 data. Using lagged health to explore the health-wealth nexus is a common approach to address the problem of mutual causality. The legitimacy of this approach, however, is problematic if there are other factors, such as the subjective time rate of discount, that can also drive the intertemporal correlation between health and wealth.

Turning to the second page of Table 3 where we list the estimates from using lagged health. We find that, compared to the estimates based on the 1991 data, most of the health-wealth and health-portfolio correlations remain obvious, though some estimates are smaller and some others are somewhat larger than their 1991 counterparts. Taking WRLs as an example, the coefficients on the *levels* of the four asset classes are highly similar to the corresponding coefficients using 1991 health indexes. However, the Probit estimate is 25%, roughly four times larger than the 1991 estimate (5.8%). Likewise, the coefficients of WRLs on the two measures of risky assets share are also much larger. Nonetheless, we do not find larger estimates of lagged PFs, with the only exception for the coefficient of financial assets share. As for the other two health measures, we find that most estimates of the CCs do not differ much from the 1991 health coefficients, but the estimates of the HASH are generally smaller and some turn insignificant.

Overall, we find that the estimations based on lagged health indexes do not produce outcomes that much differ from the evident correlations between health and assets and between health and portfolio when contemporary health indexes are employed.

Fixed-effects results and random-effects results

To gauge the possible effects of heterogeneity on the cross-sectional outcomes, we apply the FE model that controls for individual fixed effects. We report the results in the middle panel of the second page of Table 1. Compared to the OLS estimates based on cross-sectional data, the difference is striking. Taking the estimates of the WRLs, if compared to 1982 results, all coefficients reduce remarkably, and some even turn negative. Also, in sharp contrast to their 1982 counterparts, none of the FE estimates are statistically significant. The results suggest that the strong health-wealth or health-portfolio correlations identified in the cross-sectional models virtually disappear after individual fixed effects are controlled for. This is corroborated by the estimates of the CCs (in column 2), where we no longer find any significant correlation with various asset classes or asset shares, as opposed to the significant figures estimated by 1982 or 1991 cross-sectional data.

Also, estimates of the other two health indexes tell a similar story, but with a remarkable difference. First, like CCs and WRLs, the coefficients of the PFs on total assets, financial assets, and non-financial assets all reduce by over 60 percent of the corresponding 1991 estimates. Second, none of the three estimates remains statistically significant, even at the 90% confidence interval. The only exceptions are the Probit estimate and the coefficient of the risky assets share, which are both significant. Besides, these exceptions are even more prominent in the case for HASH, of which estimates are shown in column 3. While the correlations of HASH with various asset levels practically vanish, the Probit estimate and the two coefficients for the shares of risky assets remain significant, and the figures are fairly close to the corresponding 1982 estimates.

For the health-wealth correlations, one explanation for the striking differences between the FE estimates and the OLS estimates lies in unobserved individual characteristics. As analyzed in the preceding two sections, the heterogeneity in these characteristics may lead to not only cross-sectional, but intertemporal correlations between health and assets. Theoretically, any taste shifters, such as time preference, lifetime expectancy, or bequest motive, which are invariant over a relatively long period of lifetime, could be potential candidates for the characteristics. However, we believe that these unobserved characteristic do not play as much a dominating role in causing the cross-sectional correlations between health and *portfolio*, given that the FE estimates of HASH and PFs on risky assets shares and on the probability of holding risky assets remain significant.

These significant FE estimates are directly related to the next question we need to ask: can the differences between the OLS results and the FE results (especially estimates of various asset classes) be explained away by measurement errors in the health indexes? We do not much agree with this explanation, especially not for HASH, because there are three FE estimates that remain significant, and they are all related to risky assets holding – the Probit estimate (0.20) and the two coefficients for the shares of risky assets (0.12

and 0.08). At the same time, the FE estimates of HASH in other regressions all reduce to zero. Thus, it is unlikely that the measurement errors on HASH is the primary reason that attenuate the FE estimates of total assets, financial assets, and non-financial assets lower than the OLS counterparts. Because if so, the same measurement errors should also as much bias down the three significant FE estimates and make them as much lower than the OLS figures. This contradiction is crucial, as it suggests a relatively limited effect of the measurement errors on the FE estimates of HASH. The same argument applies to the case of PFs too. While the estimated FE coefficients of total assets, financial assets, and non-financial assets are all lower than the OLS estimates by around 50 to 60 percent and all turn insignificant, the FE coefficient of the risky assets share of financial assets is 0.021, which remains significant and is smaller than the 1982 OLS estimate by only around 22 percent. As for the other two health measures, as the contradiction does not exist, it is generally more difficult to assess the influences of measurement errors.

Finally, we have also applied the random-effects (RE) model as a comparison with the FE model. The results are demonstrated at the bottom panel of Table 3. In abrupt contrast to the FE estimates, the random-effects results clearly suggest strong correlations between health and assets and between health and risky portfolio, presenting a similar pattern as exhibited by 1982 OLS estimations. Also shown in the table, we have conducted the Hausman-Wu specification tests for each pair of FE and RE regressions. We mark a star (*) to specify a result that rejects the equality of the entire FE and RE estimates. The corresponding test results indicates that the difference between the RE and FE estimates is significant for *all* the regressions, and we should thus prefer the FE results.

6. Conclusions

One important issue in financial economics concerns individuals' decisions on savings and portfolio choices, as figuring out the determinants of these decisions primarily constitutes the development of capital market. Among these determinants, the role of health has been receiving increasing attention from researchers, with interests mostly focused on the causal effect of health shocks on wealth accumulation and portfolio choices.

While many studies have found evidence suggesting that negative health shocks are associated with less accumulated wealth as well as less risk-taking financial managements, the causality is less clearly identified. One concern about the causal implications found in these studies lies in unobserved individual characteristics, which may lead to over- or understatement of the health effects.

The main task of this paper has been to assess the influence of the individual heterogeneity on the cross-sectional correlations between health and different asset classes, and between health and portfolio choices, focusing on the share of risky assets. Since our primary identification strategy concentrates on comparisons of the OLS and FE estimates, we have also evaluated the impacts of measurement errors, which possibly induce a more serious attenuation bias for the FE estimates. If so, the legitimacy of our identification strategy based on the comparisons between the two models is problematic, as the impact from measurement errors is compounded with the effects of heterogeneity.

The primary findings in this paper can be summarized as follows:

1. Using cross-sectional data, the OLS results show that poorer health are significantly associated with lower levels of total assets, financial assets, non-financial assets, share of financial assets, and share of risky assets. These health-assets and health-portfolio correlations are highly robust to all the four health indexes, and remain strong when we use lagged health measures.
2. The correlations between health and *levels* of different wealth types virtually disappear in the FE mode, highlighting the possibility that both the cross-sectional and the intertemporal health-wealth correlations are driven by heterogeneity.
3. While the health effects on risky assets *share* and probability of holding risky assets also disappears in FE results for CCs and WRLs, it remains statistically significant for PFs and HASH, and the estimated health effects are relatively close to the corresponding OLS estimates. These results first imply a limited impact of measurement errors on the gaps between the OLS results and the FE estimates, standing out the role of heterogeneity. They also imply that the four health indexes may be subject to measurement errors to different degrees.
4. Altogether, our results present a considerable impact of heterogeneity on cross-sectional health-wealth nexus, but the impact appears to be less obvious on the correlation between health and risky assets holding. Further, measurement errors might not be a primary concern for comparing the OLS model and the FE model.

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Table 1: Descriptive Statistics

	1982 all	1982 balanced	1991 all
Male (%)	51.2	50.5	50.5
Assets ($1,000)			
Total assets	130.2 (381.1)	135.7 (416.4)	115.2 (313.7)
Financial	45.4 (184.1)	47.8 (208.7)	50.5 (229.9)
Non-financial	84.9 (296.3)	87.8 (320.2)	64.7 (154.2)
Risky assets	9.8 (123.6)	10.9 (144.0)	16.7 (160.1)
Financial assets share (%)	0.36 (0.34)	0.35 (0.34)	0.42 (0.40)
Risky assets share (%)	0.06 (0.18)	0.07 (0.18)	0.09 (0.21)
Health indexes			
Physical functions (PFs)	0.79 (0.29)	0.79 (0.29)	0.78 (0.27)
Chronic conditions (CCs)	0.92 (0.13)	0.93 (0.12)	0.91 (0.14)
History of heart attacks or stroke (HHAS)	0.87 (0.33)	0.89 (0.32)	0.80 (0.40)
Work-related conditions (WRLs)	0.73 (0.39)	0.73 (0.39)	0.68 (0.41)
Months of age	786 (27.6)	781 (33.2)	884 (34.2)
Marital status (%)			
Married	67.1	69.6	58.0
Widow/Widower	18.9	16.3	28.3
separated	1.6	1.8	1.3
divorced	7.8	7.8	8.0
never married	4.6	4.4	4.4
Years of schooling	11.3 (3.4)	11.3 (3.4)	11.3 (3.4)
Race (%)			
American Indian or Alaskan native	0.4	0.5	0.5
Asian or Pacific Islander	0.4	0.4	0.4
Black	8.8	9.4	9.4
White	89.3	88.8	88.8
Others	1.0	1.0	1.0
Household size	2.1 (0.92)	2.2 (0.95)	0.9 (0.84)
Insurance coverage (%)	0.92 (0.27)	0.92 (0.27)	0.99 (0.08)
Total number of children	2.54 (2.02)	2.63 (2.04)	2.62 (2.03)
Observations	15,188	10,982	10,982

1. Numbers in parentheses are standard deviations.
2. Regressors also include household locations.
3. Data source: NBS 1982 and 1991.

Table 2: Estimating Effect of Physical Functions (PFs) on Total Assets Using OLS Model

Dependent Variable: total assets	1982 all	1982 balanced	1991
Male	41.4 (6.4)	47.7 (5.7)	39.3 (5.9)
Months of age	-8.0 (-2.4)	-14.9 (-6.7)	-10.6 (-5.8)
Months of age^2	0.006 (2.9)	0.011 (7.4)	0.007 (6.3)
Marital Status (%)			
Married	--	--	--
Widow/Widower	36.0 (0.1)	54.8 (0.1)	22.8 (0.6)
separated	43.7 (0.1)	61.5 (0.1)	7.9 (0.2)
divorced	6.2 (0.0)	12.5 (0.0)	-18.7 (-0.5)
never married	14.1 (0.0)	20.7 (0.0)	-2.8 (-0.1)
Years of schooling	14.5 (14.9)	15.0 (12.0)	14.3 (14.7)
Race (%)			
American Indian or Alaskan native	--	--	--
Asian or Pacific Islander	14.5 (0.2)	2.7 (0.0)	73.1 (1.1)
Black	-10.3 (-0.2)	-26.3 (-0.4)	2.7 (0.1)
White	47.4 (0.9)	30.7 (0.5)	46.6 (1.0)
Others	56.4 (0.6)	17.8 (0.3)	52.9 (0.9)
Household size	-3.5 (-0.5)	-3.7 (-0.4)	2.0 (0.2)
Insurance coverage (%)	5.4 (0.5)	0.3 (0.0)	39.3 (0.9)
Total number of children	2.4 (1.5)	2.0 (0.9)	0.7 (0.4)
Physical functions (PFs)	36.3 (3.2)	33.6 (2.2)	52.5 (4.3)
Observations	15,188	10,982	10,982

1. Numbers in parentheses are t values.
2. Regressors also include household locations.
3. Data source: NBS 1982 and 1991.

Table 3: Estimating Effect of Health on Assets and Assets Shares

Dependent Variables:	(1) Physical Functions (PFs)	(2) Chronic Conditions (CCs)	(3) Heart Attack or Stroke History (HASH)	(4) Work-related Limitations (WRLs)
1982				
Total assets	36,273 (3.2)	80,610 (3.3)	10,870 (1.2)	41,885 (5.1)
Financial assets	17,272 (3.2)	32,929 (2.8)	9,652 (2.1)	15,170 (3.8)
Non-financial assets	19,001 (2.2)	47,682 (2.5)	1,217 (0.2)	26,715 (4.2)
Risky assets (Tobit estimates)	21,730 (12.6)	29,274 (8.1)	5,882 (6.0)	15,649 (12.3)
Risky assets (Probit estimates)	0.102 (7.5)	0.139 (5.0)	0.021 (2.2)	0.063 (6.8)
Financial assets share	0.043 (4.4)	0.038 (1.8)	0.001 (0.1)	0.021 (2.8)
Risky assets share of financial assets	0.027 (5.3)	0.049 (4.5)	0.010 (2.4)	0.019 (5.2)
Risky assets share of total assets	0.011 (3.9)	0.030 (4.7)	0.005 (2.2)	0.009 (4.1)
1982 (panel balanced)				
Total assets	33,578 (2.2)	87,810 (2.7)	16,105 (1.3)	40,464 (3.7)
Financial assets	17,119 (2.2)	33,540 (2.0)	8,518 (1.3)	14,709 (2.6)
Non-financial assets	16,459 (1.4)	54,269 (2.2)	7,586 (0.8)	25,756 (3.0)
Risky assets (Tobit estimates)	26,357 (10.1)	30,690 (5.9)	5,973 (4.0)	18,760 (10.0)
Risky assets (Probit estimates)	0.508 (6.2)	0.599 (3.8)	0.076 (1.3)	0.305 (5.5)
Financial assets share	0.049 (4.0)	0.029 (1.1)	-0.003 (-0.3)	0.017 (1.9)
Risky assets share of financial assets	0.030 (4.7)	0.046 (3.4)	0.009 (1.7)	0.023 (5.1)
Risky assets share of total assets	0.015 (4.1)	0.031 (3.9)	0.005 (1.7)	0.011 (4.2)
1991				
Total assets	52,534 (4.3)	88,751 (4.1)	16,045 (2.2)	36,231 (4.7)
Financial assets	24,283 (2.7)	37,743 (2.3)	11,406 (2.1)	15,531 (2.7)
Non-financial assets	28,251 (4.7)	51,008 (4.8)	4,639 (1.3)	20,700 (5.5)
Risky assets (Tobit estimates)	28,392 (8.3)	33,220 (5.9)	6,001 (3.7)	15,090 (7.5)
Risky assets (Probit estimates)	0.124 (6.1)	0.166 (4.7)	0.014 (1.2)	0.058 (4.7)
Financial assets share	0.013 (0.9)	-0.030 (-1.1)	0.005 (0.6)	-0.006 (-0.7)
Risky assets share of financial assets	0.040 (5.1)	0.044 (3.2)	0.006 (1.3)	0.015 (3.2)
Risky assets share of total assets	0.017 (3.5)	0.023 (2.6)	0.005 (1.7)	0.006 (1.9)

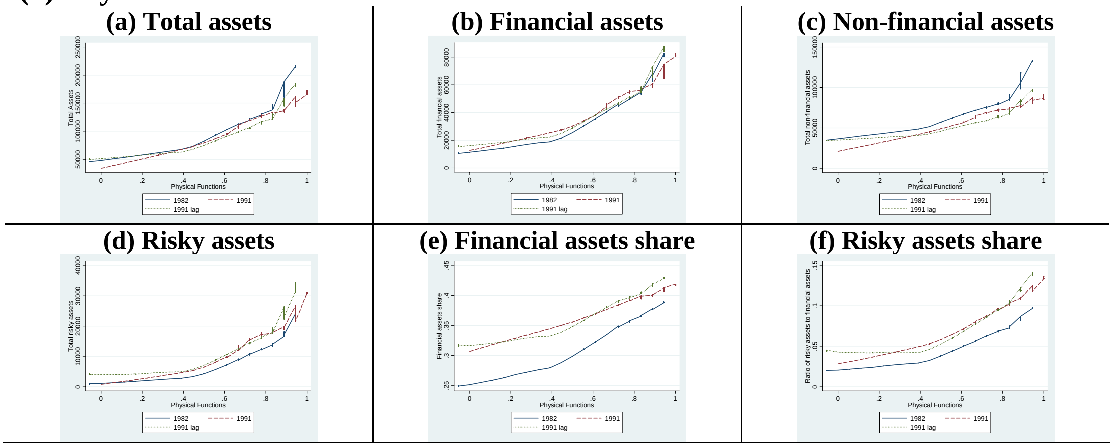
Table 3: Estimating Effect of Health on Assets and Assets Shares – continued

Dependent Variables:	(1) Physical Functions (PFs)	(2) Chronic Conditions (CCs)	(3) Heart Attack or Stroke History (HASH)	(4) Work-related Limitations (WRLs)
1991 (using lagged health)				
Total assets	28,750 (2.6)	72,259 (4.3)	13,912 (1.5)	35,620 (4.3)
Financial assets	15,744 (1.9)	32,617 (1.8)	5,900 (0.9)	18,597 (3.0)
Non-financial assets	13,006 (2.4)	39,642 (3.3)	8,011 (1.8)	17,022 (4.2)
Risky assets (Tobit estimates)	22,598 (7.4)	33,057 (5.2)	7,807 (4.1)	21,260 (9.3)
Risky assets (Probit estimates)	0.208 (2.9)	0.454 (3.1)	0.094 (1.8)	0.250 (4.9)
Financial assets share	0.031 (2.2)	0.026 (0.9)	0.002 (0.2)	0.001 (0.1)
Risky assets share of financial assets	0.013 (1.9)	0.033 (2.1)	0.007 (1.3)	0.025 (4.7)
Risky assets share of total assets	0.008 (1.7)	0.027 (2.7)	0.003 (0.8)	0.012 (3.5)
Fixed-effects				
Total assets	16,696 (1.1)	19,141 (0.8)	-2,271 (-0.3)	4,072 (0.5)
Financial assets	6,865 (0.7)	4,652 (0.3)	4,428 (0.9)	-3,481 (-0.7)
Non-financial assets	9,831 (0.7)	14,489 (0.7)	-7,199 (-0.9)	7,554 (1.1)
Risky assets (Tobit estimates)	--	--	--	--
Risky assets (Probit estimates)	0.057 (2.9)	0.007 (0.2)	0.020 (1.7)	0.006 (0.5)
Financial assets share	-0.014 (-0.8)	-0.042 (-1.5)	-0.007 (-0.6)	-0.006 (-0.6)
Risky assets share of financial assets	0.021 (2.2)	-0.010 (-0.7)	0.012 (2.1)	-0.004 (-0.7)
Risky assets share of total assets	0.004 (0.7)	-0.010 (-1.0)	0.008 (2.2)	-0.004 (-1.1)
Random-effects				
Total assets	70,877 (9.4)*	78,364 (5.6)*	6,524 (1.3)*	44,075 (9.0)*
Financial assets	35,733 (8.5)*	38,872 (4.9)*	6,428 (2.3)*	20,477 (7.4)*
Non-financial assets	39,633 (7.1)*	50,590 (4.8)*	1,630 (0.4)*	29,650 (8.1)*
Risky assets (Tobit estimates)	--	--	--	--
Risky assets (Probit estimates)	0.014 (15.2)*	0.135 (7.8)*	0.022 (3.5)*	0.072 (11.9)*
Financial assets share	0.063 (7.5)*	0.019 (1.1)*	0.000 (0.0)*	0.026 (4.6)*
Risky assets share of financial assets	0.051 (11.9)*	0.053 (6.4)*	0.008 (2.7)*	0.027 (9.2)*
Risky assets share of total assets	0.025 (9.5)*	0.019 (3.2)*	0.003 (1.4)*	0.008 (3.9)*

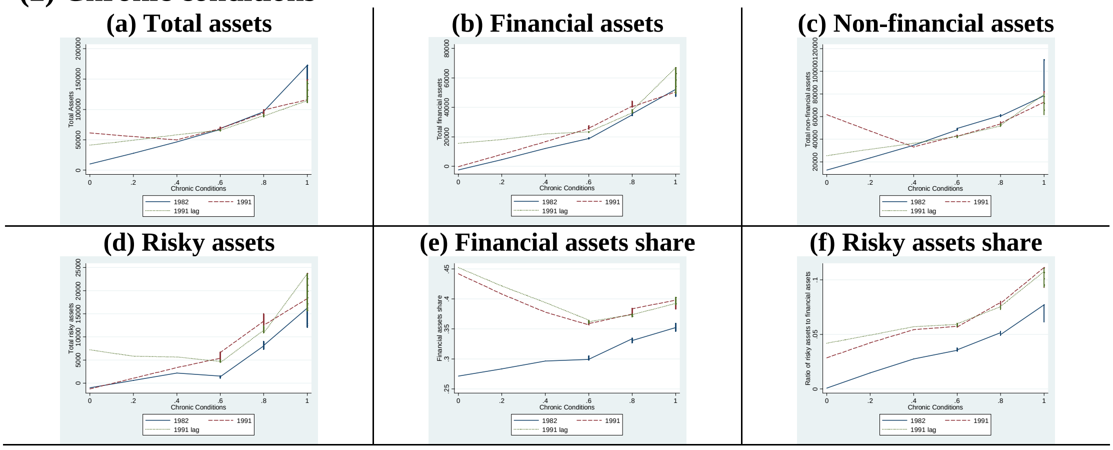
1. Numbers in parentheses are z values for Tobit estimates, and t values for all other estimates.
2. Regressors also include household locations.
3. The * refers to a Hausman Test result rejecting the null hypothesis that random-effects estimates are consistent.
4. In each regression, regressors include age, age squared, gender, marital status, years of schooling, ethnicity, household size, household demographic composition, entitlement of health insurance, and number of children. For regressions of financial assets share or risky assets share, we also impose total assets as a regressor.
5. Data source: NBS 1982 and 1991.

Figure 1: Unconditional Correlation between health and assets (and assets shares)

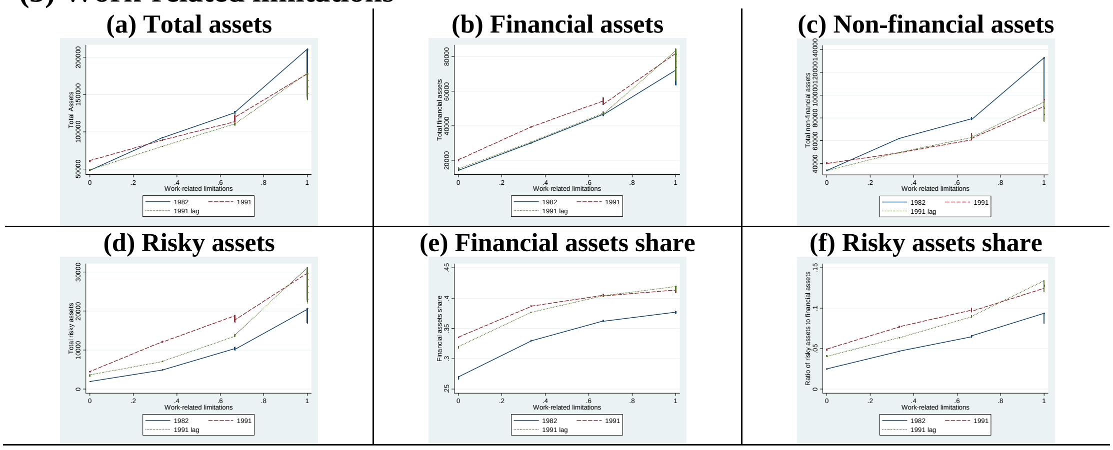
(1) Physical functions



(2) Chronic conditions



(3) Work-related limitations

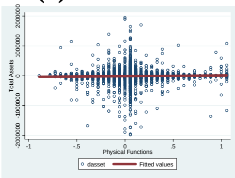


1. Data source: NBS 1982 and 1991.
2. Each fitted line is graphed by carrying out a locally weighted regression of y variable on x variable.

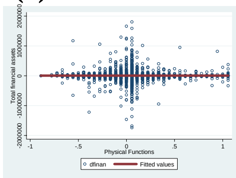
Figure 2: Unconditional Correlation between changes in health and changes in assets (and assets shares)

(1) Physical functions

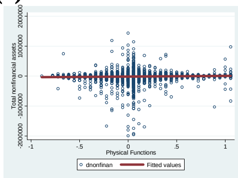
(a) Total assets



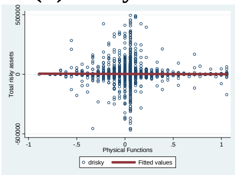
(b) Financial assets



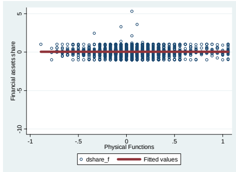
(c) Non-financial assets



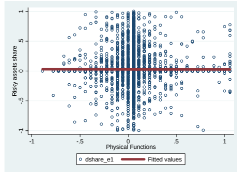
(d) Risky assets



(e) Financial assets share

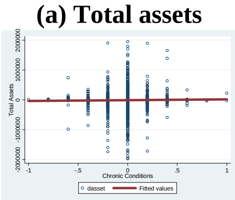


(f) Risky assets share

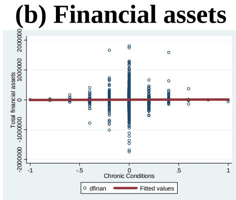


(2) Chronic conditions

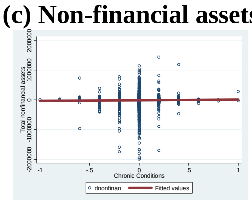
(a) Total assets



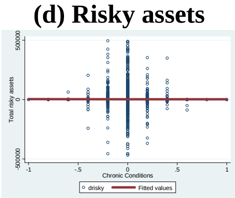
(b) Financial assets



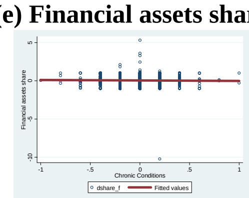
(c) Non-financial assets



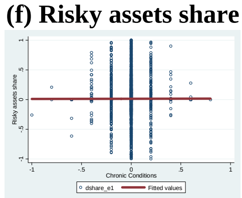
(d) Risky assets



(e) Financial assets share

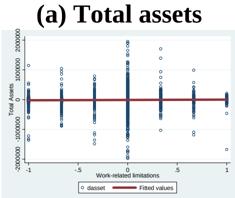


(f) Risky assets share

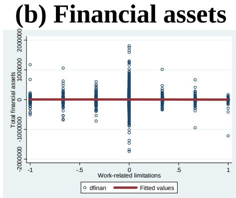


(3) Work-related limitations

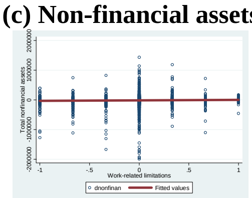
(a) Total assets



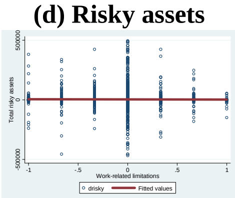
(b) Financial assets



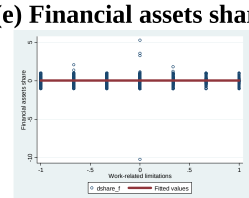
(c) Non-financial assets



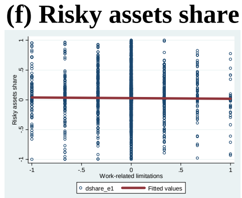
(d) Risky assets



(e) Financial assets share



(f) Risky assets share



1. Data source: NBS 1982 and 1991.
2. Each fitted line is graphed by carrying out a locally weighted regression of y variable on x variable.