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JEL Classifications: D31, H0, I10
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Gordon G. Liu[†], Franklin Qian[‡], & Xiang Zhang[§]

April 15, 2020

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This paper uses the two largest panel data sets in China to study the effects of a health shock on household income mobility. At the aggregate level, we document that households that experience a health shock exhibit much lower transition probability and upward mobility, compared with households that do not. The probability of "getting out of the low-income trap," the probability of a low-income household ending up in a position above the 20th percentile in the national income distribution, is 4.4 percentage points lower for the treated households. At the micro level, we exploit an event study approach and find that a health shock lowers household income per capita by 12.8%, and income position by 3.2 percentiles, relative to the control group. Further, we analyze household labor supply responses when a health shock happens. We do not find evidence suggesting that households adjust their labor supply at the extensive or intensive margin. Instead, labor productivity, measured as the hourly wage, decreases substantially for individuals who have experienced a health shock. Finally, we track the income mobility of households up to four years after the health shock. We find that poor households that experienced a health shock continue to exhibit lower income mobility in this period.

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1 Introduction

Based on the theoretical framework offered by Becker (1962) and Grossman (1972), a substantial body of economic research has documented the relationship between health and income in both developed and developing economies (e.g., Smith 1999; Case et al. 2002; Gertler and Gruber 2002; Case et al. 2005; Liu et al. 2008; Currie 2009; Meyer and Mok 2009; Dobkin et al. 2018). However, in the income mobility context, to what extent, and how, does a health problem impede a household's ability to climb up the income distribution? This paper is an attempt to demonstrate the extent to which health shocks prevent impacted households from moving upward in the income distribution. Specifically, we provide empirical evidence for the contemporaneous and lasting effect of a severe health shock on households' intra-generational income mobility at both aggregate and micro levels. Indeed, we find that a severe health shock has a significant negative impact on the treated households' income mobility and hurts their prospects of climbing the income ladder.

In this paper, we make use of two large panel data sets in China, the China Health and Nutrition Survey (CHNS), and the China Family Panel Study (CFPS). These two data sets provide rich information on household demographics, socioeconomic status, and health status, which allows us to track household income mobility in a relatively long time window, and estimate the impact of a severe reduction in health human capital on household income mobility.

In the first part of the paper, we focus on estimating the impact of a health shock on aggregate-level income mobility. We rank households based on their income relative to others in each survey year. We characterize income mobility based on intra-generational transition probability and upward mobility, where the first measure highlights the probability of surpassing a certain income percentile in the income distribution, and the second measure emphasizes the success rate of a household moving a positive amount in the income distribution relative to its initial income position. We define a health shock as either a severe deterioration of self-reported health status or a hospitalization. Using different health shock definitions and samples, we find that a household in the treatment group – a household with one household member receiving a health shock – consistently exhibits lower transition probability and lower upward mobility, compared with the control households, which did not experience any health shock. Central to policy interest, we find that the treated households' probability of "getting out of the low-income trap," defined as the probability of transiting out of the bottom quintile of the income distribution, conditioning on starting in the bottom quintile, is 8.4 percentage points lower than that of the control group in the CHNS sample, and 4.4 percentage points lower than that of the control group in the CFPS sample. Besides, the probability of "climbing up the income ladder," defined as the probability of surpassing its initial income position, is 9.5 percentage points lower on average for a household that experienced a health shock in the CHNS sample and 4.3 percentage points lower on average in the CFPS sample.

In the second part of the paper, we provide micro-level evidence on the effects of a health shock on households' income mobility. Using an event study design, we evaluate the effects of experiencing a health shock on a household's income per capita and income percentile in the income distribution. Under two definitions of a health shock, our estimates suggest that receiving a health shock significantly lowers a household's income per capita and income percentile. We find that, relative to the control group, a health shock causes a 12% and a 12.8% drop in household income per capita for the treatment group in the CNHS sample and CFPS sample, respectively. Compared with the post-shock mean of the control group, these estimates reflect a 1,192, or 1,643 RMB decrease in household income per capita for the treatment group in the two samples, respectively.[1] Additionally, we document a 3.93 percentile, and a 3.21 percentile drop in income position caused by a health shock in the two samples, respectively. These estimates complement our aggregate-level income mobility results by providing the average treatment effects of a health shock, and help explain the aggregate-level patterns in income mobility we observe. Taking our estimates at the aggregate and micro levels together, we see that a health shock sharply lowers a household's probability of improving its income and income percentile, and increases its risk of transiting into poverty.

Further, we explore possible channels through which a health shock affects household income mobility, by looking at household labor supply responses. Using an event study approach, we find that labor supply adjusts at neither the extensive margin nor the intensive margin for individuals who experience a health shock and their household members. We do not find a significant impact of a health shock on the probability of being employed, or any reduction in yearly working hours after a health shock, for the treated individuals. Meanwhile, we do not see any statistically significant labor supply responses from other household members (Fadlon and Nielsen 2015; Dobkin et al. 2018). However, we find that a health shock imposes a sizable negative impact on the treated individuals' labor productivity, measured by the hourly wage. We find that, in response to a health shock, the hourly wage of the individuals who receive a health shock decreases by 16% and 18% in the CHNS and CFPS samples, respectively.

We next analyze treatment heterogeneity along several dimensions. First, we provide suggestive evidence that, compared with urban households, rural households experience more substantial income loss in the face of a health shock. This finding is consistent with the idea that rural households earn income mostly from manual labor, and they are more vulnerable

[1] 1 U.S. dollar $\approx$ 5.5 RMB from 1991 to 1993, 8.3 RMB from 1998 to 2004, and gradually depreciated to 6.2 RMB at the end of 2015.

to sudden income losses when they face a health shock. Second, we document that a health shock impacts households at different income positions in the national income distribution heterogeneously. In the 1990s and 2000s, when facing a health shock, households above the 60th percentile in the national income distribution (high-income households) lost more income and dropped more in the income distribution, compared with households in the 40th - 60th percentile (middle-income households). In the 2010s, however, compared with high-income households, middle-income households lost more due to a health shock.

Finally, we explore whether the treated households continue to have lower income mobility compared with the control households after the health shock, by tracking the transition probability and upward mobility up to four years after the arrival of a health shock. Specifically, we are interested in whether households who receive a health shock continue to be caught in the low-income trap after the health shock. Our estimates suggest that the treated households have a significantly lower transition probability relative to the control households in this period. For example, in the CHNS sample, a treated household's probability of getting out of the low-income trap is 59.4%. In contrast, a control household in the bottom quintile has a 65.2% probability of succeeding. In the CFPS sample, conditioned on a household starting in the bottom quintile, we document that, compared with control households, the treated households have an 8.6 percentage points lower probability of transiting out of the bottom quintile. However, we do not find a significant difference in upward mobility between the treatment and control groups after the health shock. These findings suggest that, up to four years after a health shock, households that experienced a health shock still enjoy fewer economic opportunities, as they are more likely to be caught in the low-income trap.

This paper is related to three bodies of literature. First, it contributes to the literature that tries to understand how health human capital is related to income mobility, by presenting new causal evidence on the impact of a health shock on intra-generational income mobility. Previous research has discussed the impact of health human capital on income mobility under an inter-generational context. Through direct and indirect transmission, health human capital introduces parent-induced inequality of economic opportunities among offspring (e.g., Corak 2013; Qin et al. 2014). However, to the best of our knowledge, our paper provides the first causal evidence of a health shock on household income mobility in an intra-generational context. Second, our paper is related to a large literature on the driving forces of income mobility. In the inter-generational context, several papers have documented factors that correlate with or drive high-income mobility.[2] At the macro level, Mayer and Lopoo (2008) suggest that higher government expenditure could reduce the investment gap in human capital between rich and poor children and, thus, generate higher inter-generational income mobility. Chetty et al. (2017) find that two factors – lower economic growth rate

[2]Some earlier attempts failed to draw a clear causal inference. See Black et al. (2011) for a survey.

and more unequal income distribution – are responsible for the declining income mobility in the United States, with the latter factor playing a more critical role. At the micro level, Ermisch et al. (2006) suggest that assortative mating plays an important role in explaining inter-generational income mobility. Chetty et al. (2014) find that high income mobility is highly correlated with less residential segregation, less income inequality, better primary schools, greater social capital, and greater family stability in a commuting zone. Chetty and Hendren (2018a) and Chetty and Hendren (2018b) provide causal evidence that neighborhoods affect income mobility through the childhood exposure effect. More recently, Chetty et al. (2020) find that access to colleges varies greatly by parents' income, and the rates of upward mobility differ substantially across colleges. Third, our paper adds to the literature on intra-generational income mobility in the developing country context. For example, Khor and Pencavel (2006) and Chen and Cowell (2017) document China's high intra-generational income mobility. Sun et al. (2007) attribute this high income mobility to improvement in educational attainment, expansion of the labor force, and more migrant workers within a household. Some other studies state that specific policies, for example, land circulation, are also relevant (Zhang et al. 2007).[3]

Our paper distinguishes from past works in three important dimensions. First, to the best of our knowledge, our paper is the first to draw causal inference on the effects of a health shock on household income mobility in the intra-generational context. By evaluating the consequence of a health shock on income mobility, we quantify how a health shock affects a household's economic opportunities over time in the same generation. Second, apart from analyzing patterns of income mobility at the aggregate level following the traditional income mobility literature, we try to provide micro-founded evidence that explains the estimated aggregate-level income mobility. On the one hand, at the aggregate level, we estimate the wedge in transition probability and upward mobility between the treatment and control groups and show that households that experienced a health shock exhibit much lower income mobility. On the other hand, we take an event study approach and estimate the economic consequences of the worsened health status of one household member on the household's income percentile. By estimating the average treatment effect of a health shock on the household's income percentile, we provide micro-founded evidence that explains the estimated aggregate level income mobility. Third, a novel aspect of our paper is that we do not limit our analysis to the contemporaneous effects of a health shock. Instead, our paper adds to a relatively smaller strand of literature by looking at the lasting impact of a health shock on households' intra-generational income mobility, by tracking the short-run income mobility of the treated households after the health shock.

[3]Fan et al. (forthcoming) provide a comprehensive analysis of the rising income mobility and its correlates in China in an inter-generational context.

The rest of the paper is organized as follows. Section 2 introduces our aggregate-level income mobility measures. Section 3 describes the data and sample construction. Section 4 presents our empirical framework, in which we introduce our identification strategy and econometric model. Section 5 presents our main results on the effects of a health shock on household income mobility. Section 6 explores households' labor supply responses when faced with a health shock. Finally, we provide evidence suggesting that a health shock imposes a long-lasting impact on household income mobility. Section 7 concludes. Additional details on the data and our methodology, as well as extensive sensitivity analysis, are presented in the Online Appendix.

2 Aggregate-Level Income Mobility Measures

In this section, we introduce two income mobility measures that quantify a household's income mobility in the national income distribution, which we call aggregate-level income mobility.

2.1 Transition Probability

Following Bhattacharya and Mazumder (2011), we propose an intra-generational version of transition probability, which measures the probability that a household is above the sth quantile at time t_1, conditioning on being between quantiles s_1 and s_2 at time t_0. Let $F_0(\cdot)$ and $F_1(\cdot)$ donate the c.d.f. of the overall income distribution at times t_0 and t_1, respectively. Then the probability that the household is above the sth quantile of F_1, conditional on it being between quantiles s_1 and s_2 of $F_0(\cdot)$ is denoted by:

$$\theta(s,(s_1,s_2)) = \frac{\Pr[F_1(Y_1) > s, s_1 \leq F_0(Y_0) \leq s_2]}{\Pr[s_1 \leq F_0(Y_0) \leq s_2]} \tag{1}$$

For an easier interpretation, we consider the situation where $s_1 = 0$ and $s_2 = s$. Thus, the transition probability simplifies to:

$$\theta(s) = \frac{\Pr[F_1(Y_1) > s, F_0(Y_0) \leq s]}{\Pr[F_0(Y_0) \leq s]}$$

Using this measure, we directly measure the probability of a household ending up at a position higher than the sth quantile, conditioning on starting at a position lower than or equal to the sth quantile. Specifically, when $s = 20$, it measures the household's probability of getting out of the low-income trap.

2.2 Upward Mobility

Following Bhattacharya and Mazumder (2011) and Chetty et al. (2017), we propose an intra-generational version of upward mobility based on the household's position in the national income distribution. This upward mobility measure quantifies the probability that a household's income position at time t_1 exceeds its income position at time t_0 by a fixed amount. Let $F_0(\cdot)$ and $F_1(\cdot)$ donate the c.d.f. of the overall income distribution at times t_0 and t_1, respectively. Then the upward mobility for a household that is located above the s_1th and lower than or equal to the s_2th quantile of $F_0(\cdot)$ is denoted by:

$$v(\tau, s_1, s_2) = \Pr[F_1(Y_1) - F_0(Y_0) > \tau | s_1 < F_0(Y_0) \leq s_2] \quad (2)$$

where τ governs the distance of the movement in the income distribution.

In the main text of this paper, we consider the situation where $\tau = 0$. Thus, upward mobility is simplified as:

$$v(s_1, s_2) = \Pr[F_1(Y_1) - F_0(Y_0) > 0 | s_1 < F_0(Y_0) \leq s_2]$$

Using this measure, we directly measure the probability of a household ending up at a position higher than its previous position, conditional on the starting position higher being higher than the s_1th, and lower than or equal to the s_2th quantile. In other words, this measure quantifies a household's probability of climbing the income ladder.

2.3 Contrasting Transition Probability with Upward Mobility

The upward mobility measure is distinct from the transition probability, in that it emphasizes a household's upward movements in the income distribution from its original position, which is ignored by the transition probability measure (Bhattacharya and Mazumder 2011). The upward mobility measure takes into account those who have made upward movements but do not exceed a given threshold s. Thus, although the transition probability highlights the probability of reaching a certain threshold, the upward mobility measure emphasizes the household's movement relative to its original position.

These two measures complement each other when we compare income mobility between households with and without a health shock. On the one hand, for understanding differences in the absolute economic opportunities, defined as success rate of achieving specific economic goals, the transition probability measure works better. On the other hand, households with or without a health shock may be at different income positions before the shock happened. Thus, one could expect that households with a health shock need to achieve higher gains in income to reach a specific income position. The upward mobility measure better fits the goal of measuring the relative movement of a household from its original income position.

3 Data and Sample Construction

Our primary data source is nine waves of the CHNS from 1991 to 2015, and four waves of the CFPS from 2010 to 2016.[4] The CHNS is jointly conducted by the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health at the Chinese Center for Disease Control and Prevention. It uses a multistage, random cluster process to draw a sample of about 4,400 households in nine provinces across China.[5] The CFPS is a nationally representative, bi-annual longitudinal survey of Chinese communities, families, and individuals. The CFPS has been carried out since 2010 by the Institute of Social Science Survey of Peking University, China. The target sample includes 16,000 households and all members over age 9 in each sampled household, for a total of more than 30,000 individuals.

3.1 Definitions of a Health Shock

We define a health shock to a household as a health shock to any household member. We now describe our definitions of a health shock at the individual level, using both severely deteriorated self-reported health status and hospital admission.

3.1.1 Severe Deterioration in Self-Reported Health Status

We define an individual-level health shock as a sharp decline in one's health status from relatively good to poor based on self-reported health status. In the CHNS, the survey asks questions "How do you rate your health status?" If the respondent reports "excellent," "good," or "fair" health in wave t, and "poor" or "very poor" in wave $t+1$, we record a health shock between waves t and $t+1$.[6]

We do not just use worsened self-reported health status to proxy for a health shock, because of the concerns about potential endogeneity problems. The first possible endogeneity problem is reverse causality. That is, if we observe a decline in a household's income and worsened health simultaneously, we cannot decide the causal relationship between them: on the one hand, a health shock could reduce labor supply and result in lost income. On the

[4] The nine waves of CHNS were conducted in 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011, and 2015. The four waves of the CFPS were conducted in 2010, 2012, 2014, and 2016.

[5] Three mega cities joined the survey since 2011, and three more provinces joined since 2015. However, we do not include them in the sample. Please refer to section 3.2 for more details.

[6] Please refer to the Online Appendix section A1 for more details on the definition of self-reported health status variable.

other hand, less income could result in poorer self-reported health. The second possible endogeneity problem comes from measurement errors. The respondents are required to choose from four or five options. Nevertheless, in practice, it might be difficult for them to tell the differences between different health statuses. For example, what distinguishes "good" from "excellent" or "relatively poor" from "quite poor"? To address these two concerns, we record a health shock if and only if a household member's health changes from "fair" or better to "poor" or worse. There are two advantages to doing so. First, an individual may report worse health when his income lowers, but it is less likely for him to report "poor" health if he is not really in that status. Second, an individual may not be able to distinguish among the five options, but likely to be able to tell the difference between "good" and "poor," so there will be less measurement error under this definition of a health shock. Hence, the endogeneity problem of self-reported health can be alleviated.

However, there might be two other shortcomings of self-reported health status. Self-reported health can be regarded as an assessment of an individual's current health status: he may assess his health status based on his recent health conditions. If an individual's health status changed from "good" to "poor," but the individual subsequently recovered before the survey was conducted, we may observe no health shock in the survey, although one actually happened. Second, a fundamental assumption behind this definition is that an individual can assess his self-reported health using a consistent standard during a long period. For example, if an individual becomes more pessimistic about his health, his self-reported health could become worse even if he did not suffer from a health shock.

Considering the possible disadvantages of using self-reported health status to define health shocks, we use an event study design to estimate the effect of a health shock, which allows us to test the plausibility of parallel trends in the outcomes before a shock. Further, we propose another definition of a health shock using hospital admission records. Doing so allows us to compare the estimation results using different definitions of a health shock and test for the plausibility of using severe deterioration in self-reported health status to identify a health shock. We obtain robust results using the two definitions of a health shock.

3.1.2 Hospital Admission

We also use hospital admission records to identify health shocks, following Wagstaff (2007) and Dobkin et al. (2018). Of the two data sets, the CHNS only documents hospital admission records in the past four weeks before the survey. Hence, only a small proportion of the respondents report that they have been hospitalized. That makes it impossible to estimate the effects of a health shock, since there could be some individuals who had a hospital admission earlier than four weeks before the survey but do not report an admission. By contrast, the CFPS asks "whether you had an in-hospital treatment during the past year," which allows us to track health shocks in a year-long window. Thus, we use hospital admissions from the CFPS to detect severe health shocks and estimate their economic consequences.

3.2 Sample Construction

To construct our sample from the CHNS, we first select households that reported positive income in three adjacent waves[7] of the survey. Given that we have nine waves of CHNS data, we can construct seven such subsamples. In the second step, any households that experienced a health shock in the first two waves are dropped, and households in which more than one household member experienced a health shock in the third wave are also dropped.[8] In the third step, we do propensity score matching within each subsample. Note that there is one treated individual in each treated household. For each treated individual, we match three "placebo-treated individuals" who appear similar to the treated individuals but did not receive a health shock.[9] Specifically, we use a propensity score matching method with ten observable characteristics in the first two waves to estimate the propensity score.[10] Among these characteristics, eight are at the individual level, including age, gender, years of education, whether having health insurance, whether currently employed, yearly working hours, hourly wage, and self-reported health status; two are household-level characteristics, including urban/rural status, and household size. Because of the individual-level matching, each treated household is matched with three "placebo-treated households" that did not experience a health shock, which are henceforth the control households in our subsample. The final step of constructing the CHNS sample is to pool all the subsamples together after propensity score matching. Similarly, we construct the CFPS samples, where a hospitalization record identifies a health shock. The only difference in the sample construction process for the CFPS data is that we additionally include the household sampling weights when doing the matching.

3.3 Variable Definitions

CHNS Household Income The household income variable is the net household income constructed by the CHNS. Conceptually, household income is the sum of all sources of income and revenue minus expenditures. Nine income sources - business income, farming income,

[7]Three consecutive periods observed for each individual is the minimum length required for our econometric specification. We do not use four or more consecutive waves due to sample attrition.

[8]Recall that in each subsample, we have observations from three adjacent waves.

[9]These "placebo-treated individuals" are chosen from households that did not experience a health shock.

[10]We match treated individuals with three nearest "placebo-treated individuals" using the linearized propensity score, following Imbens and Rubin (2015).

fishing income, gardening income, livestock income, non-retirement wages, retirement income, subsidies, and other income - are included. The CHNS inflated household income to 2011 RMB.

CFPS Household Income The household income variable is the net household income constructed by CFPS, and we inflate it to 2011 RMB using the National Consumer Price Index.[11] Household income is the sum of five sources: wage income, business income, transfer income, property income, and other income.[12]

3.4 Summary Statistics

The total numbers of treated households included in our CHNS and CFPS samples are 517, and 1,455, respectively. Table 1 reports the summary statistics for the two samples for treatment and control households separately. Most of the covariates of the two groups are perfectly balanced after matching. We see that individuals who experienced a health shock are slightly more likely to have had a job before the health shock in the CFPS sample, but the difference is economically small (0.87 vs. 0.88). We also see that the treated households have slightly more household members (3.80 vs. 3.85).

4 Empirical Framework

The impact of a health shock on household income mobility can be evaluated by comparing the outcomes of households that experienced a shock with those that did not. We use an event-study design similar to that used in Jaravel et al. (2018) and estimate the following equation:

$$y_{it} = \gamma_t + \alpha_i + X_{it}\beta + \sum_{\tau=-2}^{\tau=0} \delta_\tau^{\text{All}} \mathbb{1}[D_{it}^{All} = \tau] + \sum_{\tau=-2}^{\tau=0} \delta_\tau^{\text{Treat}} \mathbb{1}[D_{it}^{Treat} = \tau] + \varepsilon_{it}, \tag{3}$$

where y_{it} denotes the outcome of household i in year t (the outcomes of interest include household income per capita and household income percentile); γ_t denotes calendar year fixed effects; and α_i denotes household fixed effects. D_{it}^{Treat} is the interaction term of the treatment dummy (whether a household member experienced a health shock) and a dummy for the wave relative to the health shock for household i in year t, where τ represents the

[11] The data can be found at http://data.stats.gov.cn/easyquery.htm?cn=C01.

[12] How CFPS asks about household income is slightly different across the four waves, and the composition of household income is slightly different across different waves. To make the household income variable comparable across all four waves, we make use of the CFPS-provided variable "household income comparable to 2010" in CFPS, which guarantees that the sources of household income stay the same.

relative wave (event-time). D_{it}^{All} is a dummy for the wave relative to a health shock for household i in year t. X_{it} is a set of controls, including the demographic characteristics and the health insurance status of the treated individual (placebo or real), household size, and urban/rural status of the household. In the following analysis, we report estimates with and without these controls. ε_{it} stands for the error term. We normalize the coefficient of the wave before the health shock, δ_{-1}^{Treat}, to zero. That is, when our identification assumption described below holds, the coefficient δ_0^{Treat} is the coefficient of interest, as it measures the causal effects of a health shock on the outcomes of interest.

First, our model permits the treated households to differ from the control households in levels of the outcome, by adding household fixed effects α_i. Second, following Jaravel et al. (2018), we add a set of leads and lags around the health shock, which are common to the control and treated households (δ_τ^{All}). By adding these leads and lags, we directly address the concern that the household fixed effects, as well as the controls, may not fully account for the trends in household income around the health shock. For example, previous literature finds a slight decrease in household income before a health shock (e.g., Dobkin et al. 2018). Moreover, the relative time effects for the treatment group δ_τ^{Treat} in the model have some important implications. In our model, the coefficients δ_τ^{Treat} in front of D_τ^{Treat} measure the average difference between the treated and control households in wave τ relative to the health shock. The specification allows us to test whether there is any difference in trends of the outcome between the treated and control households before the health shock, by examining whether the coefficient δ_{-2}^{Treat} differs from zero. This test could help check the validity of our identification assumption. Formally, similar to the spirit of Jaravel et al. (2018), our econometric model assumes the following conditional expectation function:

$$\mathbb{E}[y_{it}|D_\tau^{All}, D_\tau^{Treat}, X_{it}, t, i] = \gamma_t + \alpha_i + \delta_\tau^{All} + \delta_\tau^{Treat} + X_{it}\beta,$$

To interpret the coefficient δ_0^{Treat} as the causal effect of a health shock on the outcome, we need the following identification assumption:

$$\mathbb{E}[\mathbb{1}(D_{it}^{All} = \tau)\varepsilon_{it}|D_{it}^{All}, D_{it}^{Treat}, X_{it}, t, i] = 0 \quad \forall(t, \tau),$$

which says that the time relative to the health shock is not correlated with the error term for all households. In practice, our identification strategy may not be credible due to potential endogeneity concerns, in which case the time relative to the health shock is not strictly exogenous. One may hypothesize that it is not the health shock that results in the change in the outcome variable; instead, it is the changes in the outcome variable that cause the health shock. Take one outcome variable, for example, household income per capita. If we observe that there was a significant decline in income per capita before the health shock (that is, if we observe a significant positive δ_{-2}^{Treat}), we may be concerned that households reported poorer health due to decreasing income, and hence we observe a health shock.[13]

5 Empirical Results

In this section, we present the results on the effects of a health shock on household income mobility and consider possible explanations for why health shocks matter. We begin with the analysis of the effects on household transition probability and upward mobility. Then, in our regression analysis, we first show the effects of a health shock on income per capita, which is a direct measure of welfare, followed by the effects on household income percentile. Next, to examine how a health shock affects a household's income mobility, we evaluate the effects of a health shock on household labor supply decisions. Finally, we explore whether a health shock has different economic implications for different subgroups, by doing heterogeneity analysis along several dimensions.

5.1 Effects on Transition Probability and Upward Mobility

We begin by analyzing how a health shock affects a household's transition probability and upward mobility. Our results suggest that a health shock lowers household transition probability and upward mobility significantly.

Table 2 reports the transition probability between period -1 (one wave before the health shock) and period 0 (the wave after the health shock) in our two samples for the treatment and control households, respectively. These are samples after matching, so the transition probabilities of the treated and control groups are comparable before the health shock. Thus, the wedges in transition probability reported in Table 2 are caused by health shocks.[14] The transition probability measures the probability of a household that was below or equal to the sth quantile ending up at a position higher than the sth quantile. Thus, the disparity in transition probabilities between the treatment and control groups directly measures the difference in the economic opportunities between these two groups. Households that experienced a health shock have much lower transition probability than those that did not. Columns (1)-(3) report the transition probability estimates for the CHNS sample, where a health shock is defined as a severe deterioration in self-reported health status. As a central

[13] Although the zero coefficient of δ_{-2}^{Treat} cannot fully alleviate this concern since the pre-trend may not be identified due to the statistical power (e.g., Freyaldenhoven et al. 2019), it is the best practice we can take due to the lack of IVs to instrument for the confounds. In Freyaldenhoven et al. (2019), the authors propose a method to identify the causal effect of a treatment in the event-study setting by using a 2SLS approach.

[14] In the Online Appendix, Figure A5 and A6, we present transition probability and upward mobility for the treated and control households before the health shock. We do not observe any significant differences in transition probability or upward mobility between the treated and control groups before the health shock.

focus of policy interest, we focus on whether a health shock imposes a significant impact on the probability of "getting out of the low-income trap." Given that a household is in the bottom 20 percentiles of the income distribution in wave t, the chance of transiting out of the low-income group (the bottom quintile) in wave $t+1$ is 64.3% if the household does not suffer a health shock. However, the chance decreases by 8.4 percentage points to 55.9% if the household experienced a health shock. Considering the 64.3% transition probability for the control group, this 8.4 percentage points decrease reflects a 13.06% lower transition probability for households that experienced a health shock in the bottom 20 percentiles of the national income distribution. Estimates using the CFPS sample tell the same story. In Table 2, columns (4)-(6), we report the transition probability for the treatment and control groups using the CFPS sample, where a health shock is defined as a hospitalization. We document a similar pattern: households with a health shock exhibit much lower transition probability. In this sample, the chance of "getting out of the low-income trap" is 59.1% for a household in the control group, and it is 54.7% for a household in the treatment group. This 4.4 percentage points wedge created by a health shock reflects a 7.37% lower probability of transiting out of the low-income trap for the households in the bottom 20 percentiles of the income distribution. Overall, Table 2 shows that households with a health shock exhibit lower probability of successfully transiting from below or equal to the sth quantile to above the sth quantile, regardless of the cutoff value, s. These results suggest that a health shock plays a vital role in determining households' transition probability, regardless of the household's initial position in the income distribution.[15]

In the upward mobility analysis, we divide households into five groups based on their income position in the period before the health shock, each of which represents 20 percentiles in the national income distribution. Table 3 reports the upward probability for households in each of these groups separately.[16] Overall, we observe that experiencing a health shock lowers a household's ability to climb the income ladder, namely, the ability to surpass its previous income percentile. Using the CHNS sample in columns (1)-(3), households in the treatment group have a 9.5 percentage points lower probability of climbing the income ladder compared with the control group. Compared with the mean of the control group, this estimate suggests an 18.73% lower upward mobility for households that experienced a health shock. The upward mobility estimates using the CFPS sample are reported in columns (4)-(6). Households in the treatment group have 4.3 percentage points lower upward mobility on average. These estimates reflect an 8.81% lower upward mobility for the treatment group compared with the control group. The findings also show that a health shock imposes

[15]In the Online Appendix, Figure A1 plots the transition probability between period -1 (one wave before the health shock) and period 0 (the wave after the health shock) for the control and treatment groups separately, in intervals of 5 percentile points varies from 5 to 95.

[16]Figure A2 provides a graphical illustration.

heterogeneous effects on the upward mobility of households at different income positions. In the CHNS sample, which speaks more to the trends in the 1990s and 2000s, upward mobility drops the most for households in the top two quintiles, while households that were initially between percentiles 20 and 60 are not significantly affected. In the CFPS sample, which emphasizes trends in the 2010s, health shocks impose relatively larger impacts on households that were initially between percentiles 20 and 60. These results show that in recent years, although the top income-earners have been more likely to maintain their ability to move upward, it has been less likely for the middle-income households to climb the income ladder in the face of a health shock.

5.2 Effects on Household Income

Table 4 presents the effects of a health shock on log income per capita. Our estimates suggest that a health shock leads to a substantial amount of income loss. Using the CHNS sample without any controls in column (1), we find that a health shock results in a 13.1% decrease in household income per capita for households that experienced a health shock, relative to the control group. In column (2), we control for a set of individual- and household-level characteristics. Our estimates do not change much, as find that a health shock lowers the treated households' income per capita by 12% relative to the control households. This estimate reflects a 1,192 RMB decrease in household income per capita for the treatment group relative to the control-group mean of 9,939 RMB. Using the CFPS sample in columns (3)-(4), we observe similar patterns. When we do not include any controls, a health shock introduces a 12.2% income loss for the treatment group relative to the control group. In column (4), we include individual- and household-level characteristics as control. We document that a health shock results in 12.8% lower income per capita for the treated households. Compared with the post-shock control group mean of 12,833, this 12.8% relative change reflects a 1,643 RMB decrease in household income per capita.

Comparing our estimates with the 8.2% and 6.5% annual household income increase in China for urban and rural households, respectively, during 1991 and 2012, it is clear that a household that experienced a health shock suffered a substantial welfare loss and had a much larger likelihood of falling into poverty.[17] Further, the estimated effects of a health shock to household income per capita are similar using different samples, speaking to the fact that health always plays an essential role in determining household income throughout our sample period. Finally, the relatively small and statistically insignificant pre-trends under different definitions of a health shock and using different samples mitigate the reverse-causality concern and lend credence to our identification strategy.

[17] Data on urban and rural household income per capita are from the National Bureau of Statistics of China at http://data.stats.gov.cn/easyquery.htm?cn=C01.

5.3 Effects on Household Income Percentile

We next analyze the effects of a health shock on the household's income percentile. By evaluating the effects of a health shock on income rank, we are answering the following question: "What are the consequences of a change in health status on a household's relative position in the income distribution?"

There are three advantages of using household income percentile as the outcome variable in our analysis. First, there has been a strand of literature suggesting that relative income, instead of absolute income, affects individuals' subjective well-being. For example, Clark et al. (2009) suggest that individuals are rank-sensitive: they are more satisfied as their percentile ranking improves; Card et al. (2012) use an experiment to demonstrate that job satisfaction depends on relative pay comparisons. Thus, changes in the position in the income distribution directly affect a household's subjective well-being, and analyzing the effects of a health shock on household income position is of great normative importance. Second, estimating the effects of a health shock on a household's income percentile provides micro-level evidence on how a health shock affects a household's movement in the income distribution, which explains our estimates of the effects of a health shock on aggregate-level income mobility in section 5.1. Recall that upward mobility quantifies the proportion of households that successfully move up a given distance in the income distribution, and the transition probability measures the proportion of households who successfully transit to a specific income position. However, these aggregate-level income mobility measures do not speak to the distance that a household moves when it experienced a health shock. Our estimates using income percentile as the outcome variable complement the aggregate-level mobility measures, by calculating the average treatment effect of a health shock on a treated household's income position relative to other households.

Table 5 presents the results on the effects of a health shock on household's income percentile. We find that a health shock significantly lowers the household income position in the national income distribution. Using the CHNS sample in column (1), where a health shock is defined as a severe deterioration in self-reported health status, we find that a health shock causes a 3.94 percentile drop in the income distribution. In column (2), we control for a set of individual- and household-level characteristics. Our estimates suggest that a health shock results in a 3.53 percentile drop in the income distribution. We observe similar patterns using the CFPS sample. Column (3) reports our estimates when no control variables are included, and in column (4), we control for a set of individual- and household-level characteristics. The point estimates suggest that a health shock lowers income position by 3.1 and 3.21 percentiles, respectively.

5.4 Household Labor Supply Responses

From the analysis so far, We conclude that a health shock causes a substantial decrease in household income and significantly lowers households' income percentile. In this section, we discuss households' labor supply responses to a health shock.

There are three reasons why a health shock could affect household income through the labor supply channel. First, a health shock may directly change the labor supply decision of the individuals who experienced a health shock, on both the extensive and intensive margins. On the extensive margin, individuals who experienced a health shock may become unemployed in the labor market. On the intensive margin, individuals who experienced a severe health shock may reduce their labor supply or exit from full-time work. Under both scenarios, household income would be lower due to the unearned income of those individuals who receive a health shock. Second, for the individuals who experienced it, a health shock lowers their labor productivity, especially for those who work in manual labor jobs. In a competitive labor market, the wage rate equals the marginal productivity of labor. Thus, a health shock would lower the treated individual's wage, even holding his labor supply constant. Third, a health shock on one household member could impact the labor supply decisions of other household members, although the response is theoretically ambiguous. On the one hand, past research has emphasized that self-insurance is an essential channel through which households insure themselves against income shocks. When an income shock happens to one household member, the labor supply of other household members will increase to compensate for the income losses (Ashenfelter 1980, Cullen and Gruber 2000). On the other hand, there are several reasons why a negative health shock could lower the labor supply of other household members. First, theoretically, all household members jointly provide the public goods to be consumed within a family (Blundell et al. 2005, Cherchye et al. 2012).[18] Thus, when a household member receives a health shock, the other household members need to spend relatively more time producing public goods for the household. Second, it can be readily seen that a health shock may increase the marginal utility of leisure. For example, treated individuals may require assistance with activities. In this case, if other household members care for the ill member, the leisure time spent on caring for these treated individuals may create higher marginal utility.

Considering these channels, we analyze the treated individuals', as well as their household members' labor supply responses to a health shock. To do the analysis, we construct two sets of individual-level samples. The first set consists of individuals who experienced a health shock, and all individuals in the control group; the second sample consists of household members of the treated individuals and all individuals in the control group.

We estimate Equation 3 using our four constructed individual-level samples and switch

[18] Examples of the provision of public goods include caring for children, and doing housework.

the outcomes to the labor supply measures of interest (including whether employed, yearly working hours, and hourly wage). Figure 1 reports the estimated labor supply response. In Figure 1A, we examine whether a health shock imposes any significant impact on the labor supply at the extensive margin. We find that those who experienced a health shock, as well as their household members, do not have any significant difference in the probability of being employed, compared with the individuals in the control group. In Figure 1B, we plot the treatment effects on yearly working hours for those who were employed before and after the health shock. Again, we do not see any responses to a health shock at the intensive margin. Conditional on being employed, people who experience a health shock do not significantly adjust their labor supply hours. Meanwhile, we do not find any evidence suggesting that the household members of the treated individuals respond to a health shock by adjusting their labor supply hours. These findings on labor supply responses stand in line with Fadlon and Nielsen (2015) and Dobkin et al. (2018), who document that spousal labor supply does not respond to non-fatal health shocks. However, in Figure 1C, we see that a health shock significantly lowers labor productivity of the individuals who experienced a health shock. In the CHNS sample, a health shock lowers the hourly wage of the treated individuals by 16%, compared with the individuals in the control households. In the CFPS sample, we find that the hourly wage of the treated individuals decreases by 18%, compared with individuals in the control group once a health shock occurs.

5.5 Treatment Effect Heterogeneity and Implications

The estimated overall effects mask economically interesting heterogeneity. To analyze whether a health shock has different economic implications for different subgroups, we estimate the following equation:

$$\begin{aligned} y_{it} =& \gamma_t + \alpha_i + X_{it}\beta + Z_i\theta + \sum_{\tau=-2}^{\tau=0} \delta_\tau^{\text{All}} \mathbb{1}[D_{it}^{All} = \tau] + \sum_{\tau=-2}^{\tau=0} \delta_\tau^{\text{Treat}} \mathbb{1}[D_{it}^{Treat} = \tau] \\ &+ \sum_{\tau=-2}^{\tau=0} \delta_\tau^{All,Z_i} \mathbb{1}[D_{it}^{All,} = \tau] Z_i + \sum_{\tau=-2}^{\tau=0} \delta_\tau^{Treat,Z_i} \mathbb{1}[D_{it}^{Treat} = \tau] Z_i + \varepsilon_{it} \end{aligned} \tag{4}$$

where y_{it} denotes the outcome of household i in year t (the outcomes of interest include income per capita and the household's income percentile); γ_t denotes calendar year fixed effects, and α_i denotes household fixed effects; D_τ^{Treat} is the interaction term of the treatment dummy (whether a household member experienced a health shock) and a dummy for the wave relative to the health shock, where τ represents the relative wave (event-time). D_τ^{All} is a dummy for the wave relative to a health shock. Z_i is a dummy variable for the heterogeneity that we are interested in, which can be either urban/rural status or initial income group, in the wave prior to the health shock. X_{it} is a set of controls, including the demographic characteristics as well as the health insurance status of the treated individual (placebo or real), household size, and urban/rural status of the household. ε_{it} stands for the error term. In this specification, the coefficient of interest is $\delta_{\tau}^{Treat,Z_i}$. We normalize treatment effects for the reference group to zero.[19]

We first explore whether a health shock imposes heterogeneous impacts on urban and rural residents. Figure 2 plots the differences in treatment effects between urban and rural households, using the treatment effects for urban households as reference. We see that rural households suffer relatively more in the face of a health shock. In the CHNS sample, we observe that, compared with an urban treated household, a health shock imposes a 9% larger negative impact in household income per capita, and causes an additional 4.41 percentile drop on household income percentile, for a rural treated household. In the CFPS sample, we document a 15% larger negative impact on household income, and an additional 2.28 percentile drop in household income percentile for a treated rural household, compared with a treated urban household. These findings are in line with the idea that rural households earn income mostly by providing manual labor. In this way, rural households are more vulnerable to income losses when faced with a health shock.

We next investigate whether a health shock has different impacts on households in different income positions. Again, we group households into five income groups based on their income position in the wave before the health shock, each of which represents 20 percentiles in the national income distribution. Figure 3 plots the heterogeneity in the treatment effects between different income groups, using households initially between the 40th and 60th percentiles (the medium group) as our reference group. In the CHNS sample, we see that a health shock imposes a relatively greater impact on households that are above the 60th percentile in the national income distribution, relative to the households in the medium group. Further, we do not observe statistically distinguishable differences in the treatment effects between the medium group and households in the bottom 40 percentiles in the national income distribution. However, we do not observe this pattern in the CFPS sample. Our estimates using the CFPS data suggest that the households that were initially between the 60th and 80th percentiles in the national income distribution lose relatively less in the face of a health shock, compare with the reference group, while the treatment effects on all other income groups are statistically indistinguishable. We see that these estimates using two different samples are in line with our aggregate-level findings – high-income households are more capable of maintaining their income position in the face of a health shock in recent years, while the middle- and low-income households lose relatively more.

[19] In our analysis, we treat urban households, or households initially between the 40th and 60th percentiles, as our reference group.

6 Short-Run Income Mobility after a Health Shock

The estimates in Sections 5.1 to 5.3 report how a health shock affects transition probability, upward mobility, income, and income position for households that experience the shocks, relative to other households. However, these estimates only reflect the contemporaneous impact of a health shock on household income mobility. In this section, we track the short-run income mobility of the treated households up to four years after the health shock. We see that, compared with the households in the control group, although the treated households have similar upward mobility, they have much lower transition probability. These results suggest that a health shock imposes not only contemporaneous but also lasting impacts on household income mobility. Meanwhile, we see that the lasting negative impacts on income mobility are larger for low-income households, suggesting that poorer households are more likely to get caught in the low-income trap after a health shock.

For this analysis, we first construct subsamples using households that reported positive income in three adjacent waves of the survey. Second, in each subsample, we require the health shock to happen between the first and the second wave. In this way, we can track household income mobility between the second and the third waves and see whether there are any differences in income mobility between the treatment and control groups after the health shock. Third, we explore matching methods that are similar to those we used before and match each treated household with three control households.[20] Once we have these subsamples, we pool them together.

Table 6 presents the post-shock transition probability for the treatment and control groups, respectively.[21] The table delivers two main messages. First, after the health shock, households that experienced a health shock have much lower transition probability compared with those that did not. Columns (1)-(3) report the transition probability estimates for the CHNS sample, where a health shock is defined as a severe deterioration in self-reported health status. Given a household in the bottom 20 percentiles of the income distribution in wave t, its chance of "getting out of the low-income trap" in wave $t+1$ is 65.2% if the household does not suffer from a health shock. However, the chance decreases by 5.9 percentage points to 59.4% if one of the household's members experienced a health shock. In columns (4)-(6), we report the transition probability for the treatment and control groups for the CFPS sample. We see a similar pattern: households with a health shock are more prone to becoming caught

[20]For the matching, we only use the ten observable characteristics in the first wave to estimate the propensity score. Eight of these characteristics are at the individual level, including age, gender, years of education, whether having health insurance, whether currently employed, yearly working hours, hourly wage, and self-reported health status; two are household-level characteristics: urban/rural status, and household size.

[21]In the Online Appendix, Figure A3 plots the transition probability between period 0 (one wave after the health shock) and period 1 for the control and treatment groups, separately, in intervals of 5 percentile points varies from 5 to 95.

in the low-income trap. In this sample, the chance of moving out of the bottom quintile is 58.5% for a household in the control group, but it is 49.9% for a household in the treatment group. This 8.6 percentage points wedge created by a health shock reflects a 14.7% higher probability of being trapped for the treated households. Second, there is a clear gradient structure in the lasting impacts of a health shock on transition probability. Table 6 shows that, the higher is the cutoff s, the smaller is the difference in transition probability between the treated and control households. This evident gradient shows that, once receiving a health shock, poorer households are less likely to reach a given threshold in the income distribution.

Table 7 reports the post-shock upward mobility for the treatment and control groups, respectively.[22] From this table, we see that the treated and control households experience similar upward mobility.[23] These upward mobility estimates suggest that the treated households have a similar ability to surpass their initial income position, compared with the households in the control group. Taking our findings for transition probability and upward mobility together, although the treated households can move upward from their income position after the health shock, they enjoy fewer economic opportunities compared with other households in the same income position. The lack of economic opportunities in the years after the health shock highlights that, apart from compensating for the medical expenditures, the provision of continued financial support is needed to address the plight of households who receive a health shock.

7 Conclusion

Income mobility could serve as an equalizer of long-term income inequality. Thus, understanding the key factors that help households maintain high income mobility is of great importance.

This paper uses the two largest survey data sets in China to study the effects of a health shock on household income mobility. At the aggregate level, we find that households that experience a health shock exhibit significantly lower transition probability and upward mobility. At the micro level, we take an event study approach and document that a health shock produces a substantial income loss for the treated households and lower their income percentile. We also explore household labor supply decisions in response to a health shock. We do not find evidence that a health shock affects the labor supply of the treated individuals or their household members. However, the labor productivity of the treated individuals, measured by the hourly wage, decreases substantially after a health shock.

[22]Figure A4 provides a graphical illustration.

[23]Except for the top 20% households in the CHNS sample, and the bottom 20% households in the CFPS sample.

The main lesson of our analysis is that health human capital plays an important role in determining households' income mobility. This finding could be important for some policy making, for example, the design of unemployment insurance in China. Our analysis throughout this paper is primarily descriptive. In order to draw inferences on the optimal health insurance or social insurance design, additional assumptions would be required estimating the marginal utility of consumption and the welfare costs of government transfers. However, we hope that the tools in, for example, Blundell et al. (2016), Chetty and Finkelstein (2013), and Low and Pistaferri (2015) will help surmount these complications and shed light on these research questions.

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Table 1: Summary Statistics

	CHNS Sample		CFPS Sample	
	Control (1)	Treatment (2)	Control (1)	Treatment (2)
Individual Characteristics				
Age	52.33	51.70	51.62	51.35
	(14.67)	(14.57)	(13.43)	(13.31)
Female	0.41	0.41	0.47	0.46
	(0.49)	(0.49)	(0.50)	(0.50)
Years of Education	5.15	5.16	7.28	7.19
	(4.16)	(4.13)	(4.60)	(4.36)
Health Insurance	0.36	0.37	0.90	0.91
	(0.48)	(0.48)	(0.30)	(0.29)
Currently Working pre-shock	0.99	0.99	0.87	0.88
	(0.10)	(0.09)	(0.34)	(0.32)
Currently Working post-shock	0.99	0.99	0.99	0.98
	(0.09)	(0.10)	(0.11)	(0.14)
Yearly Working Hours pre-shock	1,824.68	1,744.80	2,498.70	2,594.31
	(981.28)	(946.23)	(893.01)	(1,007.55)
Yearly Working Hours post-shock	1,652.05	1,454.99	2,542.47	2,518.46
	(1,057.76)	(1,003.19)	(1,035.94)	(1,093.03)
Hourly-wage pre-shock	3.63	3.13	10.14	9.69
	(5.03)	(2.81)	(11.53)	(12.69)
Hourly-wage post-shock	7.79	5.84	12.43	10.89
	(17.97)	(8.57)	(17.83)	(12.93)
Household Characteristics				
Household Size	3.92	3.88	3.80	3.86
	(1.59)	(1.56)	(1.65)	(1.72)
Urban	0.21	0.22	0.50	0.49
	(0.41)	(0.41)	(0.50)	(0.50)
Income per capita pre-shock	6,578.37	6,163.88	10,323.54	10,353.94
	(7,160.34)	(7,530.68)	(10,872.10)	(10,612.27)
Income per capita post-shock	9,938.92	7,843.48	12,654.95	11,645.84
	(12,265.97)	(10,558.36)	(13,067.45)	(12,404.98)
Number of Households	1,551	517	4,365	1,455

Notes: This table reports the summary statistics of the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status, and the CFPS sample, where a health shock is identified by a hospitalization record, for the treatment and control groups. The treatment group refers to households that experienced a health shock. The control group refers to households with no health shock. Income per capita and hourly wage have been adjusted to 2011 RMB.

Table 2: Transition Probability by Treatment Status

	CHNS Sample			**CFPS Sample**		
Percentile	**Control** (1)	**Treatment** (2)	**Difference** (3)	**Control** (4)	**Treatment** (5)	**Difference** (6)
20%	0.643	0.559	-0.084	0.591	0.547	-0.044
	(0.026)	(0.047)	(0.054)	(0.024)	(0.040.)	(0.047)
40%	0.388	0.343	-0.045	0.371	0.326	-0.045
	(0.019)	(0.030)	(0.039)	(0.015)	(0.027)	(0.031)
60%	0.239	0.200	-0.039	0.205	0.165	-0.040
	(0.013)	(0.021)	(0.025)	(0.011)	(0.016)	(0.018)
80%	0.132	0.062	-0.070	0.103	0.081	-0.022
	(0.011)	(0.012)	(0.015)	(0.006)	(0.011)	(0.014)

Notes: This table reports the transition probability for the treatment and control groups in our two samples. Columns (1)-(3) report the estimates for the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Columns (4)-(6) report the estimates of the CFPS sample, where a health shock is identified by a hospitalization record. The treatment group refers to households that experienced a health shock. The control group refers to households with no health shock. The transition probability measures the probability that a household ends up at a position higher than the sth quantile in wave t, conditioning on starting at a position lower than or equal to the sth quantile in wave $t-1$. The health shock happens between times $t-1$ and t. The "Control" and "Treatment" columns report the transition probabilities for the treatment and control groups, respectively. The "Difference" columns report the difference in the transition probabilities between the treatment and control groups. Bootstrapped standard errors are in parenthesis.

Table 3: Upward Mobility by Treatment Status

	CHNS Sample			CFPS Sample		
Income Group	**Control**	**Treatment**	**Difference**	**Control**	**Treatment**	**Difference**
	(1)	(2)	(3)	(4)	(5)	(6)
Bottom 20%	0.815	0.724	-0.091	0.788	0.752	-0.036
	(0.021)	(0.042)	(0.046)	(0.020)	(0.035)	(0.041)
20%-40%	0.573	0.574	0.001	0.597	0.512	-0.085
	(0.026)	(0.047)	(0.058)	(0.021)	(0.038)	(0.042)
40%-60%	0.466	0.442	-0.023	0.474	0.395	-0.079
	(0.027)	(0.052)	(0.054)	(0.023)	(0.033)	(0.039)
60%-80%	0.385	0.181	-0.204	0.365	0.363	-0.002
	(0.031)	(0.041)	(0.053)	(0.022)	(0.041)	(0.048)
Top 20%	0.296	0.139	-0.157	0.215	0.202	-0.013
	(0.026)	(0.035)	(0.044)	(0.021)	(0.030)	(0.038)
Average	0.507	0.412	-0.095	0.488	0.445	-0.043

Notes: This table reports the upward mobility for the treatment and control groups in our two samples by initial income group. We group households into five income groups based on their initial income position, with each income group representing 20 percentiles in the national income distribution. Columns (1)-(3) report the estimates for the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Columns (4)-(6) report the estimates for the CFPS sample, where a health shock is identified by a hospitalization record. The treatment group refers to households that experienced a health shock. The control group refers to households with no health shock. Upward mobility measures the probability that a household ends up in an income group higher than its original one. The "Control" and "Treatment" columns report upward mobility for the treatment and control groups, respectively. The "Difference" columns report the difference in upward mobility between the treatment and control groups. Bootstrapped standard errors are in parenthesis.

Table 4: Effects of a Health Shock on Log Household Income per Capita

	CHNS Sample		CFPS Sample	
	(1)	(2)	(3)	(4)
δ_{-2}^{Treat}	0.010	0.019	-0.028	-0.020
	(0.046)	(0.045)	(0.055)	(0.056)
δ_{0}^{Treat}	-0.131	-0.120	-0.122	-0.128
	(0.049)	(0.048)	(0.054)	(0.054)
Control Mean Post-Treatment	9938.93	9938.93	12832.99	12832.99
Household FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	6,204	6,204	17,460	17,460
R-squared	0.696	0.707	0.609	0.611

Notes: This table reports the estimated effects of a health shock on log household income per capita using Equation (3). Columns (1)-(2) report the estimates using the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Columns (3)-(4) report the estimates using the CFPS sample, where a health shock is identified by a hospitalization record. The coefficients δ_{-1}^{Treat} are normalized to zero. The coefficients δ_{0}^{Treat} are the estimated treatment effects. "Control mean post-treatment" reports the mean household income per capita of the control group in event period 0 (where the health shock happens between periods -1 and 0). Standard errors are clustered at the household level.

Table 5: Effects of a Health Shock on Household Income Percentile

	CHNS Sample		CFPS Sample	
	(1)	(2)	(3)	(4)
δ_{-2}^{Treat}	0.180	0.470	-0.584	-0.437
	(1.590)	(1.558)	(1.221)	(1.226)
δ_{0}^{Treat}	-3.939	-3.526	-3.097	-3.205
	(1.593)	(1.561)	(1.124)	(1.119)
Control Mean Post-Treatment	49.42	49.42	49.98	49.98
Observations	6,204	6,204	17,460	17,460
R-squared	0.594	0.610	0.671	0.673
Household FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: This table reports the estimated effects of a health shock on household income percentile using Equation (3). Columns (1)-(2) report the estimates using the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Columns (3)-(4) report the estimates using the CFPS sample, where a health shock is identified by a hospitalization record. The coefficients δ_{-1}^{Treat} are normalized to zero. The coefficients δ_{0}^{Treat} are the estimated treatment effects. "Control mean post-treatment" reports the mean household income percentile of the control group in event period 0 (where the health shock happens between periods -1 and 0). Standard errors are clustered at the household level.

Table 6: Transition Probability after the Health Shock by Treatment Status

	CHNS Sample			CFPS Sample		
Percentile	Control (1)	Treatment (2)	Difference (3)	Control (4)	Treatment (5)	Difference (6)
20%	0.652	0.594	-0.059	0.585	0.499	-0.086
	(0.024)	(0.034)	(0.040)	(0.016)	(0.041)	(0.044)
40%	0.387	0.349	-0.038	0.373	0.324	-0.048
	(0.017)	(0.026)	(0.031)	(0.011)	(0.026)	(0.027)
60%	0.232	0.209	-0.023	0.191	0.168	-0.023
	(0.013)	(0.020)	(0.024)	(0.007)	(0.018)	(0.018)
80%	0.119	0.108	-0.011	0.076	0.080	0.004
	(0.009)	(0.015)	(0.019)	(0.004)	(0.009)	(0.011)

Notes: This table reports the transition probability after a health shock for the treatment and control groups in our two samples. Columns (1)-(3) report the estimates for the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Columns (4)-(6) report the estimates for the CFPS sample, where a health shock is identified by a hospitalization record. The treatment group refers to households that experienced a health shock. The control group refers to households with no health shock. The transition probability measures the probability that a household ends up in a position higher than the sth quantile conditioning on starting at a position lower than or equal to the sth quantile. The "Control" and "Treatment" columns report the transition probabilities for the treatment and control groups, respectively. The "Difference" columns report the difference in the transition probability between the treatment and control groups. Bootstrapped standard errors are in parenthesis.

Table 7: Upward Mobility after the Health Shock by Treatment Status

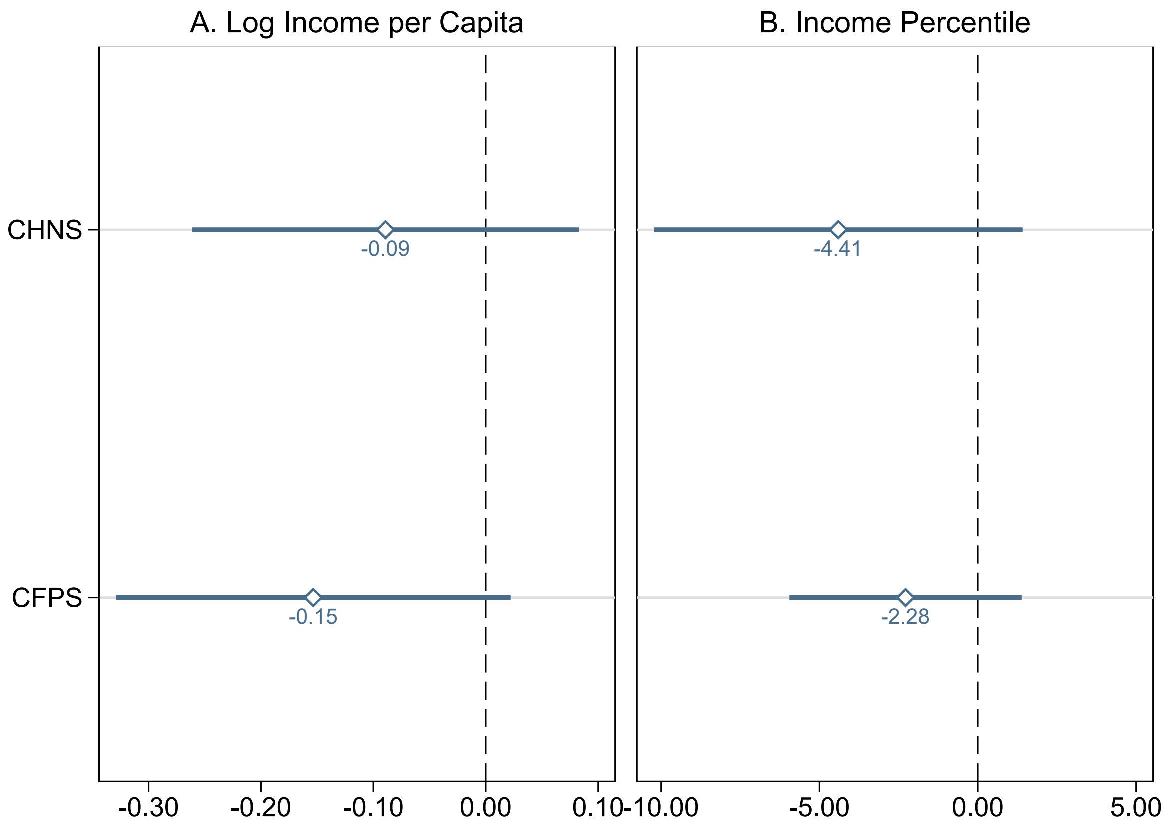
	CHNS Sample			**CFPS Sample**		
Initial Income Group	**Control**	**Treatment**	**Difference**	**Control**	**Treatment**	**Difference**
	(1)	(2)	(3)	(4)	(5)	(6)
Bottom 20%	0.825	0.794	-0.031	0.790	0.708	-0.081
	(0.018)	(0.031)	(0.038)	(0.014)	(0.034)	(0.035)
20%-40%	0.582	0.637	0.055	0.587	0.559	-0.028
	(0.026)	(0.038)	(0.047)	(0.015)	(0.040)	(0.044)
40%-60%	0.468	0.477	0.009	0.420	0.430	0.009
	(0.025)	(0.044)	(0.051)	(0.015)	(0.037)	(0.040)
60%-80%	0.383	0.330	-0.053	0.330	0.342	0.012
	(0.025)	(0.046)	(0.051)	(0.015)	(0.033)	(0.038)
Top 20%	0.249	0.125	-0.124	0.201	0.215	0.014
	(0.023)	(0.039)	(0.047)	(0.015)	(0.051)	(0.053)
Average	0.501	0.473	-0.029	0.466	0.451	-0.015

Notes: This table reports the upward mobility after the health shock for the treatment and control groups in our two samples by initial income group. We group households into five income groups based on their initial income position, with each income group representing 20 percentiles in the national income distribution. Columns (1)-(3) report the estimates for the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Columns (4)-(6) report the estimates for the CFPS sample, where a health shock is identified by a hospitalization record. The treatment group refers to households that experienced a health shock. The control group refers to households with no health shock. Upward mobility measures the probability that a household ends up in a income group higher than its original one. The "Control" and "Treatment" columns report upward mobility for the treatment and control groups, respectively. The "Difference" columns report the difference in upward mobility between the treatment and control groups. Bootstrapped standard errors are in parenthesis.

Figure 1: Labor Supply Responses to a Health Shock

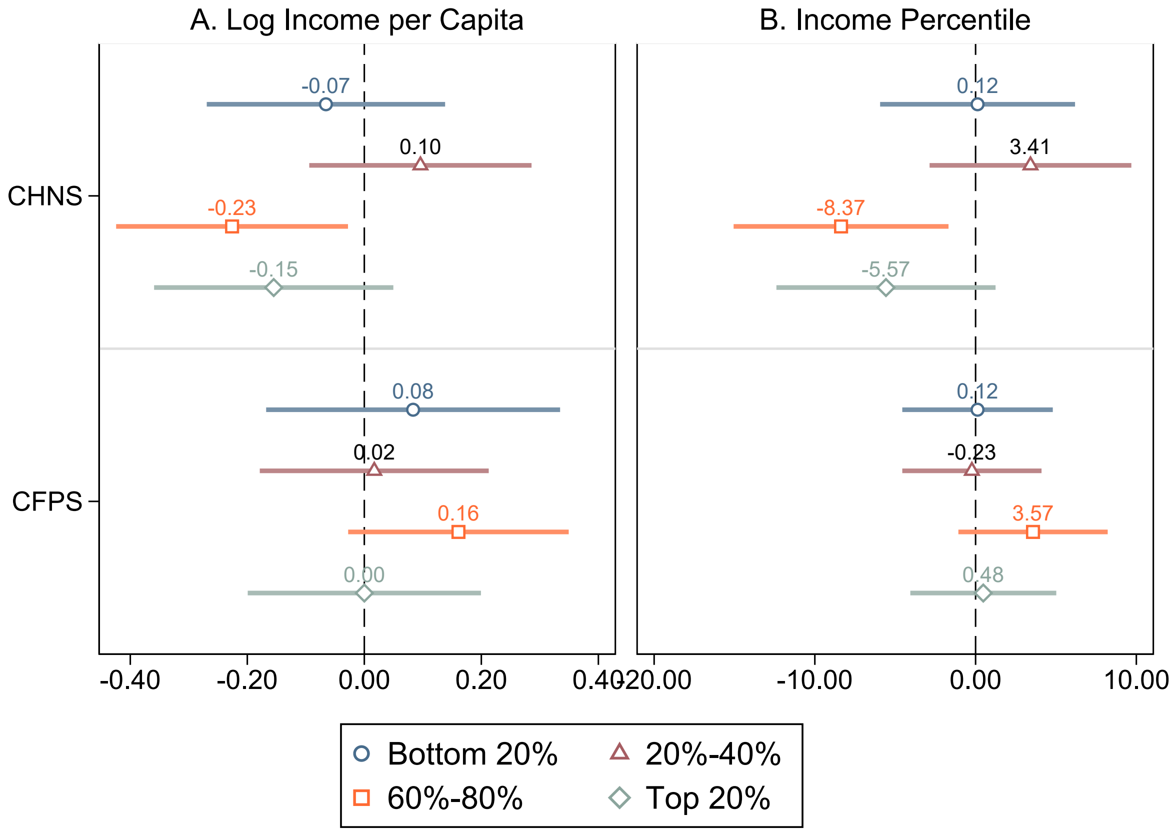
Notes: This figure plots the labor supply responses of treated individuals, as well as their household members, by estimating Equation (3). Figure A presents the estimated effects of a health shock on the probability of being employed. Figure B plots the estimated effects of a health shock on yearly working hours, conditional on the individuals being employed before and after the health shock. Figure C plots the estimated effects of a health shock on the log hourly wage, conditional on the individuals being employed both before and after the health shock. In the CHNS sample, a health shock is identified by a severe deterioration in self-reported health status. In the CFPS sample, a health shock is identified by a hospitalization record. The horizontal line represents the 90% confidence interval. Standard errors are clustered at the individual level.

Figure 2: Heterogeneity in Treatment Status: By Urban/Rural Status



Notes: We estimate the differences in the treatment effects between urban and rural households using Equation (4) (using treatment effects on urban households as reference). Figure A presents the difference in the estimated effects of a health shock on the household income per capita. Figure B plots the difference in the estimated effects of a health shock on the household income percentile. In the CHNS sample, a health shock is identified by a severe deterioration in self-reported health status. In the CFPS sample, a health shock is identified by a hospitalization record. The horizontal line represents the 90% confidence interval. Standard errors are clustered at the household level.

Figure 3: Heterogeneity in Treatment Status: By Income Group



Notes: We estimate the differences in the treatment effects between urban and rural households using Equation (4) (using treatment effects on households between 40th and 60th percentiles of the national income distribution as reference). We group households into five income groups based on their initial income position, with each income group representing 20 percentiles in the national income distribution. Figure A presents the difference in the estimated effects of a health shock on the household income per capita. Figure B plots the difference in the estimated effects of a health shock on household income percentile. In the CHNS sample, a health shock is identified by a severe deterioration in self-reported health status. In the CFPS sample, a health shock is identified by a hospitalization record. The horizontal line represents the 90% confidence interval. Standard errors are clustered at the household level.

A Appendix

A.1 Additional Variable Definitions

Self-Reported Health Status The CHNS ask questions related to "How do you rate your health status?" In the CHNS, there were four levels of health status before 2009: "excellent," "good," "fair," and "poor." In the 2009, 2011, and 2015 surveys, there was an additional choice, "very poor," and the respondents were required to choose one from the five options.

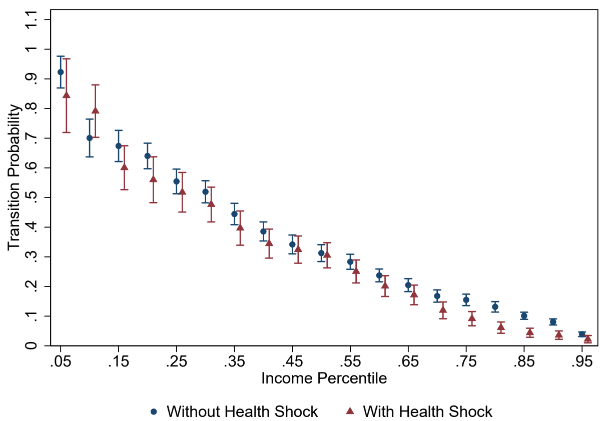
Change in Health Status We define change in the health status following Gertler and Gruber (2002). We consider a household memver to have "better health status" if his self-reported health status changes from "good or fair" or "poor" to "excellent," and to have "worse health status" if his self-reported health status changes from "excellent" or "good or fair" to "poor," and to have "unchanged health status" otherwise. In the CHNS, "excellent" health is defined as "excellent" self-reported health status, "good or fair" health is defined as "good" or "fair" self-reported health status, and "poor" refers to "poor" or "very poor" health status.

A.2 Health Shock and Transition Probability

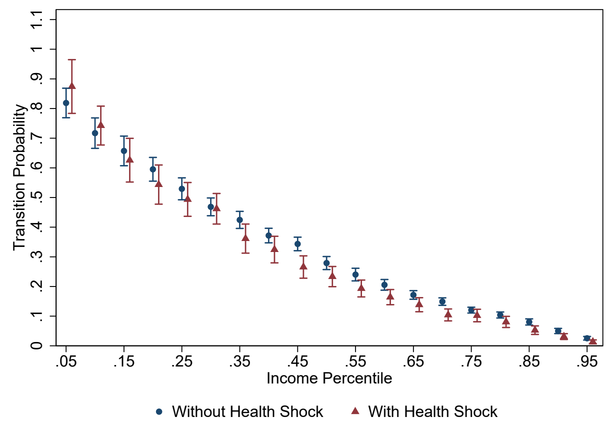
In this section, we plot the the transition probability between period -1 (one wave before the health shock) and period 0 (the wave after the health shock) in our two samples (CHNS sample and CFPS sample) for the treatment and control households, respectively, in intervals of 5 percentile points from 5 to 95.

Figure A1: Health Shock and Transition Probability

(a) CHNS Sample



(b) CFPS Sample



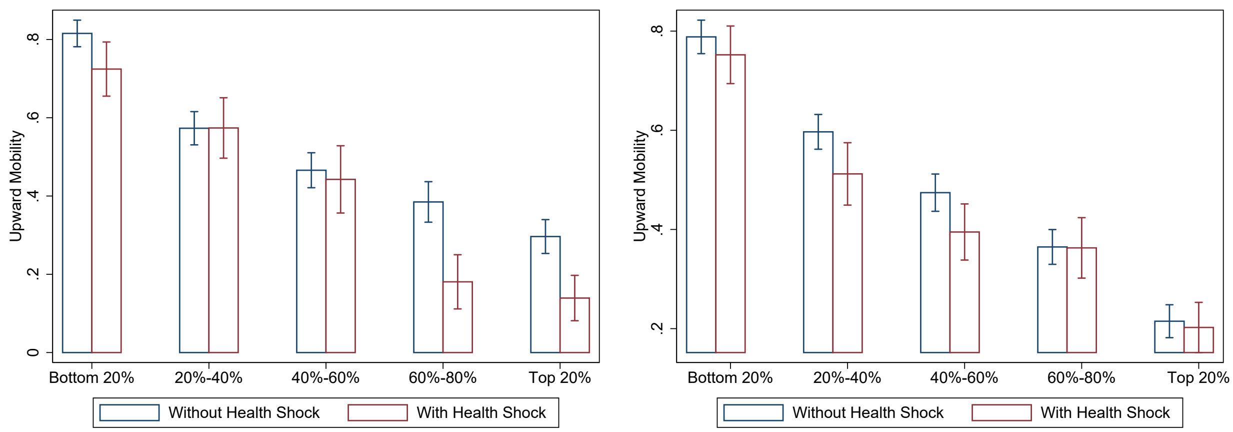
Notes: This figure plots the transition probability for the treatment and control groups in our two samples. Figure (a) presents the transition probability for the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Figure (b) plots the transition probability for the CFPS sample, where a health shock is identified by a hospitalization record. The treatment group refers to households that experienced a health shock. The control group refers to households with no health shock. The vertical line represents the 90% confidence interval computed based on the bootstrapped standard error.

A.3 Health Shock and Upward Mobility

In this section, we plot the the upward mobility between period -1 (one wave before the health shock) and period 0 (the wave after the health shock) in our two samples (CHNS sample and CFPS sample) for the treatment and control households, respectively.

Figure A2: Health Shock and Upward Mobility

(a) CHNS Sample (b) CFPS Sample



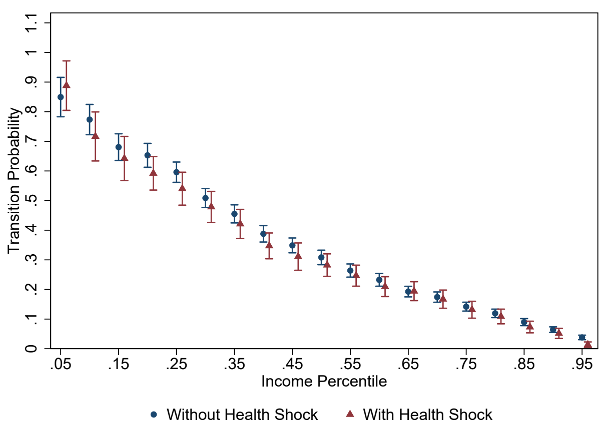
Notes: This figure plots upward mobility for the treatment and control groups in our two samples by initial income group. We group households into five income groups based on their initial income position, with each income group representing 20 percentiles in the national income distribution. Figure (a) presents the upward mobility of the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Figure (b) plots the upward mobility of the CFPS sample, where a health shock is identified by a hospitalization record. The treatment group refers to households that experienced a health shock. The control group refers to households with no health shock. The vertical line represents the 90% confidence interval computed based on the bootstrapped standard error.

A.4 Post-Shock Transition Probability Figures

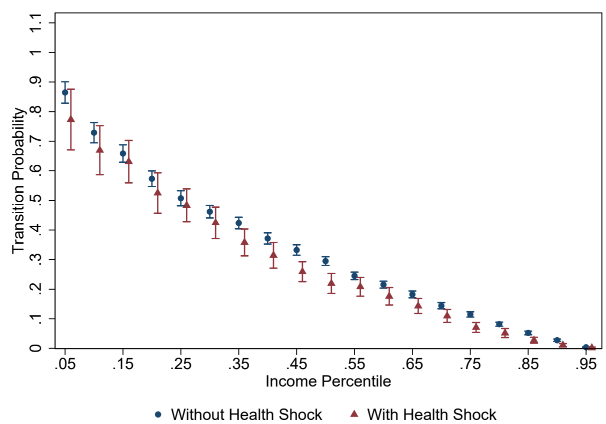
In this section, we plot the the transition probability between period 0 (the wave after the health shock) and period 1 in our two samples (CHNS sample and CFPS sample) for the treatment and control households, respectively, in intervals of 5 percentile points from 5 to 95.

Figure A3: Health Shock and Transition Probability

(a) CHNS Sample



(b) CFPS Sample



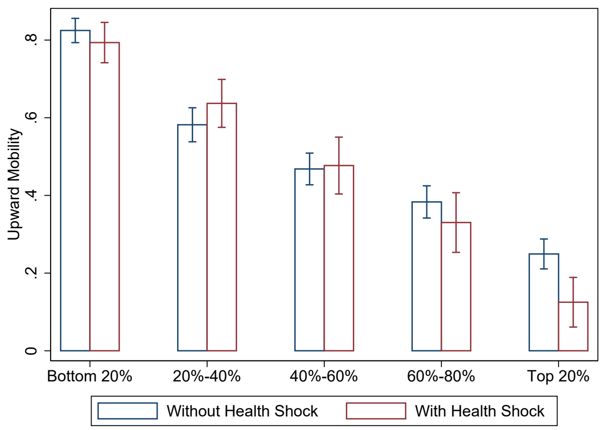
Notes: This figure plots the transition probability after the health shock for the treatment and control groups in our two samples. Figure (a) presents the transition probability of the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Figure (b) plots the transition probability of the CFPS sample, where a health shock is identified by a hospitalization record. The treatment group refers to households that experienced a health shock. The control group refers to households with no health shock. The vertical line represents the 90% confidence interval computed based on the bootstrapped standard error.

A.5 Post-Shock Upward Mobility Figures

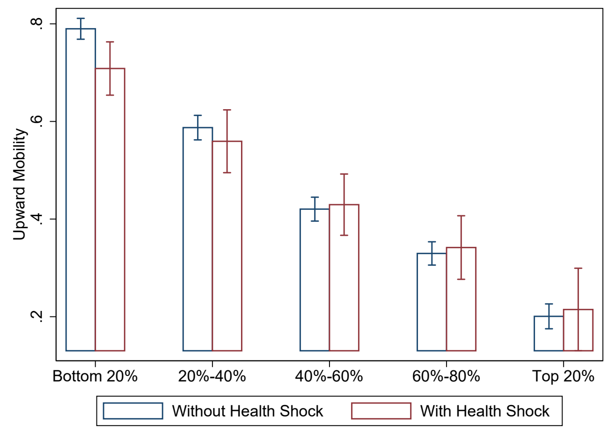
In this section, we plot the upward mobility between period 0 (the wave after the health shock) and period 1 in our two samples (CHNS sample and CFPS sample) for the treatment and control households, respectively.

Figure A4: Health Shock and Upward Mobility

(a) CHNS Sample



(b) CFPS Sample



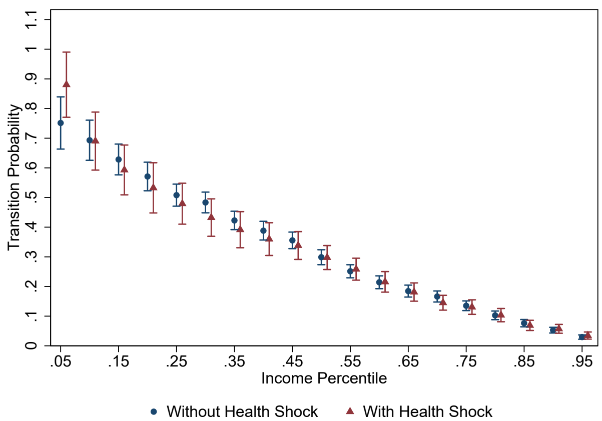
Notes: This figure plots the upward mobility after the health shock for the treatment and control groups in our two samples by initial income group. We group households into five income groups based on their initial income position, with each income group representing 20 percentiles in the national income distribution. Figure (a) presents the upward mobility of the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Figure (b) plots the upward mobility of the CFPS sample, where a health shock is identified by a hospitalization record. The treatment group refers to households that experienced a health shock. The control group refers to households with no health shock. The vertical line represents the 90% confidence interval computed based on the bootstrapped standard error.

A.6 Pre-Shock Transition Probability Figures

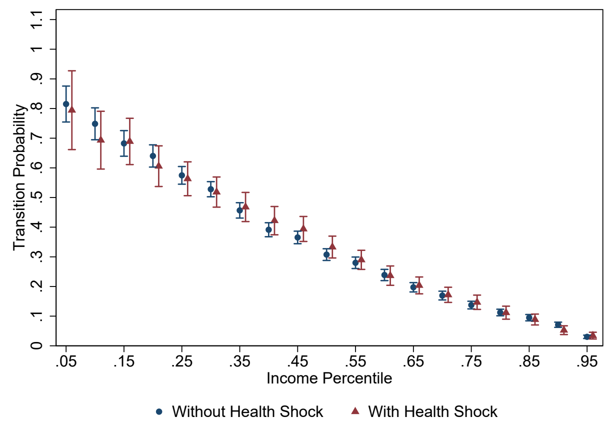
In this section, we plot the the transition probability between period -2 (two waves before the health shock) and period -1 (the wave before the health shock) in our two samples (CHNS sample and CFPS sample) for the treatment and control households, respectively, in intervals of 5 percentile points from 5 to 95.

Figure A5: Transition Probability before the Health Shock

(a) CHNS Sample



(b) CFPS Sample



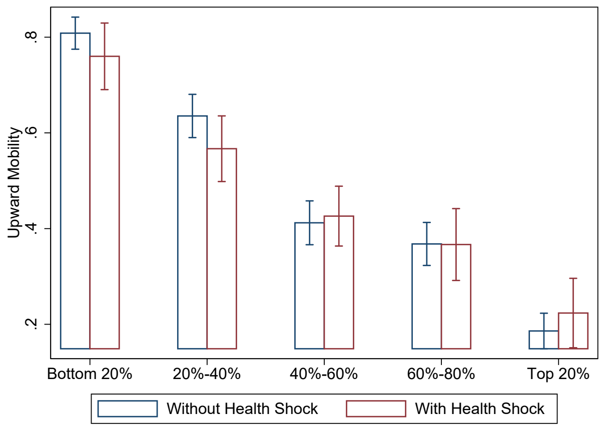
Notes: This figure plots the transition probability before the health shock for the treatment and control groups in our two samples. Figure (a) presents the transition probability of the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Figure (b) plots the transition probability of the CFPS sample, where a health shock is identified by a hospitalization record. The treatment group refers to households that experienced a health shock. The control group refers to households with no health shock. The vertical line represents the 90% confidence interval computed based on the bootstrapped standard error.

A.7 Pre-Shock Upward Mobility Figures

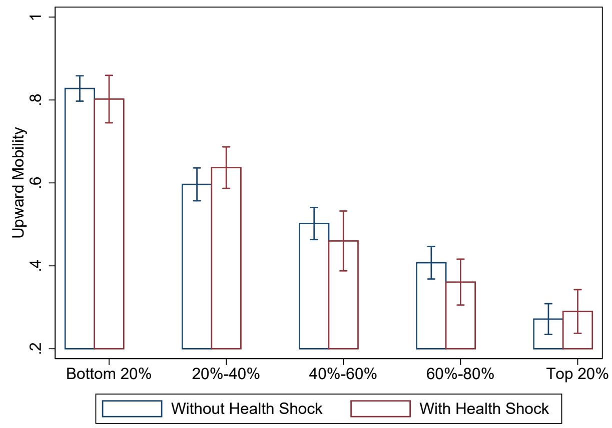
In this section, we plot the upward mobility between period -2 (two waves before the health shock) and period -1 (the wave before the health shock) in our two samples (CHNS sample and CFPS sample) for the treatment and control households, respectively.

Figure A6: Upward Mobility before the Health Shock

(a) CHNS Sample



(b) CFPS Sample



Notes: This figure plots upward mobility before the health shock for the treatment and control groups in our two samples by initial income group. We group households into five income groups based on their initial income position, with each income group representing 20 percentiles in the national income distribution. Figure (a) presents the upward mobility of the CHNS sample, where a health shock is identified by a severe deterioration in self-reported health status. Figure (b) plots the upward mobility of the CFPS sample, where a health shock is identified by a hospitalization record. The treatment group refers to households that experienced a health shock. The control group refers to households with no health shock. The vertical line represents the 90% confidence interval computed based on the bootstrapped standard error.