Health Inequality: Role of Insurance and Technological Progress

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Abstract

The paper investigates the role of insurance and technological progress on the rising health inequality across income groups. We develop a life-cycle model of an economy where individuals decide consumption-savings, whether to take up health insurance, when to visit a doctor and how much to invest in their health capital. Our estimates show that the timing of the health investments explain a substantial part of health inequality across wealth/ income groups. We find that while rich and poor have comparable health investments, there are substantial differences in the timing of the investments. The estimated model is able to explain about 65% of the gap in life-expectancy across income groups observed in data. We show that different types of technological innovation interacts with the timing of the investment and has a first order effect on disparities. On one hand, a non-uniform increase in the productivity of the medical sector – one where there are improvements in treating early stages of cancer for example, but none for stage 4 – can lead to increase in inequality in Life-expectancy. On contrast, a uniform increase in the productivity of the healthcare sector, leads to a reduction in disparities.

Keywords: Health Inequality, Technological Progress, Health Insurance

JEL Classification: I12, I13, I14, O11

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1. Introduction

There is a huge disparity in health outcomes across income groups in the US. Using the data from 2000-2014, Chetty et al. (2016) found that the gap in life expectancy between the poorest 1% and richest 1% was 14.6 years for males and 10.1 years for females. Another remarkable finding was that during the same period, the life expectancy for males increased by 2.34 years for the top income group but only by 0.32 years for the bottom income group[1]. Similarly for females, the increment in life expectancy was 2.91 years for those in the top income group, but only 0.32 years for the bottom income group. Skinner and Zhou (2004) document that while the inequality measured by health care expenditures across income groups went down during 1987-2001, the inequality in health outcomes increased. In a more recent paper, Ales, Hosseini, and Jones (2012) study inequality in total health spending (sum of insurance, Medicare, Medicaid and out-of-pocket) across income groups and conclude that the inequality in spending is only a bit higher than what would be justified solely based on production efficiency.

It is quite puzzling that while the total healthcare spending looks very similar across income groups, the health outcomes are very different and have worsened over time.

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This paper uses data obtained from the restricted-use file of the National Longitudinal Mortality Study and Mortality Differentials Across American Communities. The access to the two datasets at the U.S. Census Bureau was sponsored by National Center for Health Statistics, which is gratefully acknowledged. This paper also uses data from restricted use versions of merged NHIS-MEPS accessed via Agency for Healthcare Research and Quality Data Center. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Agency for Healthcare Research and Quality, National Longitudinal Mortality Study, Mortality Differentials across American Communities, the Bureau of the Census, or the NLMS-MDAC project sponsors: the National Heart, Lung, and Blood Institute, the National Cancer Institute, the National Institute on Aging, and the National Center for Health Statistics.
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[1] Mean income for top income group was $256,000 and $17,000 for the bottom income

The literature in the past has focused on behavioral factors such as smoking and role of education; however, it seems unlikely that smoking and education alone can explain not only the inequality in cross section but also the increasing and diverging trend, as documented in Chetty et al. (2016). In this backdrop, this paper explores the role of health insurance and its interaction with medical technological progress to explain part of the rising health inequality[2] in the US over the past decade.

There are significant differences in individuals across income and insurance status. Using National Longitudinal Mortality Survey (NLMS), Mortality Differentials Across Communities (MDAC) and linked National Health Interview Survey (NHIS)- Medical Expenditures Panel Survey (MEPS) from 2000s, we present the following empirical facts. For those in the bottom 40 percentile of income distribution, 35 percent of the individuals have no insurance as opposed to only 5 percent in the top 20 percentile of the income group. Moreover, possibly due to the lack of insurance, time since last checkup is significantly higher for the uninsured than those with private insurance. For individuals with preexisting heart conditions, the time since last cholesterol checkup for uninsured individuals was at least 25 percent more than the private insurance individuals across age.[3] Unconditional mortality rates and mortality rates conditional on having a medical condition are substantially higher for poor than the rich (source: MDAC). We also see that while larger fraction of poor have zero medical spending, they also have very high expenditures- they spend more on Hospitalizations and Emergency Rooms while rich spend more on Outpatient visits. Interestingly, for individuals in lower income group, visiting doctor seems to have little effect on transition from poor health to good health while visits to the doctor significantly improves the transition from poor to good health for rich.

Motivated by these empirical facts and following the strand of literature modeling health as health capital starting from the seminal papers by Grossman (1972) and Gilleskie (1998), we build a life-cycle model explicitly incorporating the decisions to purchase health insurance, timing to visit the doctor and how much to invest in their health capital. It endogenizes health accumulation usually assumed exogenous such as De Nardi et al. (2017) while incorporates the timing of the investment such as Gilleskie (1998) in a life-cycle model. Unlike Ozkan (2014) and Hong et al. (2015), our model doesn't rely on different technologies or preferences for health investments and is thus

[2]Defined as the difference in life expectancy at the age of 25

[3]See appendix.

closer to the standard class of models.

Given that the health shocks can arrive continually, our model brings continuous time methods[4], a popular tool used in macroeconomics and finance, into a problem involving individual's health related decisions, as done recently by Agarwal et al. (2019) in the context of kidney exchange. We summarize our findings from the model, which is consistent from the data, below:

- While the total health spending across income groups is similar, the timing of the spending is very different for the rich and poor. Lower wealth individuals have a highly elastic visit decision.
- Fixing health, wealthy spend more on their health over the next year, thus transitioning to a better health with a higher probability.
- Health inequality starts off low at the beginning of working-life and increases substantially by the age of 45. Our estimates show that the timing of the health investments, explain a substantial part (65 percent) of health inequality across wealth/income groups.
- The type of technological progress and its interaction with the visit decision is one of the key determinants of increased health disparities. A uniform increase in productivity of the healthcare sector lowers the inequality while a non-uniform increase increases the disparity.
- Poor uninsured individual defers getting the treatment until his health deteriorates significantly, poorer individuals aren't able to improve their health even by spending the same amount of money, i.e. they don't get the bang for the buck.

We can provide an example to narrate our results. Suppose that the medical technology today is such that cancer until stage 2 can be treated. While the rich, frequently going to see the doctor, is able to diagnose cancer at stage 1, the poor, having deferred the treatment, is able to diagnose only when his cancer is in stage 3[5]. Thus, he not only ends up spending the same amount as a rich person in any given year, he is also not

[4]See Achdou, Han, Lasry, Lions, and Moll (2017) for a detailed explanation of an algorithm to solve continuous time models numerically.

[5]See, for example, Walker et al. (2014) and Niu et al. (2013) which use Surveillance, Epidemiology, and End Results (SEER) registry data to document the differences in diagnosis stage of cancer across insurance groups providing basis for our example here.

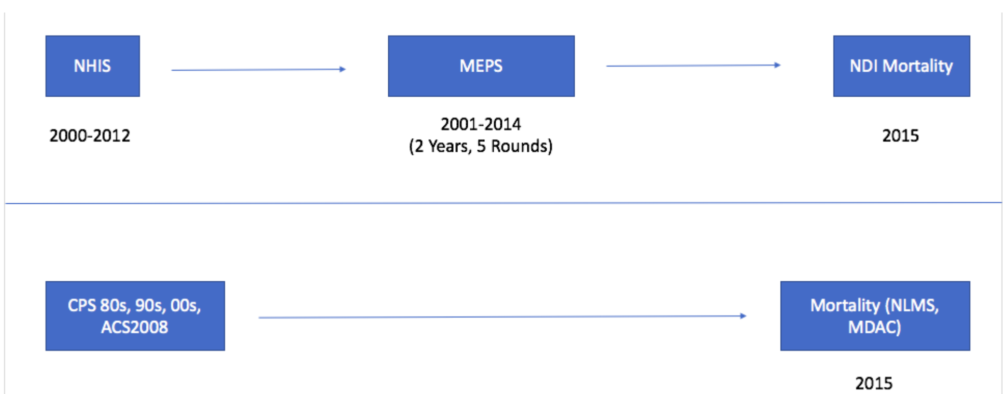
able to reap the benefits of the medical technological progress that we have witnessed. It is consistent with the fact that the type of cancer for which the survival rates have converged the most for affluent and less affluent over the past 2 decades is Hodgkin Lymphoma [6] for which the survival rate is relatively flat across cancer stages[7] while the cancer for which the survival rates have diverged the most is Oesophageal cancer which has a steep one-year mortality rate across the cancer stages[8].

Our rich quantitative model – estimated from the newly available data – is well suited to: understand and quantify the channel through which health insurance affects individual's decisions on health spending, frequency of visits to the doctor, health outcomes such as mortality; understand the channels through which income groups benefit differently from the medical technological progress and guiding policy to ensure health equity.

The model can be easily extended to quantify the impact of making health insurance premium not dependent on pre-existing health conditions (Affordable Care Act) on health outcomes, worker productivity, hours worked and output; evaluate lower age for Medicare and "Medicare-for-all" on worker productivity, working hours and their health outcomes; and effect of population aging on the optimal design of health policies.

The remaining of the paper is divided as follows: section 2 provides the motivating empirical facts, section 3.3 describes the model, followed by estimation and results, section 8 concludes.

2. Data



[6] Cancer Research UK, Accessed April 2021
[7] Cancer Research UK
[8] Source: UK Cancer Cancer Research UK Accessed: April 2021

The dataset is constructed from four main sources, namely, Merged National Health Interview Survey (NHIS)-Medical Expenditure Panel Survey (MEPS) and National Longitudinal Mortality Survey (NLMS) and Mortality Differentials Across Communities (MDAC). MEPS is a rolling panel and provides us with 5 snapshots over two years, its sample is drawn from the cross sectional NHIS. A merged dataset thus allows us to track individuals for 3 years in 6 snapshots from the start in year 2000 - 2015 along with ex-post mortality status until 2015 irrelspective of the sample year. We provide a brief description of the datasets here.

1. Merged National Health Interview Survey (NHIS) - Medical Expenditure Panel Survey (MEPS): We use harmonized Integrated Public Use Microdata Series (IPUMS)-NHIS data from 1996-2015 and augment it with variables from Medical Expenditure Panel Survey (MEPS) including the recently available harmonized IPUMS-MEPS. We use the restricted link-file to merge individuals across the two datasets. Variables from NHIS include (not an exhaustive list):

    - Demographic and Socio-Economic Variables: Education, Income, Age, Sex, Occupation, Family Income, Hours worked, Health Insurance: type and coverage
    - Health Care Utilization: Number of shots , Number of visits to doctor in the past 12 months, time since physical breast exam, blood stool test, genetic test, mammogram, skin cancer exam, CT scan
    - Health Outcomes: Body Mass Index, Bed Disability Days, lost days of work, history of diseases requiring diagnosis including asthma, cancer, coronary heart disease, diabetes, emphysema, heart attack, etc., date and detailed cause of death

    Variables from MEPS include (not an exhaustive list):

    - Demographic and Socio-Economic Variables: Education, Income, Age, Sex, Occupation, Family Income, County and State of Residence
    - Medical Conditions: life-threatening including cancer, diabetes, high cholesterol, hypertension, heart disease, and stroke; chronic conditions including arthritis, asthma
    - Event-level Medical Visit, ICD-9 Diagnosis and Procedure Code, Expenditure and Charge: Detailed event-level visit and expenditure variables; Expenditure

by visit type such as outpatient, hospitalization, emergency; Expenditure by payment source such as private insurance, Medicaid and out of pocket

- Health Insurance: type and nature of coverage under each plan; duration of coverage; payment source of policy premium; employer and non-employer related coverage
- Preventive Care: Mammogram, Pap test, breast exam, PSA test, physical exam, blood pressure reading, and flu shot

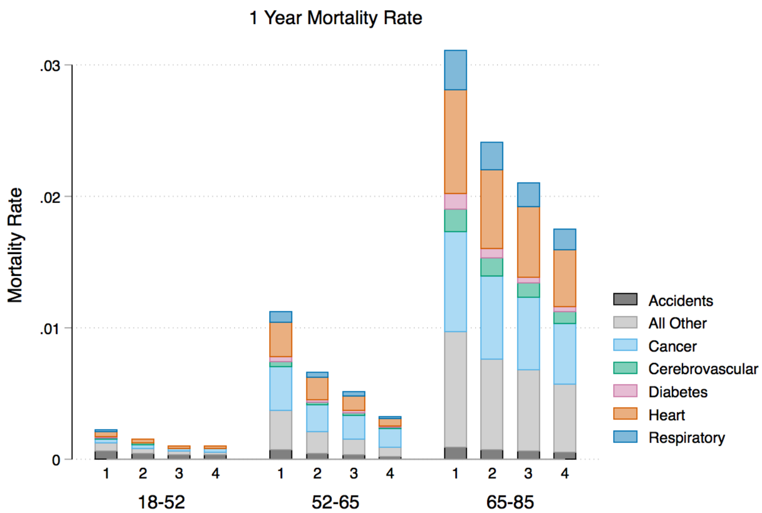
2. National Longitudinal Mortality Survey (NLMS) and Mortality Differentials Across Communities (MDAC): Besides the demographic and socio-economic variables described earlier, NLMS includes detailed date and cause of death across multiple CPS waves from 1980- 2008. In particular, we get three normalized waves for 1983, 1993, 2003 where they track the cause of death for 6 years starting the date of interview or one 1990 wave where they track the cause of death for 11 years. Some waves include additional information on tobacco use. Similar to NLMS, MDAC covers individuals interviewed in ACS 2008 and their matched mortality details until 2015. Together, NLMS and MDAC would provide us with about 9 million records in various waves from 1980 to 2015 and merged mortality information from death certificate until 2015 (upto 35 years of mortality tracking). Detailed zip codes and longitudes, latitudes of residence are also available in this dataset.

Due to absence of a life-cycle panels of the individuals, we use family income or wealth adjusted for family size as a proxy for permanent income. Quartiles are determined by income or wealth distribution for age decade (25-35, 35-45, and so on). Amongst these two measures, family income is consistently available across all datasets relative to wealth and therefore, this is the measure we primarily use for analysis. We conduct robustness checks with wealth. If income or wealth is not observed for some datasets (such as NLMS-MDAC), we use poverty percent which adjusts for family size[9]. Note that in order to account for the life-cycle pattern in income and wealth, the quartile cut-offs are based on age decade (25-35, 35-45, and so on). Unless otherwise stated, the bottom quartile will be referred to as poor and top quartile as rich.

2.1 Health outcomes and health spending: a Puzzle

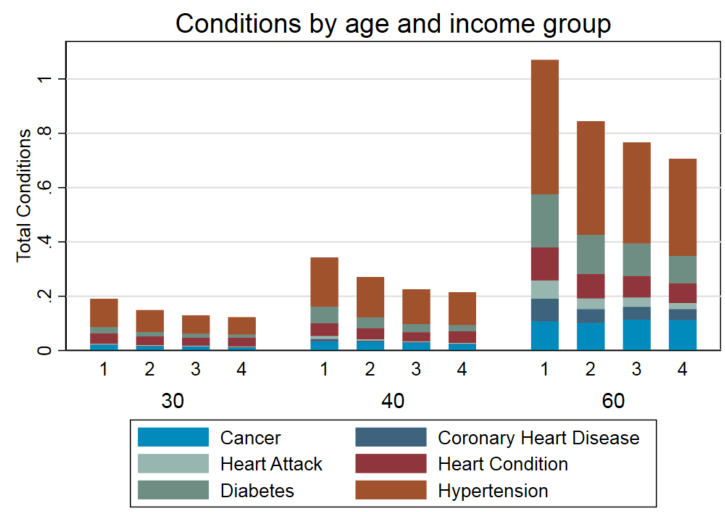
[9] Details on poverty variable here

Figure 1: 1-Year Mortality Rates by Age and Income



Source: NLMS-MDAC

Figure 2: Conditions by Age and Income



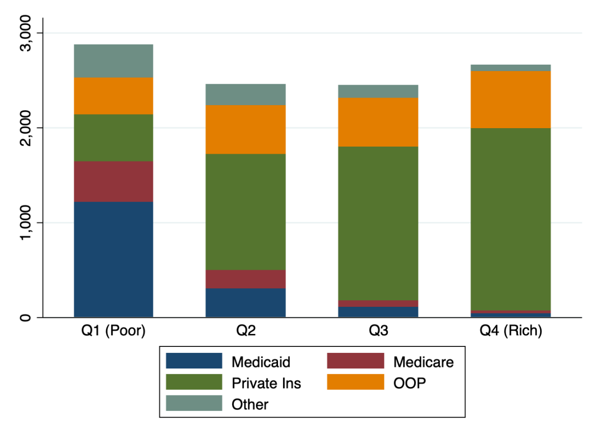
Source: NHIS-MEPS

Poor and rich have comparable total medical spending, but very different outcomes

The leading cause of death across the income distribution were cancer and heart conditions based on one-year crude mortality from MDAC. As shown in Figure 1, we see that across all age groups and cause of death, individuals in fourth quartile of family income distribution[10] have a lower aggregate and cause-specific mortality-rate compared to individuals in first quartile of family income distribution. This pattern has been well documented in the literature including Chetty et al. (2016). For those in 52-65 age group, the mortality-rate of top quartile of income is less than half of the mortality-rate of the bottom quartile of income. This inequality in health outcomes isn't limited to mortality as documented in Figure 2. Across the age-distribution, individuals in bottom quartile of family income distribution report having more medical conditions such as hypertension and diabetes, compared to their rich counterparts. For individuals in age group 55-65, average number of conditions in a person in bottom quartile is more than one, which is about 50% higher than average number of medical conditions in a person in the top family income quartile.

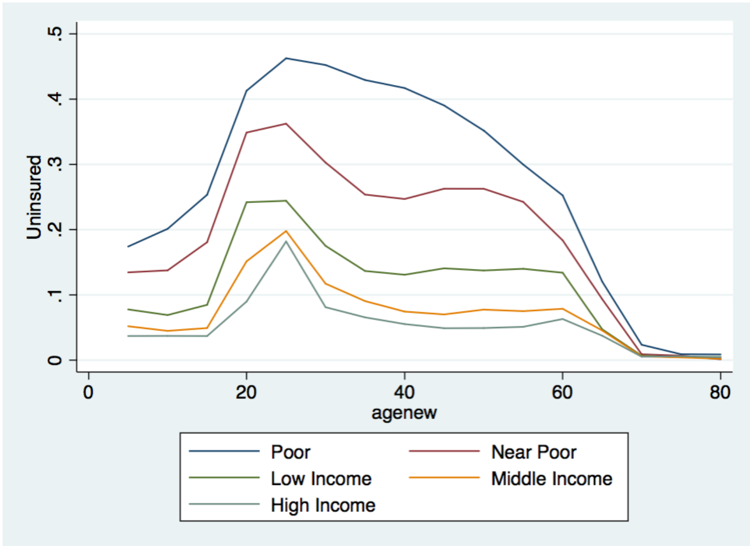
[10]The patterns are very similar when we define the quartiles based on wealth.

Figure 3: Medical Investment Age 35-45



Source: NHIS-MEPS

Figure 4: Fraction Uninsured by Income and Age



Source: NLMS-MDAC

As documented by Ales, Hosseini, and Jones (2012), we see that the mean total medical spending including the portion covered by private insurance, Medicaid, Medicare, and out-of-pocket looks comparable across family income distribution. For instance in ages 35-45, individuals in bottom quartile of the family income distribution spent a little more than \$ 3,500 annually while those in top quartile of the distribution spend about \$ 3,100 annually as shown in figure 7. Similar pattern holds for other age groups, as shown in Appendix.

It's also not surprising given the large literature on this that about 40% of those in bottom 20% of family distribution are uninsured. Consequently, breaking down the spending by source of payment reveals that very low fraction of poor's total medical spending comes from private insurance.

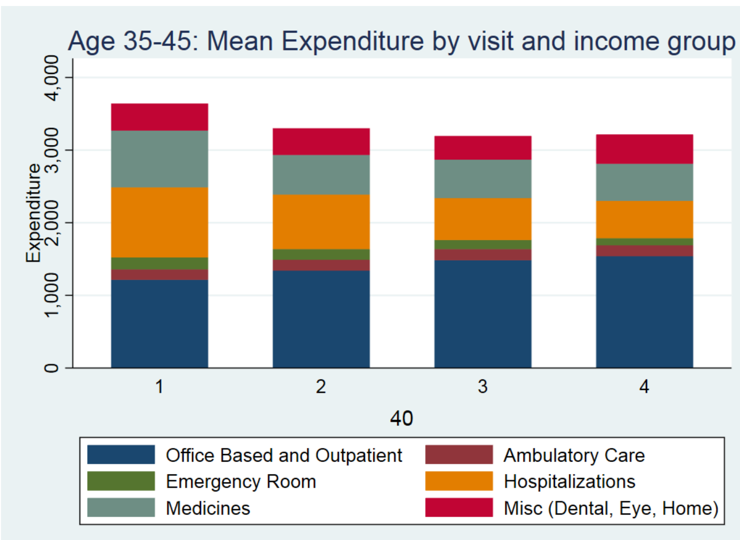
A natural question that arises from looking at the two facts documented in the literature is: why is it that while the rich and poor end up spending roughly the same amount in absolute dollars on their medical spending annually, the outcomes are so drastically different. Moreover, why is it getting worse over time? The answer to this question has huge consequences for public policy: for example, if poor are already spending comparable to the rich, will there be any returns from expanding Medicaid eligibility? Why is it that poor are not getting bang for their buck?

In order to understand the sources, we will now dig deeper into the data. To the best of our knowledge, the empirical facts in the next section are relatively unexplored in the literature.

2.2 Empirical Facts

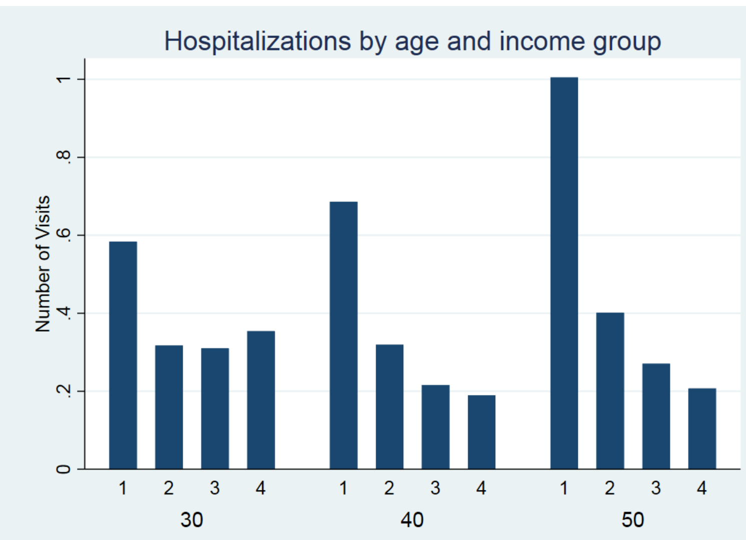
Fact 1. Poor spend more on Hospitalizations and Emergency Rooms while rich spend more on Outpatient visits

Figure 5: Mean Expenditure by Visit, Age 35-45



Source: NHIS-MEPS

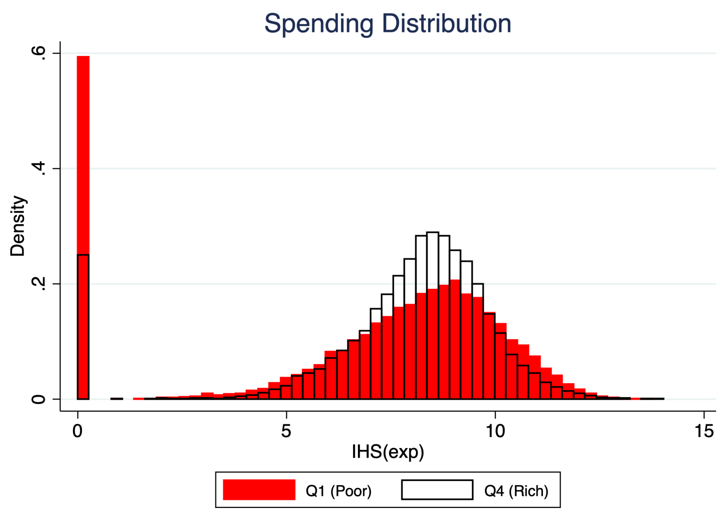
Figure 6: Number of Hospitalizations by Age and Income



Source: NHIS-MEPS

While the rich and poor, defined based on family income quartiles, spend comparable amounts in total medical expenditures, those in bottom quartile of the distribution spend significantly more on hospitalizations ($1000 for first quartile vs $500 for the top quartile for ages 35-45) and emergency room while those in top quartile of the distribution spend more on office based and outpatient visits ($1100 for the first quartile vs $1500 for the top quartile for ages 35-45, Figure 5). This is also evident from the number of hospitalizations in Figure 6. Individuals in top income quartile had less than a third of hospitalizations than bottom income quartile for age 35-45.

Figure 7: Medical Expenditure Age 45-55 (IHS transformation)



Source: NHIS-MEPS

In figure 7, we document the inverse hyperbolic sine (IHS) transformation of the distribution of medical expenditures for 1st and 4th quartile based on family income. We observe that while larger fraction of poor have zero medical spending, they also have thicker tails in expenditure distribution, which suggests that while they are less likely to go for a doctoral visit in any given year, if they do, they end up spending more than the rich who are going for doctoral visits.

It is also important to understand how the spending or expenditure is reported. Spending or expenditure is anything for which the provider was compensated for and thus it does not include uncompensated care[11], which would likely increase poor's spending. Note that the expenditure/ spending is the amount that finally gets paid, i.e. the negotiated amount after the discounts and is lower than the charge. There are certain limitations to this spending data. First, prices are not known. Therefore, if the insurance providers negotiate a better price for the same quantity, the poor get a lower quantity of medical goods even after spending the same amount. It is also worth noting that public provisions such as Medicaid, which is available for the poor subject to income

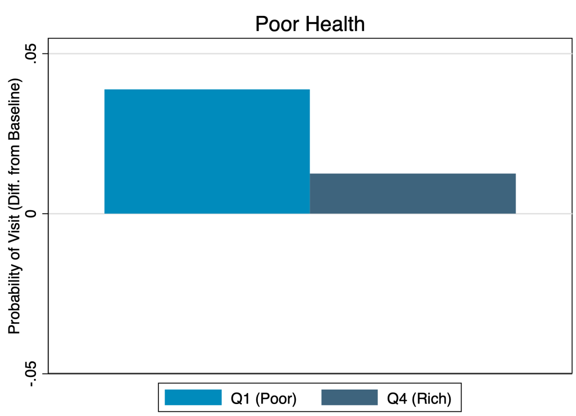
[11]Uncompensated costs were about $41 Billion or 1% of the total medical expenditure. Source: https://www.aha.org/fact-sheets/2020-01-06-fact-sheet-uncompensated-hospital-care-cost

and asset criteria pays for more than a third of poor's medical spending and Medicare, which consists of about 10% of the expenditure for the poor as in figure 7 for those in 45-55 ages, are one of the most efficient negotiators and negotiate some of the lowest prices for the medical services (see for example, Clemens and Gottlieb (2017)).

Second, another potential concern is that the same service is being provided to the poor, at a higher price, simply because they visit the ER while rich visit outpatient. To address these concerns to the extent we can based on the available data, we look at the average, charge-to-expenditure ratio over the working ages. For the rich charge-to-expenditure ratio goes from 1.4 early in the life-cycle to 1.5 after 65 while it goes from 4.7 early in the life-cycle to 1.5 for later ages for the poor. This suggests that, if anything, the services being provided to poor are negotiated intensely as opposed to rich. For the visits for which we expect similar service – such as ambulatory optometrist or ambulatory dentist – the charge-to-expenditure ratio is comparable all across the income spectrum with rich (1.2) only slightly lower than poor (1.4). This can be further done at the service level, such as Magnetic Resonance Imaging, MRI or an X-Ray, something that will be added in the later versions due to data limitations.

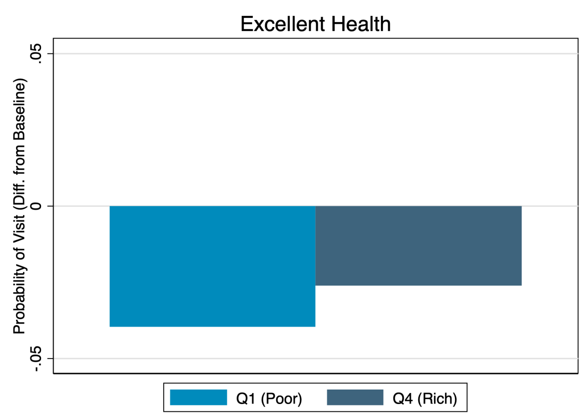
Fact 2. Rich individuals go to the doctor in a much healthier state

Figure 8: Elasticity w.r.to. Health State: Poor vs Rich



Source: NLMS-MDAC

Figure 9: Elasticity w.r.to. Health State: Poor vs Rich



Source: NHIS-MEPS

Notes: Includes individual fixed effect regression of doctoral visit from t to $t+1$ on health in time t, run separately by income groups. Base set to average health in each income group regression.

Figures 8 and 9 document the elasticity of doctoral visit w.r.to self-reported health status for rich and poor. To this end, we run two individual fixed effect regressions for each income groups with base set as average health state. The variation for this regression comes from the panel component where we observe an individual and its doctoral visit decision on his/ her health status. We plot the regression coefficient associated with the health status dummy with values poor health and excellent health for each income group regression.

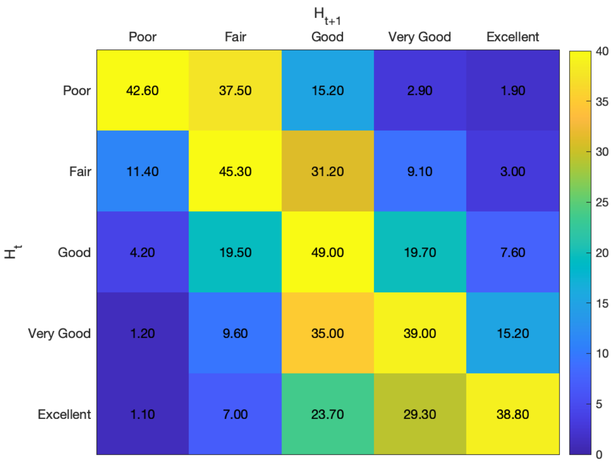
The results indicate that poor individuals visit decision is highly elastic w.r.to their health state. Compared to a poor person in average health, a poor person in poor health is 4% points more likely to go to the doctor. This number is only 1% points for the rich. Similarly, compared to a poor person in average health, a poor person in excellent health is 4% points less likely to go to the doctor. This indicates that while rich go to the doctor all the time, poor only go to the doctor in poor health. These results suggest that compared to the rich, poor individuals wait until their health deteriorates to a much worse health state before they go to the doctor and get the treatment. Note that for this analysis, we do not need the self-report status to be comparable across income groups since the coefficients are identified off of the *change* in health status.

Fact 3. Going to the doctor improves rich individuals' health more than that of poor

In Figure 10 and 11, we compare the annual transitions in health for individuals in the first quartile and fourth quartile of family income distribution conditional on medical visit. For those in poor health in time t, 42% of poor remain in poor health while compared to 35.8% for rich. Similarly, more than 56% of poor in fair health remain in poor or fair health compared to 37% for the rich. The pattern is similar across age groups, as shown in the appendix.

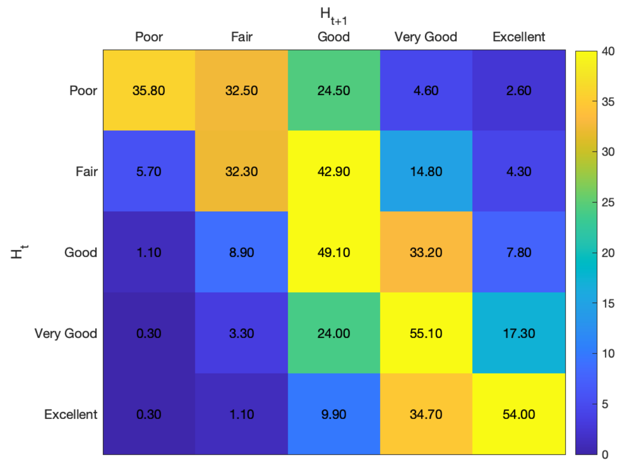
This is also a good place to emphasize the need to model the visit decision – if we compare the transition matrix of those who didn't go to the doctor, shown in figure 12 with those who did in 10, we see that those who didn't go to the doctor transitioned to a better health with a higher probability. Simply put, those whose health got better were also the ones who didn't demand any healthcare, i.e. didn't need to go to the doctor. Thus, modeling visit decision is crucial to understand the health related outcomes.

Figure 10: Transition matrix | visit: Poor aged 35-45



Source: NHIS-MEPS

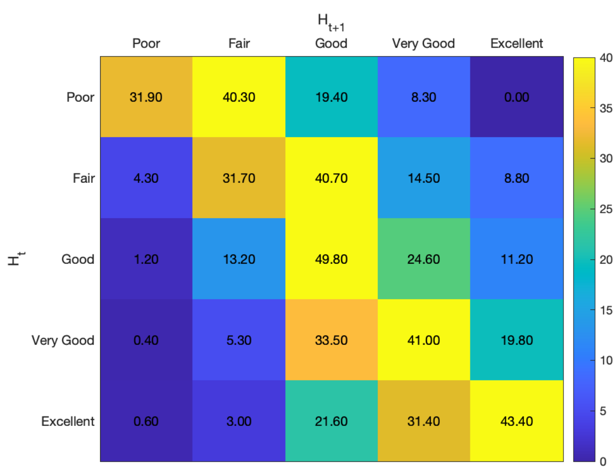
Figure 11: Transition matrix | visit: Rich aged 35-45



Source: NHIS-MEPS

Notes: Raw transition matrix from H_t to H_{t+1} on annual data

Figure 12: Transition matrix | no visit: Poor aged 35-45



Source: NHIS-MEPS

Fact 4. Cancer related innovation is a major contributor in increased health disparities

We find that, conditional on surviving until age 20, there is a gap of about 8 years in the top and bottom quartile of the family income distribution. From 1983 to 2003, those in bottom quartile have gained about 2 years and 5 months, those in top quartile have gained 4 years and 7 months. This aggregate pattern of increasing life-expectancy gap is also consistent with others that have looked at the aggregate life-expectancy such as Chetty et al. (2016).

In order to understand the underlying components of the changes in life-expectancy, we do a decomposition by age and cause specific mortality across four family income groups adjusted for family size[12], a lá Becker et al. (2005).

Let S_k be the survival rate implied by a cause of death, k. If there are K competing causes of death, assumed independent, survival rate is given by $S = \prod_{k=1}^{K} S(k)$. As is standard, survival function directly maps into life-expectancy[13]. With time, the survival rate changes and is now given by S'. Now, if we were to compute the survival rate if only the cause of death $i \in \{1, 2, ..K\}$ had changed from S_i to S'_i. The counterfactual survival rate is given by, $S_{ci} = \prod_{k \neq i} S(k) S'_i$. Thus, the life-expectancy implied by the survival rate S_{ci} would be counterfactual life-expectancy, if only cause-of-death i were to change. A direct implication of this is that the change in life-expectancy implied by the survival rate S_{ci} and S would be the change in life-expectancy if there were changes in cause-of-death i.

Similarly, we can extend this to age and cause specific survival where $S_{k,a}$ be the survival rate implied by a cause of death, k for age, a. The counterfactual survival rate if only the cause of death $i \in \{1, 2, ..K\}$ for age a had changed from $S_{i,a}$ to $S_{i',a}$ is given by, $S_{c,i,a} = \prod_{k \neq i} S_{k,a} S_{i',a}$. We implement the above decomposition by considering 8 major cause of death groupings defined by NCHS and age groups 20-50, 50-80 and 80+. We take the groupings as in Becker et al. (2005), but add the category 80+ to understand the gains at the end-of-life cycle separately. We use the geometric average of the 6-year mortality rates from 1983 using NLMS wave a and define it as an average mortality rate in 1980s while use wave c for the average mortality rate in 2000s. This is done to

[12] We define the groups using age adjusted poverty percent variable which adjusts for family size

[13] We use period life-expectancy which is commonly used by the US Social Security Administration in its projects. It tries to obtain the expected duration a person of a given age at time t is going to live if he/ she were subject to the same mortality rate as experienced by the whole population in period t. More details cane be found here: https://www.ssa.gov/oact/NOTES/as120/LifeTables˙Body.html

increase the sample size by exploiting whole person-year observation, given the age and mortality specific decomposition we are interested in.

While the improvements in heart related causes have contributed the highest gains in life-expectancy, their distributional impact have been limited. As shown in Table 1, while poor have gained 2.6 years in life-expectancy due to heart related causes, rich have gained 2.7 years in life-expectancy. It is malignant neoplasms (cancer) that have contributed significantly to the rising health inequality across rich and poor over the two decades from 1983 to 2003. An age-based decomposition of life-expectancy gains tells us that while most gains have been for ages 50-80, gains above 80 years have also contributed to the rise in health inequality across income groups. Drug-overuse is attributed in accident and is consistent with the fact that they weren't large until 2010s while our mortality followup ends in 2010 in the above table. Category others include Alzheimer's and other forms of dementia, whose occurance has gone up in the recent decades.

One limitation of this analysis is that we use poverty percentiles to define income groups instead of wealth or permanent income. This is due to the fact that we only have cross section information and mortality follow-up in NLMS-MDAC and thus, are unable to do such decomposition by other classification. Another limitation of this decomposition is that it since it uses population mortality/ survival rates, it treats large reduction in mortality rates for small fraction of population similar to small reduction in mortality rates for large fraction of population. We perform robustness checks for this pattern across finer age bin and the results are similar.

Table 1: Gains in Life-expectancy: 1980s to 2000s

	Q1 (Poor)	Q2	Q3	Q4 (Rich)
Life-expectancy 1983	70.7	74.2	77.4	79.2
Total Change (1983 - 2003)	2.4	2.7	3.1	4.7
By cause of death:				
Accident	0.1	0.1	0.2	0.2
Other	-1.1	-0.6	-0.6	-0.2
Malignant neoplasms	0.3	0.3	0.7	1.2
Cerebrovascular	0.4	0.2	0.2	0.4
Diabetes	-0.2	-0.1	-0.0	-0.1
Heart	2.8	2.6	2.8	2.9
Respiratory	-0.0	0.1	-0.1	0.2
Unknown	-0.0	-0.0	-0.0	0.0
By age group:				
20-50	-0.1	0.3	0.0	0.5
50-80	2.2	1.7	2.4	3.3
80+	0.2	0.7	0.7	0.9

Life-expectancy conditional on surviving until age 20.

3. Model

Based on the empirical findings, we develop a life-cycle model of an economy where individuals decide consumption-savings, whether to take up health insurance, when to visit a doctor and how much to invest in their health capital. The model brings continuous time methods, a popular tool used in macroeconomics and finance, into a problem involving individual's health related decisions[14], and is set up based on our data availability.

[14]See for example, Agarwal et al. (2019) who use continuous time to model kidney exchanges

3.1 Setup

Timeline

Individuals are born young with initial wealth and initial health. While wealth is continuous state variable, health is a discrete state from 1-5 with 1 being poor health and 5 being excellent health, as observed in data. Individuals' transition from one health to another as governed by the Poisson intensities. They age when hit by age Poisson η and die when hit by the death Poisson $\lambda(h,a)$. The stochastic evolution of health can be thought of as consisting four parts: deterioration governed by intensities d_h^a as a function of health, h and age, a, improvement governed by intensities ν_h^a, sudden illnesses which could lead to mortality governed by intensities λ_h^a and stochastic aging governed by intensity η[15]. Other than the standard consumption-saving decisions, individuals face two crucial decisions: whether or not to buy private insurance at the actuary fair premium and subsequently, given their insurance status and wealth, when to go for a medical visit and invest in their health.

Note that in the current version of the model, there is no information asymmetry. In particular, we assume that individuals observe their health capital with/without medical visit or in other words, health is common knowledge at all times. We leave more interesting version in which health capital cannot be observed perfectly, for future research.

Evolution of health capital

The evolution of health capital follows a Poisson process with an exogenous depreciation, which is governed by d_h^a, and endogenous appreciation, which is governed by ν_h^a. d_h^a is the intensity with which a person of age a, goes from state h to $h-1$. Improving one's health is governed by intensity ν_h^a, which is the intensity with which a person of age a goes from state h to $h+1$. Individuals age at a rate η which is set to match the interval of 10 years in each age state., i.e. on average a person stays in an age group for 10 years before aging and transitioning to the next age group. Note that upon aging, the health and wealth of the individual remains the same although at an older age, the health is allowed to depreciate at a higher intensity. Individuals in health state h and age a die and exit the model with intensity λ_h^a. All the intensities are allowed to vary by health, h, and age, a to allow for the fact that healthier individuals are more like to die at

[15]It is analogous to a continuous time life-cycle model with finite horizon. Stochastic aging helps us make the model stationary and reduce the computation burden, a standard practice.

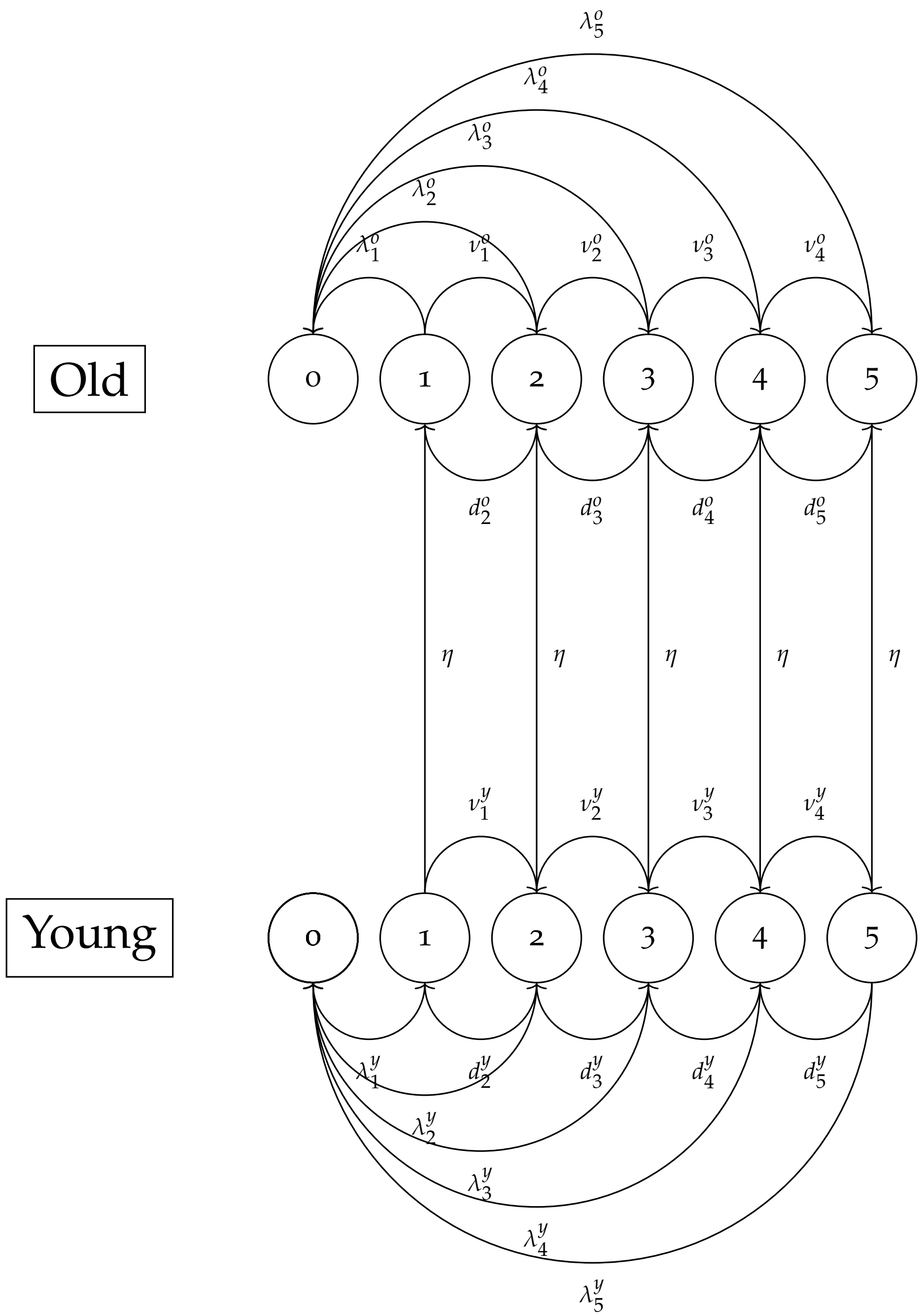


Figure 13: Illustrative health evolution with two ages

a much lower rate compared to individuals in poor or bad health at the same age ($h = 1$ or 2).

Figure 13 illustrates the evolution process for two age groups - 'Young' and 'Old'. Consider a young individual born in good health state, i.e. in node 4 for the figure. He can transition to average health, i.e. node 3, with intensity d_4^y, transition to a better health state, i.e. node 5, intensity ν_4^y, get hit by the aging Poisson with intensity η and transition to node 4 of state 'Old' or be hit by the mortality shock λ_4^y and exit the model. Note that exit, depicted by node 0, is an absorbing state.

An alternative way to think about the health evolution process is that it is a modified birth and death process adjusted to account for mortality, aging and endogenous Poisson intensities. The formulation is general enough to capture a potential increase in the depreciation of health as individuals age and a reduction in health improvement. Due to data limitations, we only allow for one step above or below in health transitions. Given that we only observe five snapshots for the two years the individual is observed in data, we do not know the exact time the individual stayed in a particular health state or the transition path of health followed. For example, we observe that an individual is in health state 4 in quarter 1 and health state 2 in quarter 2, we won't be able to see if he transitioned directly from 4 to 2 or he went from 4 to 2 via 3 or even 1 for that matter. Therefore, this is an identifying restriction that we need to impose to be able to pin down the Poisson intensities. Since we observe the exact duration of exit in our data, we allow exit from all health states. While the assumption for health transitions may sound restrictive, given that the model is in continuous time, probability of any transition in any interval is non-zero. Note that continuous time allows us to think about the evolution continually as opposed to discrete time where we typically have to put stronger restrictions on when the choices can be made.

Health capital investment

At time t, individuals observe their health h_t, wealth w_t and the Poisson of going to a better health state ν, their (endogenous) insurance status I_0. Individuals can invest in the likelihood of transitioning to a better health, i.e. invest in the Poisson intensity ν. The evolution process of ν is a function of two parts: (1) an exogenous natural improvement rate $\nu_0(a)$, which depends on age a, to capture the feature of data that individuals transition to a better health state without doctoral visits; (2) an endogenous component Am^{α_m}, which depends on m or the amount of medical spending optimally chosen by the individual to invest in their health capital which has a technology with Total Factor Productivity A and a returns to scale parameter of α_m. The evolution equation is as follows:

$$\nu' \;=\; \nu_0(a) + Am^{\alpha_m}$$

We assume that individuals choose medical spending but it is analogous to a altruistic physician who makes the plan of care decision for the person. Every time, an individual transitions to a better or lower health state, ν resets to ν_0. Absent this reset, investments in ν would be completely persistent and individuals would simply invest once to get to a very high ν and never invest again. This setup also captures the idea that there is some uncertainty associated with a doctoral visit. Since the individuals are investing in the probabilities or Poisson intensities, it is possible that they spend a lot of money but are not able to get to a better health state.

Investing in medical spending is a function of insurance status I_0. They face a fixed cost of going to the doctor $k(I_0)$ (or deductible) and a proportional out-of-pocket cost depending on their insurance status $m(1 - q(I_0))$ where $q(I_0)$ can be thought of as co-payment (= 0 if uninsured). It is important to emphasize that because of the fixed cost $k(I_0)$, the individuals don't invest in their health continually and it becomes a stopping time problem where individuals choose to invest in their health by visiting the doctor as a discrete choice. Thus, the wealth evolves as:

$$\overbrace{w'}^{\text{Wealth after visit}} = \overbrace{w}^{\text{Wealth before visit}} - \overbrace{k(I_0)}^{\text{Fixed Cost}} - \overbrace{m(1 - q(I_0))}^{\text{Out-of-pocket Cost}}$$

Thus, individuals optimally choose when to visit the doctor and how much to spend on medical care. There are various channels through which individuals may want a better health: direct utility from a better health, higher labor productivity resulting in higher labor income, lower likelihood of dying and getting the terminal value and getting a better insurance premium when the premium Poisson realizes.

Wealth and Income

An individual earns an income $\theta(h)y(e, a)$ which varies by education, e and age a. We also allow for income to be scaled by labor productivity $\theta(h)$ which is an increasing function of health h. Individual consumes c and pays an health insurance premium p, if insured (otherwise, it is set to 0). They also earn a rate of return r on wealth w_t. The budget constraint is standard and is given by:

$$dw_t = \left(rw_t + \theta(h)y(e,a) - c_t - p\right) dt$$

Utility Function

Individuals derive utility from consumption c and their health h and the specification is as follows:

$$u(c,h) = (1+\phi(h))\frac{c^{1-\gamma}-1}{1-\gamma} \tag{1}$$

We chose a multiplicative form to allow for the possibility that individuals can derive more utility from consumption when they're at a better health state. Note, however, that we are not imposing that health and consumption are complements vs substitutes as the functional form of $\phi(h)$ can handle either possibilities. [CITATIONS TBA]

Insurance take-up problem

Insurance take-up is governed by a Poisson process of intensity ϕ. This implies that individuals are given the option to take up insurance at random intervals through their life cycle. When this option occurs (or at the time of Poisson realization), they are offered a premium, $p(h,a)$ based on their health h and age a. Individuals then decide whether or not to take up insurance. If they do, then the premium stays the same until another (random) realization of the Poisson. Insurance premium and risk sharing is obtained from the data.

3.2 Individual's Problem

The individual's problem is composed of two branches: (1) a continuation region, where the individuals do not go to the doctor and the only decisions are consumption-savings and taking-up private insurance in case of Poisson realization; (2) a stopping region where individuals go to the doctor and invest in their health capital.

In the continuation region, the value includes the flow utility $u(c,h)$ from consumption – augmented with the health state – and captures the idea that individuals may derive more utility from consumption in a healthier state. The value also incorporates the dynamic effects from aging, transitioning to a better $(h+1)$ or worse $(h-1)$ health,likelihood and value from dying and the change in value associated with the insurance choice. The continuation region Γ^C is described as follows:

$$
\begin{aligned}
&\rho V(w,h,\nu,a,I,p) = \max_c \{u(c,h) + V_w[\theta(h)y(a) + rw - c - p]\} \\
&\underbrace{\eta[V(w,h,\nu,a+1,I,p) - V(.)]}_{\text{aging to } a+1} + \underbrace{\nu[V(w,h+1,\nu_0,a,I,p) - V(.)]}_{\text{transition to } h+1} + \\
&\underbrace{d(h,a)[V(w,h-1,\nu_0,a,I,p) - V(.)]}_{\text{transition to } h-1} + \underbrace{\lambda^T(h,a)[V^T - V(.)]}_{\text{death}} + \\
&\underbrace{\phi[\bar{V}(w,h,\nu,a,I',p') - V(.)]}_{\text{insurance choice}} \qquad (2)
\end{aligned}
$$

On the other hand, in the stopping region, given their decision to invest in health, they choose medical expenditure m_t which increases ν, i.e. lowers the expected duration of going to the better health state, according to equation (6). The cost of medical expenditure depends on the fixed cost of going to the doctor $k(I_0)$ and out-of-pocket cost $m(1-q(I_0))$. The impact on wealth is given by equation (5). The stopping region Γ^S is described as follows:

$$
\begin{aligned}
&V(w,h,\nu,a) = V^*(w',h,\nu',a) && (3)\\
\text{where, } &\bar{V}(w,h,\nu,a,I',p') = max\left\{ \overbrace{V(w,h,\nu,a,1,p(h,a))}^{\text{insurance}}, \overbrace{V(w,h,\nu,a,0,0)}^{\text{no insurance}} \right\} \\
&V^*(w,h,\nu,a) = \max_m V^i(w',h,\nu',a) && (4)\\
&w' = w - k(I_0) - mq(I_0) && (5)\\
&\nu' = \nu_0(a) + Am^{\alpha_m} && (6)\\
& && (7)
\end{aligned}
$$

It is important to emphasize that because of the fixed cost $k(I_0)$, the individuals don't invest in their health continually and it becomes a stopping time problem where individuals choose to invest in their health by visiting the doctor as a discrete choice.

Thus, under the assumptions of at most linear growth and Lipschitz continuity,[16] the individual's problem can be written compactly as,

[16] By Øksendal and Sulem (2005, Theorem 1.19), the solution to Levy SDEs exists

$$\min \Big\{ \rho V(w,h,\nu,a,I,p) - \max_c \{u(c,h) + V_w[\theta(h)y(a) + rw - c - p]\}$$
$$- \eta[V(w,h,\nu,a+1,I,p) - V(.)] - \nu[V(w,h+1,\nu_0,a,I,p) - V(.)] - d(h,a)[V(w,h-1,\nu_0,a,I,p) - V(.)]$$
$$- \lambda^T(h,a)[V^T - V(.)] - \phi[\bar{V}(w,h,\nu,a,I',p') - V(.)], V(w,h,\nu,a) - V^*(w',h,\nu',a) \Big\} = 0 \tag{8}$$

or

$$\min \Big\{ \Gamma^C, \Gamma^S \Big\} = 0 \tag{9}$$

Optimal stopping would be $\tau(w,h,\nu,a)$.

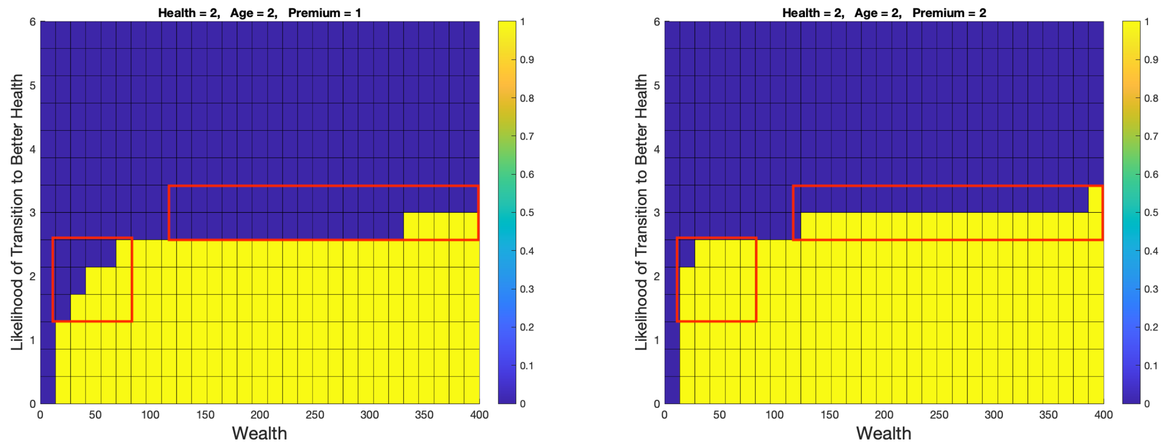
Following Øksendal and Sulem (2005, Theorem 3.2) Integrovariational Inequality for Optimal Stopping, the maximization problem in **??** is same as solving the following HJBII in (9).

3.3 Policy Function: Doctoral visit

To provide a description of one of the key choices of the model, we look at the visit decision for an individual at age 35-45 in bad health[17] (Figure 14). We plot the decision to visit the doctor as a function of their wealth and improvement intensity, fixed age and health status. As a result of the fixed cost, there are wealth effects in the visit decision. Fixing the likelihood of going to a better health state before going to the doctor (y axis), we see that as wealth increases, more individuals go to the doctor. For each level of wealth, there is cutoff in improvement intensity below which the individual goes for the doctoral visit and health investment. It is also clear that rich individuals go to the doctor much earlier (at a higher improvement intensity) as compared those who are poor. On the other hand, comparing insured and uninsured, there are states of the world where insured individuals would go to the doctor while uninsured individuals would not.

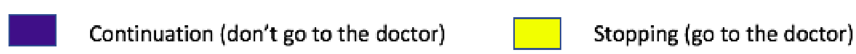
[17]The whole policy function is a multi-dimensional object, we look at some cross-sections of this multi-dimensional object.

Figure 14: Visit Decision, Age 35-45



Uninsured, Bad Health

Insured, Bad Health



4. Estimation

The goal of the estimation strategy is to reduce the number of parameters by imposing flexible functional forms so as to optimize on the parameters while ensuring that the functional forms remain flexible. In the related spirit, we calibrate some parameters that we cannot separately identify in the model and estimate some of the orthogonal parameters outside of the model. Lastly, we use Simulated Method of Moments to target choices (visits, investment) and transitions (improvements and changes in health) by age and health. In particular, we leave the moments by wealth untargeted and show an untargeted fit with respect to wealth moments as an external validity exercise in the next section.

We estimate the model on insured individuals, thus as such the current estimates can be thought of as partial equilibrium where everyone has private insurance. A natural limitation is that in the policy simulations, the general equilibrium effect – via clearing the insurance prices – would be missing and we would point out scenarios in which it could play an important role. Another limitation of the current estimation strategy is that it excludes public provisions of disability and Medicaid. In the appendix, we write down the ways to incorporate these provisions along with an Insurance firms' problem and the estimation with those is left for future work.

4.1 Specification

We allow for 6 age groups in the model, each with a 10 year range, starting from 25 years up to 85 years. As observed in data, there are 5 health states: 1 (Poor) to 5 (Excellent). We impose certain simplifying assumptions to ensure feasibility in estimation. The exogenous depreciation of health capital d_h^a is assumed to be the same across health states for a specific age a i.e. $d_h^a = d^a \quad \forall h = \{1, 2, 3, 4, 5\}$. d^a is specified as a Power function of age, and is given by:

$$d^a = d_0 + d_1 a + d_2 a^2 \tag{10}$$

The natural improvement component of ν is also specified as Power function of age, and is given by:

$$\nu_0(a) = n_0 + n_1 a + n_2 a^2 \tag{11}$$

For exit probabilities λ_h^a, we assume proportional increase of mortality rates across by age, keeping the gradient of health from λ_h^6. In other words, we allow for 5 factors, F_{25-35} - F_{65-75} such that:

$$\lambda_h^a \quad = \quad \begin{cases} \lambda_h^6 / F_{25-35} \text{ if age } \in \{25 - 35\} \\ \lambda_h^6 / F_{35-45} \text{ if age } \in \{35 - 45\} \\ \lambda_h^6 / F_{45-55} \text{ if age } \in \{45 - 55\} \\ \lambda_h^6 / F_{55-65} \text{ if age } \in \{55 - 65\} \\ \lambda_h^6 / F_{65-75} \text{ if age } \in \{65 - 75\} \end{cases} \tag{12}$$

We specify the utility cost of health $\phi(h)$ as a Power function of health:

$$\phi(h) = \phi_0 + \phi_1 h + \phi_2 h^2 \tag{13}$$

Table 2: Set Outside of the Model

Parameter	Meaning	Value
ρ	Discount rate	0.06
r	Interest Rate	0.05
γ	Risk Aversion	1.5
T	Exit Age	85
s	Initial Age	25
V^T	Terminal Value	10M

4.2 Parameters Estimated Outside the Model

We select our sample from NLMS and NHIS-MEPS as the privately insured individuals aged 25-85 with 10-year intervals. We interpret the categorical variable of self-reported health status from Poor to Excellent Health as the measure of health in the model from 1-5.

We estimate the exit probabilities for age 75-85 from the data by taking 15-day exit rates. The underlying assumption is that the health status doesn't change in this 15 day period and that the instantaneous exit rate is unaffected by the endogenous objects in the model. We also estimate the 5 factors, namely F_{25-35} - F_{65-75}, from the aggregate age-specific instantaneous mortality. Productivity by health is estimated by using individual fixed effect in the earnings regression where the base is set to poor health. Average annual insurance premium and fraction out-of-pocket is used for insurance premium and co-payment fraction respectively. We feed in the joint distribution of health-wealth at the age 25 as initial condition to our model. These are presented in Table 3.

Table 3: Estimated Outside of the Model

Meaning	Parameter	Value
Mortality Poisson, Age 75-85, h = 1	λ_1^6	0.116
Mortality Poisson, Age 75-85, h = 2	λ_2^6	0.024
Mortality Poisson, Age 75-85, h = 3	λ_3^6	0.0127
Mortality Poisson, Age 75-85, h = 4	λ_4^6	0.0057
Mortality Poisson, Age 75-85, h = 5	λ_5^6	0.00325
Survival Factor, Age 65-75	F_{65-75}	1.56
Survival Factor, Age 55-65	F_{55-65}	4.16
Survival Factor, Age 45-55	F_{45-55}	20.6
Survival Factor, Age 35-45	F_{35-45}	22.6
Survival Factor, Age 25-35	F_{25-35}	22.6
Productivity by Health	$\theta(h)$	(1, 1.03, 1.03, 1.04, 1.04)
Income by Education and Age ($10,000)	$y(a)$	(taken from data)
Insurance Premium	p	0.4
OOP Fraction	$q(I_0)$	0.3
Aging Poisson, all ages	η	$\frac{1}{10}$
Joint distribution health and wealth, age 25	$f(h_0, w_0)$	(taken from data)

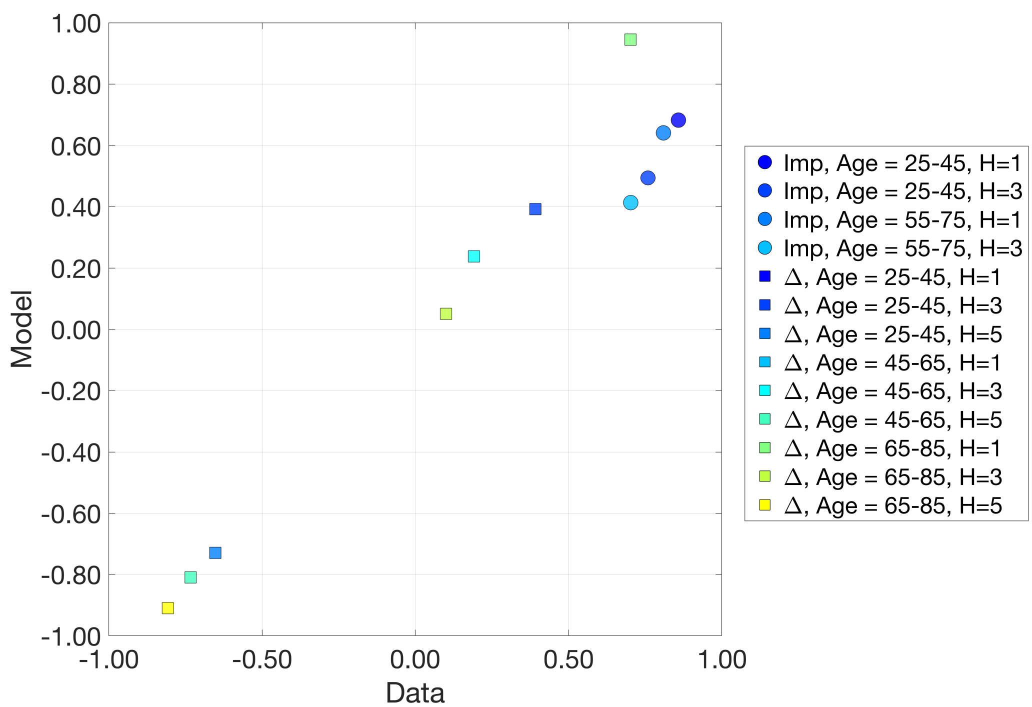
Table 2 presents the parameters set outside the model.

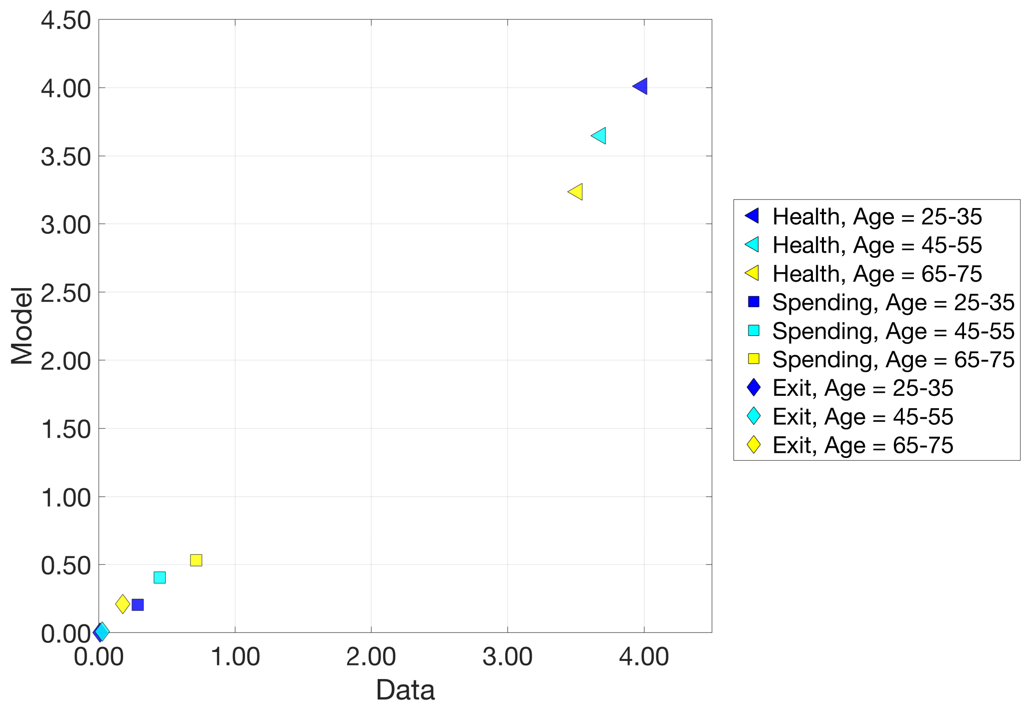
4.3 Estimates

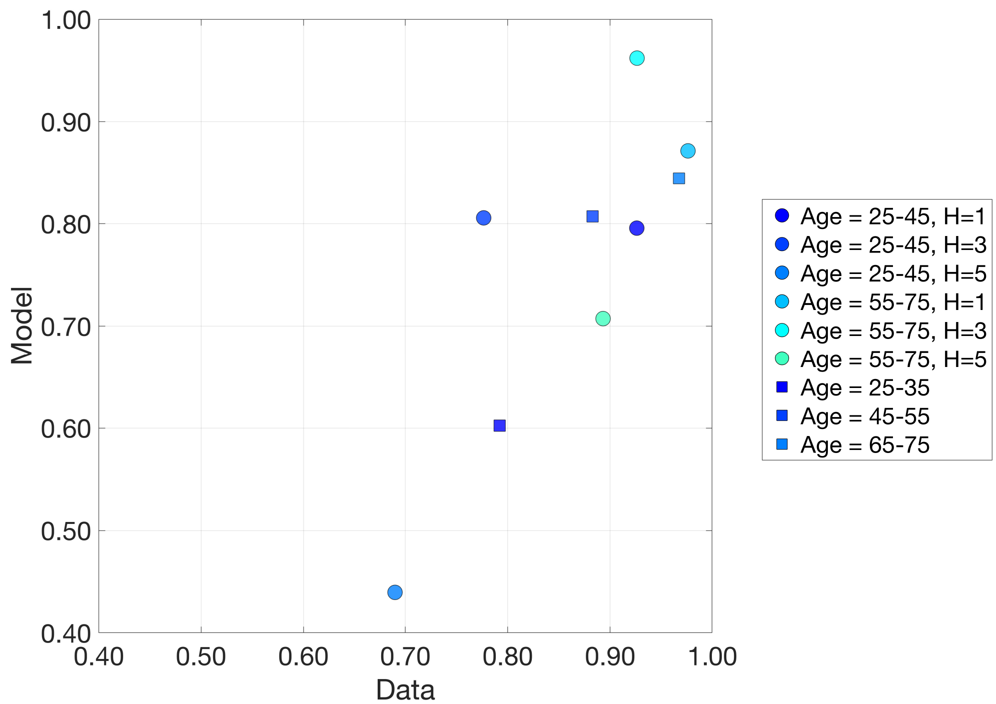
The remaining parameters to be estimated include health production parameters A and α_m, fixed cost of doctoral visit, k, depreciation and improvement parameters d_0, d_1, d_2

and ν_0 ν_1 ν_2 and the utility parameters ϕ_0, ϕ_1 and ϕ_2. While a lot of moments co-move with parameters, the idea behind identification is to use observable heterogeneity in the decisions such as fraction visit and spending across health and age to pin down Poisson intensities along with differences in outcomes such as improvement and changes in health across age and health to pin down technology parameters. Fixed cost is backed out by the average fraction of visit for age group 45-55. We report the set of targeted moments and the model fit in table 8.

Before we look at the un-targeted moments, we interpret the estimates from the targeted moments. Given that the fraction who visit is high, 0.84 in the data, the implied fixed cost is equivalent to \$ 213 per visit. i.e. on average those who are insured pay \$213 per visit as equivalent monetary cost to visit the doctor. The expected duration before going to a worse health state is 1 years and 3 months for those aged 25-35 and this number goes down to 9 months for individuals in age 65-75. The natural improvement duration is 2 years to go to a better health state for those ages 25-35 while those in 65-75 group never go to a better health state naturally. The estimates imply the marginal utility of consumption at same level of consumption for average health is about 2.52 times that in poor health. This last results is consistent with Finkelstein et al. (2013).



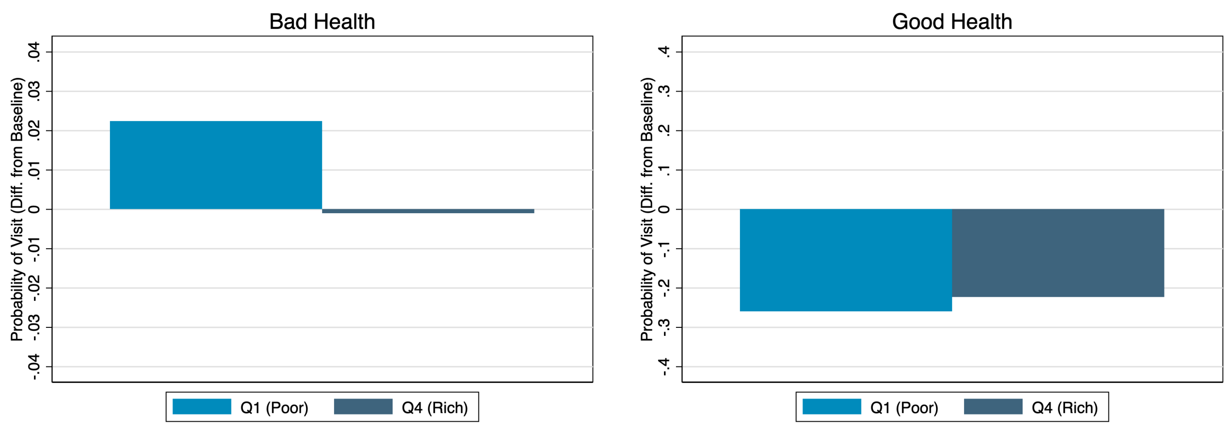

4.50
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
Model
0.00
1.00
2.00
3.00
4.00
Data
Health, Age = 25-35
Health, Age = 45-55
Health, Age = 65-75
Spending, Age = 25-35
Spending, Age = 45-55
Spending, Age = 65-75
Exit, Age = 25-35
Exit, Age = 45-55
Exit, Age = 65-75


1.00
0.90
0.80
0.70
0.60
0.50
0.40
Model
0.40
0.50
0.60
0.70
0.80
0.90
1.00
Data
Age = 25-45, H=1
Age = 25-45, H=3
Age = 25-45, H=5
Age = 55-75, H=1
Age = 55-75, H=3
Age = 55-75, H=5
Age = 25-35
Age = 45-55
Age = 65-75

5. Results

The model is estimated on insured individuals (those with private insurance) and we feed in the insurance prices from the data to allow for endogenous take-up and compare the model to the data. We slice our model and data patterns across health, wealth and age to illustrate the model fit for the un-targeted moments and to show the mechanisms in the model.

5.1 Visit decision by health status



We run an analogous exercise as in the data section where we run two individual fixed effect regressions for each income groups with base set as average health state. While the model is simulated monthly, we perform the regression using quarterly frequency – same as the data – for better comparison. We plot the regression coefficient associated with the health status dummy with values poor health and excellent health for each income group regression. The results indicate that poor individuals visit decision is highly elastic w.r.to their health state. An implication of this is that the poor individuals go to the doctor in a much more unhealthier state than the rich. Compared to a poor person in average health, a poor person in poor health is 2% points more likely to go to the doctor. This number is quantitatively 0 for the rich. Similarly, compared to a poor person in average health, a poor person in excellent health is 25% points less likely to go to the doctor.

While the qualitative sign is the same in the model and in data and elasticity for bad health is comparable to data (2% vs 4%), the elasticity for good health in the model is higher compared to data (25% vs 4%). It is not surprising since in the model, only way in which a person in good health goes to the doctor is if his/ her health goes down since that is the best health possible. In other words, it may be an artifact of a bounded health state. A way to address this would be to allow for people to invest in lowering depreciation intensity, d_h^a, which would be more preventive spending where individuals can invest in lowering the likelihood of going to a worse health state.

5.2 Spending across health status

Table 4: Model: Age 35-45

	Health				
	1	2	3	4	5
Q1 (Poor)	0.58	0.62	0.56	0.41	0.19
Q2	0.80	0.79	0.78	0.72	0.37
Q3	0.55	0.59	0.57	0.45	0.27
Q4 (Rich)	0.76	0.78	0.57	0.31	0.21

Table 5: Data: Age 35-45

	Health				
	1	2	3	4	5
Q1 (Poor)	0.60	0.33	0.21	0.17	0.12
Q2	0.73	0.41	0.25	0.18	0.13
Q3	0.77	0.47	0.29	0.21	0.15
Q4 (Rich)	0.74	0.46	0.32	0.24	0.18

We present the quarterly spending by health and wealth from the model and data in Table 4 and 5, respectively. Fixing health, wealthy spend more on their health over the next year thus transitioning to a better health with a higher probability. In our estimated model, individuals who are in poor health (Health = 1) in the first quarter, those in the top quartile of the wealth distribution, end up spending 31% more compared to those in the bottom quartile. This pattern is true across all health states[18]. We also show that this compares well with the medical spending data by family income adjusted for family size and age quartile. [19]

5.3 Transitions into Better Health

As a result of the higher spending by the rich, they move on to transition to a better health with a higher probability in the next quarter, as we show in 15 where we plot the

[18] It holds for all ages, however, ages 35-45 are shown here for exposition.

[19] Moments by wealth are pending from the data center and will be added in future work.

coefficient of wealth group dummy for quartile 2 to 4 as a percent of the base (quartile 1 or poor) of a regression of H_{t+1} controlling for H_t and age for individuals who visited the doctor in the past year. We find that after controlling for age and health in time t, those in top quartile have a health that is 45% higher than those in the bottom quartile. The analogous – yet imperfect – object that we have in data where we do the similar exercise albeit on family income group show that those in the top quartile of the family income distribution have 18% higher health level in the next year compared those in bottom family income quartile. One caution is that we are interpreting the categorical variable of health as an index from 1-5. For this, we perform similar analysis for a binary variable for health, as is common in the literature [CITE DENARDI], as well as a multinomial logit, and get similar results.

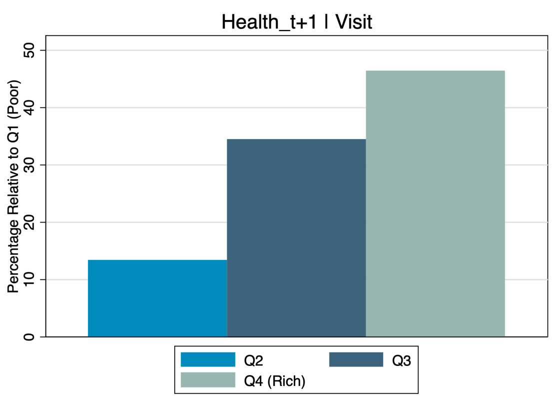


Figure 15: Model (by Wealth)

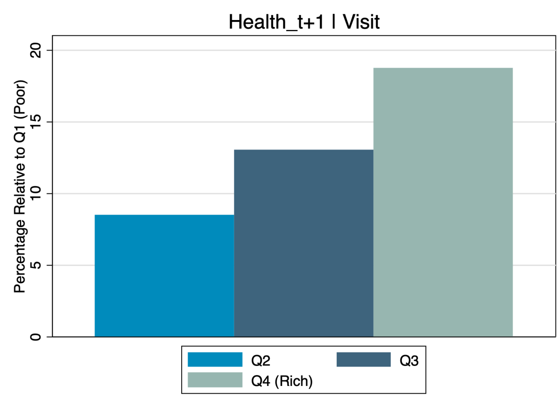


Figure 16: Data (by Family Income)

Source: NHIS-MEPS
Notes: Regress: Health$_{t+1}$ on Health$_t$, Age, Age^2; base set to family income (Data) or wealth (Model) poor

5.4 Exit Rates by Health

As a result of higher spending conditional on health and higher likelihood of getting into better health conditional on visit, those in top quartiles also have a lower mortality rate compared to those in bottom quartile for same age and health in the previous quarter, as we show in 6. Note, however, that the mortality rates are low for ages 35-45, therefore the moment in the model and in the data is a noisy one.

Table 6: Model: Percent Exit Age 35-45

	Health				
	1	2	3	4	5
Q1 (Poor)	3.1	1.6	0.8	0.4	0.2
Q2	3.2	1.8	0.7	0.4	0.2
Q3	3.1	1.1	0.7	0.2	0.2
Q4 (Rich)	2.7	1.5	0.7	0.3	0.2

Table 7: Data: Exit Age 35-45

	Health				
	1	2	3	4	5
Q1 (Poor)	4.8	1.5	0.7	0.3	0.2
Q2	5.4	1.3	0.5	0.2	0.1
Q3	4.0	1.0	0.5	0.4	0.3
Q4 (Rich)	3.1	1.4	0.3	0.3	0.2

5.5 Health inequality goes up over the life-cycle

There is little inequality measured by the difference in average health for top and bottom wealth quartiles at the age of 25, this gradually increases over the working life with the gap reaching its peak for the ages 45 and above, as shown in figure 17. Since we do not have this moment released from the NHIS-MEPS, we look at the analogue in PSID where we oberve wealth in certain waves and health is a binary variable of good vs bad. We see that the model does a reasonable job of capturing the inequality in average health over the life-cycle, although while the inequality goes down at the later years of life (65-75) in data – possibly due to more unhealthy individuals exiting the sample. It's also the case that the model over-predicts the role of medical spending for the rich since their health doesn't depreciate at the end of life-cycle as much as it does in the data.

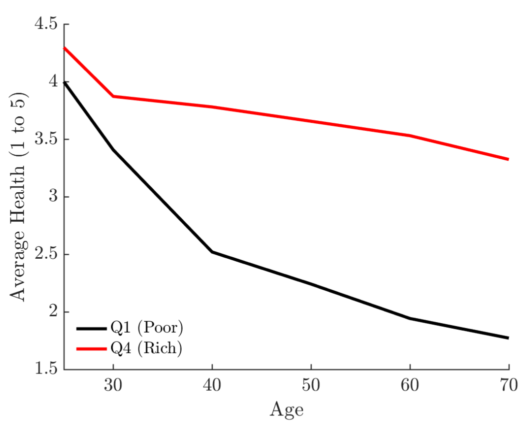


Figure 17: Model

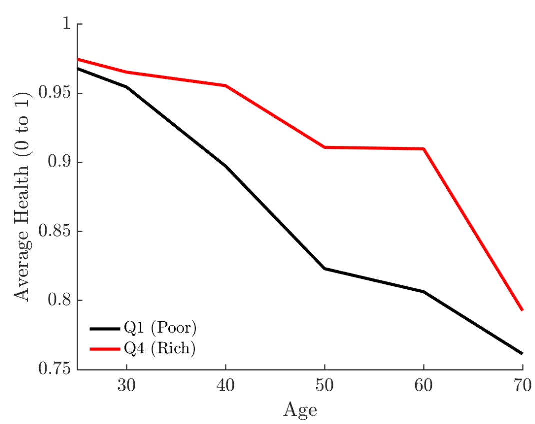


Figure 18: Data Analogue in PSID

5.6 Spending and Outcomes

The model – estimated for the individuals having insurance – and feeding in insurance prices from the data, is able to predict about 65% of the gap in life-expectancy between the top and the bottom quartiles. The model also does a good job of capturing the flatness in medical spending across wealth groups – an untargetted moment – for the younger ages. In particular, note that the higher mortality rates for the poor relative to the rich is not driven by higher spending by the rich. If anything, rich spend *lower* than the poor for ages 35-45 and 45-55 while their mortality rates are lower than those in top quartile.

Table 8: Model

	Wealth Quartiles			
	Q1	Q2	Q3	Q4
Life-Expectancy	1.00	1.03	1.08	1.09
Mean Spending 35-45	1.00	1.27	0.75	0.75
Mean Spending 45-55	1.00	0.83	0.60	0.89
Mean Spending 55-65	1.00	1.55	0.94	1.67
100 x Mortality 35-45	1.00	0.98	0.50	0.40
100 x Mortality 45-55	1.00	0.54	0.42	0.33
100 x Mortality 55-65	1.00	0.82	0.34	0.38

Table 9: Data

Wealth Quartiles			
Q1	Q2	Q3	Q4
1.00	1.05	1.10	1.14
1.00	1.01	1.03	1.12
1.00	0.92	0.94	0.96
1.00	1.11	1.05	1.14
1.00	0.86	0.91	0.58
1.00	0.88	0.75	0.56
1.00	0.65	0.56	0.44

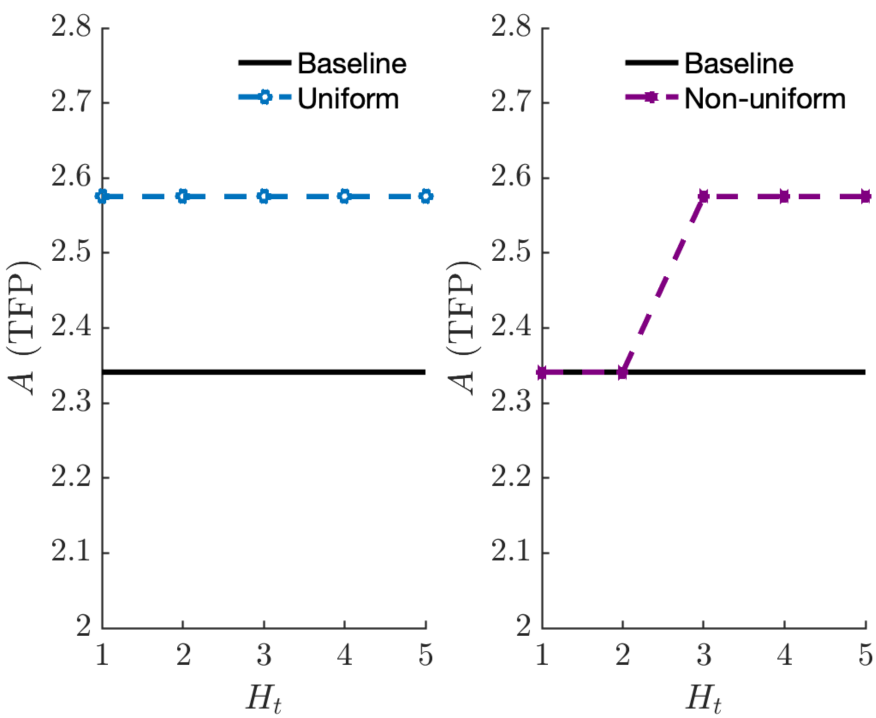
6. Quantitative Experiments

6.1 Technology

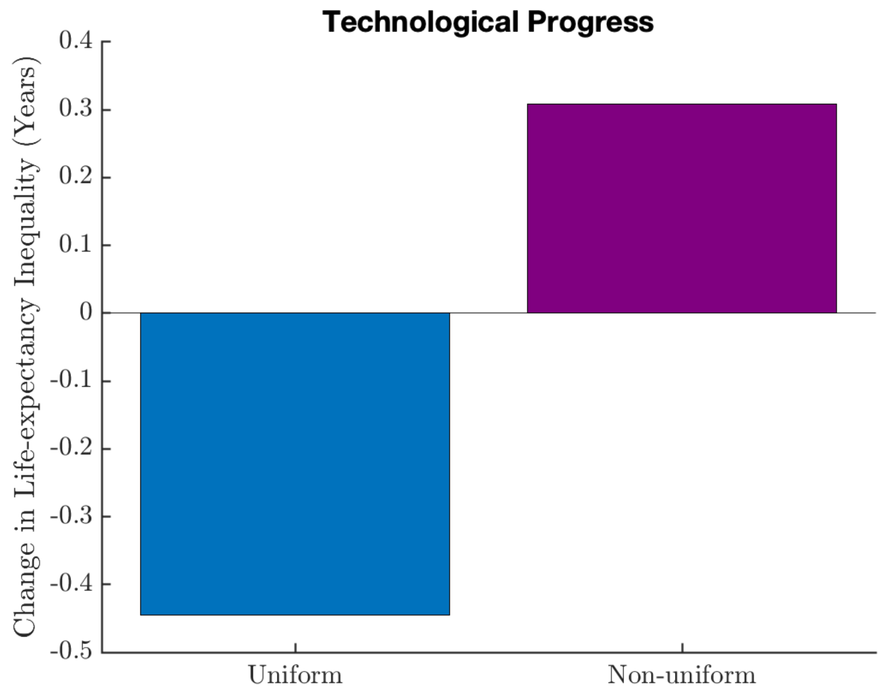
In order to understand the role of technological progress in the rising health inequality in the US, we perform two counterfactuals:

1. Uniform (across health states) increase in TFP (10%): this is a case where the medical innovation is happens across all the health spectrum.

2. Non-uniform (across health states) increase in TFP (10%): this is a case where technology only improves for early diagnosis – such as cancer stage I – but not for later stages of cancer. The experiment is shown in the picture below.



We find that a uniform increase in the productivity of the healthcare sector reduces the inequality in life expectancy. Both poor and rich alike benefit from the progress and have higher life-expectancy but the poor – starting from a lower initial life-expectancy – gain more than the rich, leading to an overall reduction in the gap.



On the other hand, a non-uniform increase in TFP – one where the medical system gets better at treating early illnesses but not at treating terminal cancer, disproportionately improves the life-expectancy for the rich and not for the poor. Thus, the timing of the health investment interacts with the technological progress to worsen the inequalities.

6.2 Insurance

The role of private insurance on the inequality is ambiguous. On one hand, an option to buy private insurance may increase disparities since only the rich would be willing to pay the premium and buy insurance to diversify their health risks and smoothen out their consumption. On the other hand, unhealthy individuals would be the ones selecting into health insurance due to the well documented adverse selection in the insurance markets. This can be clearly seen in the insurance take-up problem in Figure 19 and 20. While for those in excellent health, only the wealthy take up private insurance, for those in good health, there is a selection of people whose expected duration of going to a better health is low or in other words, those who anticipate going for a doctoral visit, take up private insurance. The threshold below which people take-up private insurance is increasing in wealth.

On net, we find that the two effects cancel out and the effect of removing health insurance markets would lead to a modest reduction in inequality between the two and the bottom quartiles. not sure what this means

Figure 19: Good Health

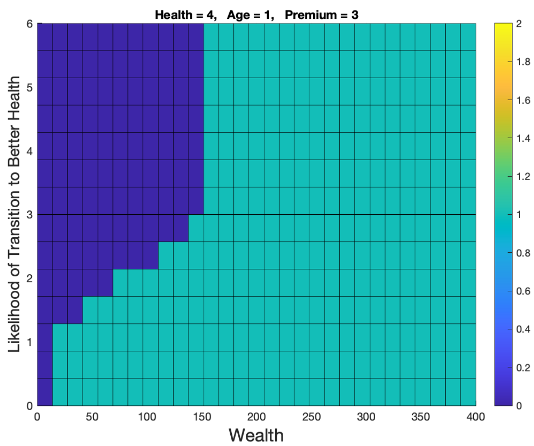
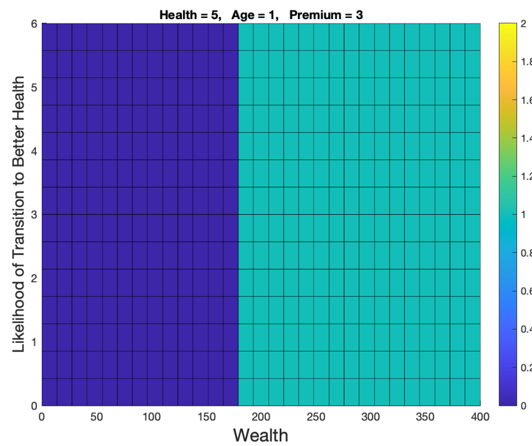


Figure 20: Excellent Health



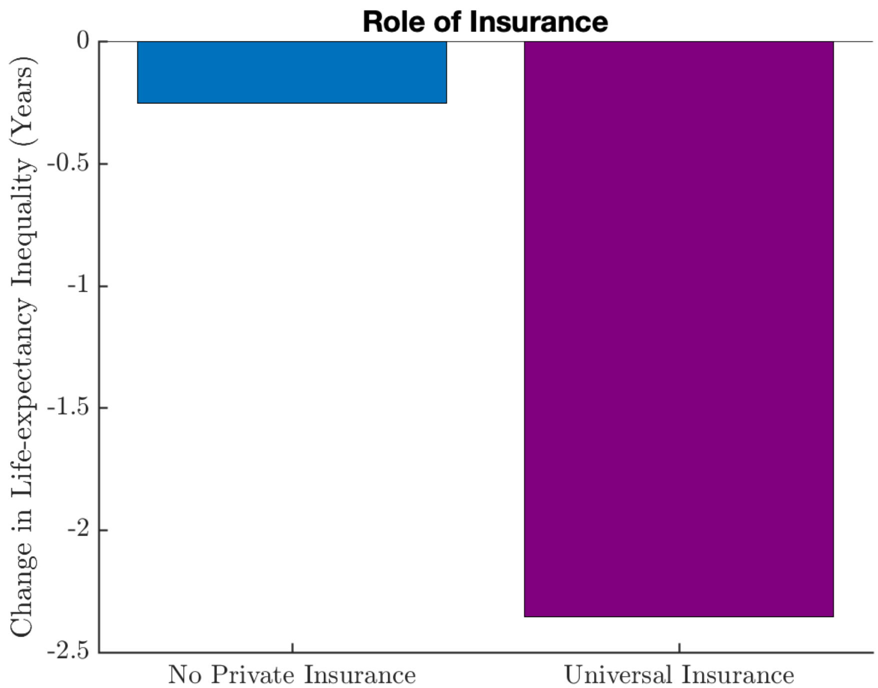
Two experiments:

1. We take away the insurance choice

2. Give everyone a public health insurance financed by a flat 15% income tax along with 30% cost sharing

Universal insurance sponsored by a flat income tax, leads to a reduction in health inequality by increasing the life-expectancy of the poor while not affecting the life-expectancy of the rich.

We should emphasize here that the policy experiments involving Private insurance and universal insurance maybe missing general equilibrium effects through the insurance firms problem. Who takes up private insurance would be different depending on whether or not insurance firms are allowed to cream-skim by sharing a higher premium for the unhealthy individuals. Regulatory environment may also be important here wherein in Affordable Care Act, the insurance firms weren't allowed to price-discriminate. This is something left for future work.



6.3 External validation: Insurance and Mortality

Effect of Medicaid on Mortality

NLMS data provides us with three cross sectional waves of initial survey which includes demographic and socio-economic status and the only "panel" component is whether an individual died at the end of 6 years or not along with the cause of death, if any. An ideal survey would have been the one with panel data along with cause of death data mapped from death certificate. Due to unavailability of such a data which is also publicly available, we make the assumption that socio-economic status, insurance status and type of insurance remand the same for the next six years. This could be problematic because of Medicaid access to poor children, thus we exclude children aged 0-18 years. Since Medicare is available, in principle, to almost everyone above the age of 65, we also exclude elderly people with age > 65 from our sample. Note that while federal government mandated minimum poverty level cutoff, states had flexibility in deciding their own eligibility criteria.

We exploit the variation in state-wide eligibility cutoff in year 2000 to estimate the effect of Medicaid on mortality. Let's describe the ideal discontinuity design setting.

Suppose a state has Medicaid cutoff as 75% of federal poverty line (FPL). We would see a discontinuity in the fraction having Medicaid at this cutoff and can look at individuals in that state with 74% of FPL and 76% of FPL. Since fine income bins are missing in the public use NLMS data, we compare the individuals in 50-75% of FPL in states where they were eligible for Medicaid and others in which they weren't. We obtain the state-wide eligbilty cutoff in 2000 from Broaddus et al. (2002) and follow Blundell and Dias (2009) to estimate the Local Average Treatment Effect (LATE) defined as:

$$\alpha^{RD}(z^*) = \frac{P(Y_{t+6} = 1|z = 2) - P(Y_{t+6} = 1|z = 1)}{P(Medicaid = 1|z = 2) - P(Medicaid = 1|z = 1)} \tag{14}$$

Where z is a categorical variable when $z = 1$ for states for which 50-75% FPL were ineligible for Medicaid and $z = 2$ for states in which they were. After controlling for income, education, age, sex, average education and income in the state the (local average treatment) effect of Medicaid is 9.5% points less likely to die compared to the ones who don't have Medicaid (Table 10).

Table 10: Effect of Insurance on Mortality

	Logit6a	PSM_6a	Logit6b	PSM_6b	Logit6c	PSM_6c	RD6c
1 if Medicaid	0.0141***		0.0135***		0.0139***		-0.0952***
	[0.0013]		[0.0011]		[0.0008]		[0.0253]
1 if Private Insurance	-0.0052***	-0.0054***	-0.0026***	-0.0035***	-0.0016***	-0.0018***	
	[0.0008]	[0.0012]	[0.0007]	[0.0010]	[0.0006]	[0.0007]	
Adjusted Income	-0.0005***		-0.0008***		-0.0007***		
	[0.0002]		[0.0001]		[0.0001]		
Age	0.0040***		0.0033***		0.0020***		
	[0.0002]		[0.0002]		[0.0002]		
Female	-0.0132***		-0.0107***		-0.0062***		
	[0.0005]		[0.0005]		[0.0004]		
1 if Medicare	0.0121***		0.0133***		0.0145***		
	[0.0010]		[0.0009]		[0.0007]		
Observations	301327	282423	365109	335939	443521	407441	39642
Baseline		0.0231***		0.0157***		0.0121***	
		[0.0007]		[0.0002]		[0.0002]	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard Errors are in brackets.

Note: Outcome variable is mortality in the next 6 years across all columns. Marginal effects are tabulated. PSMxx stands for nearest neighbor Propensity Score Matching, RDxx stands for Regression Discontinuity, Logitxx shows the marginals of a simple logistic regression of whether or not an individual dies at the end of 6 years on insurance status, education, age, age sq, income, income square and sex (some of which have been suppressed from the table). xx denotes the corresponding wave number of NLMS, where 6a represents early 1980s, 6b represents early 1990s and 6c represents early 2000s.

Effect of Private Insurance on Mortality

We first estimate a logit regression of mortality on insurance, age, education and income. The exact specification is described in table 10 column 1, 3 and 5 for three waves of NLMS. Our reduced form regression specification in table suffers from potential selection problem. In particular, the decision to take up health insurance may not be random and the there could be idiosyncratic gains from treatment. In order to get around the selection problem, we use the propensity score matching estimator a la Heckman et al. (1998)[20]. Following Caliendo and Kopeinig (2008), our parameter of interest is the average treatment on the treated $\alpha^{ATT} = E[Y(1)|D = 1] - E[Y(0)|D = 1]$, where D is a dummy for insurance and Y is the probability of dying in the next 6 years[21]. We make the following identifying assumptions:

> Assumption 1 (Conditional Independence Assumption): $Y(0), Y(1) \perp D|P(X)$
>
> Assumption 2 (Common Support Assumption): $0 < P(D = 1|X) < 1$

The estimator can be written as:

$$\alpha^{ATT}_{PSM} = E_{P(X)|D=1}\{E[P(Y_{t+6} = 1)|D = 1, P(X)] - E[P(Y_{t+6} = 0)|D = 0, P(X)]\} \tag{15}$$

We use nearest-neighbor matching and check for common support assumption in figure 35, 36 and 37 and leave out the bins without overlap to ensure that common support assumption is not violated. Our propensity score specification is the following:

$$P(D = 1|age, sex, income) = \beta_0 + \beta_1 \text{ x } age + \beta_2 \text{ x } sex + \beta_3 \text{ x } income + \beta_4 \text{ x } education \tag{16}$$

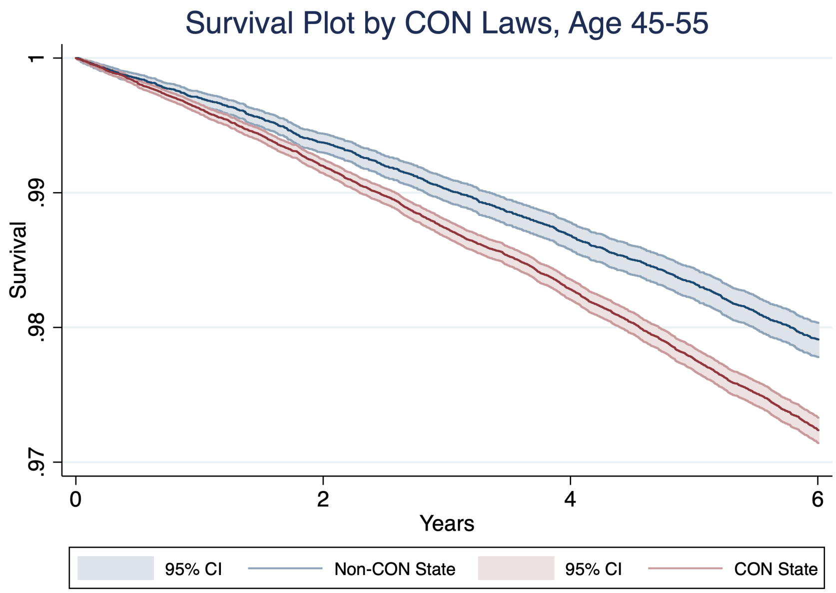
Standard errors were calculating following Abadie and Imbens (2016) work on propensity score matching. Note that our matching estimate could still have some selection problem. In particular, we can only match based on observables. However, the selection could also be happening because of unobservables. As described in table 10, having private insurance reduces the probability of dying in the next 6 years by about 15-25% of the baseline (uninsured individuals) in the age group 18-65 for different waves.

[20]See Heckman et al. (1998), Todd (1999) and Blundell and Dias (2009) for a detailed overview of the alternative approaches.

[21]NLMS matches the mortality status only for 6 years after the interview

CON Laws and Mortality

Figure 21: Survival Plot: CON vs Non-CON States, Age 45-55



NEED TO ADD SOMETHING ABOUT FIXED COST BEING HIGHER FOR CON STATES

7. Extensions

The model can be easily extended to incorporate various interesting mechanisms we discussed in the results section.

Insurance Firm's Problem

Insurance provider is a risk neutral agent who sets the actuary fair premium in the presence of a (exogenous) stopping time determined by the individuals opting for insurance.

$$
\begin{aligned}
\rho F(w,h,\nu,a,I,p_0) &= p_0 + \underbrace{\eta[F(w,h,\nu,a+1,I,p) - F(.)]}_{\text{aging to } a+1} + \\
&\underbrace{\nu[F(w,h+1,\nu_0,a,I,p) - F(.)]}_{\text{transition to } h+1} + \underbrace{d(h,a)[F(w,h-1,\nu_0,a,I,p) - F(.)]}_{\text{transition to } h-1} + \\
&\underbrace{\lambda^T(h,a)[0 - F(.)]}_{\text{death}} + \quad \underbrace{\phi[\bar{F}(w,h,\nu,a,I',p') - F(.)]}_{\text{insurance choice from individual's problem}} \\
\bar{F}(w,h,\nu,a,I',p') &= \begin{cases} 0, \text{ if } I^* = 0 \\ F(w,h,\nu,a,I,p(h,a)) \text{ if } I^* = 1 \end{cases}
\end{aligned}
$$

$F(w,h,\nu,a,I,p_0)$ is the value of the insurance firm who is in contract with an individual for insurance premium p_0, whose wealth is w, health is h and so on. Value matching condition at exogenous stopping time for the firm is:

$$
\begin{aligned}
\lim_{\tau \to 1} F(.) &= -mq(I) + F(w',h,\nu',a,I,p) && (17) \\
w' &= w - k(I_0) - m(1 - q(I_0)) && (18) \\
\nu' &= \nu_0(a) + Am^{\alpha_m}
\end{aligned}
$$

Free entry condition determines p_0. Insurance firms can offer health insurance in alternative premium contracts: a) where insurance premium can depend on the health status and b) under ACA where insurance premium cannot depend on health status.

Disability Stage

Disability can be modeled as an absorbing state, where exit rate is given by λ^D, health is given by h^D and disability income is given by y^D. Given that long-term disability makes one eligible for Medicare, it can be modeled at these individuals needing $\bar{m}$ investments continually and not as discrete intervals as a choice – such as dialysis treatment for end-stage renal failure, which comes from Medicare.

Thus, the HJB becomes:

$$
\rho V^D(w,h^D) = \max_c \{u(c,h^D) + V_w^D[y^D + rw - c]\} + \lambda^D(V^T - V^D) \tag{19}
$$

Simple guess and verify gives us,

$$V^D(w, h^D) = \frac{(y^D + rw)^{1-\gamma}}{r(1-\gamma)} \left(\frac{(\rho + \lambda^D) - r(1-\gamma)}{r\gamma} \right)^{-\gamma} + \left(\frac{1}{\rho + \lambda^D} \right) \left(\omega \frac{{h^D}^{1-\sigma}}{1-\sigma} + \lambda^D V^T \right) \quad (20)$$

8. Conclusion

The paper investigates the role of insurance and technological progress on the rising health inequality across income groups, that has been recently documented. We develop a life-cycle model of an economy where individuals decide consumption-savings, whether to take up health insurance, when to visit a doctor and how much to invest in their health capital.

Our estimates show that the timing of the health investments, explain a substantial part of health inequality across wealth/ income groups. We find that while rich and poor have comparable health investments, there are substantial differences in the timing of the investments. Poor have a highly elastic doctoral and medical investments decision, rich's demand for health is much less elastic with regards to their health status. As a result, rich are able to transition to a better health upon visiting the doctor at a higher rate than poor.

The estimated model is able to explain about 65% of the gap in life-expectancy across income groups observed in data. We show that the type of technological innovation interacts with the timing of the investment and has a first order effect on disparities. On one hand, a non-uniform increase in the productivity of the medical sector – one where there are improvements in early cures in cancer for example, but none for terminal cancer – can lead to increase in inequality in life-expectancy. Poor uninsured individuals, having deferred the treatment aren't able to reap the benefits of the technological progress, thus resulting in poorer outcomes. This is consistent with our empirical finding that cancer related medical innovations seem to be one of the biggest sources of increased health disparities over the past few decades.

This is in contrast to a uniform increase in the productivity of the healthcare sector, which leads to a reduction in disparities. Lastly, we show that a public health insurance scheme, funded by flat-income tax, could go a long way in decreasing the inequality.

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Appendix: Tables

Table 11: (Robustness) Gains in Life-expectancy, Age4: 1983 to 2003

	0-25%	25-50%	50-75%	75-100%
Life-expectancy 1983	71.5	74.4	76.4	77.9
Total Change (1983 - 2003)	2.6	3.0	2.8	3.8
By cause of death:				
Accident	0.2	0.1	0.1	0.2
Other	-0.5	-0.3	-0.2	0.1
Malignant neoplasms	0.5	0.6	0.6	0.9
Cerebrovascular	0.3	0.3	0.2	0.3
Diabetes	-0.2	-0.1	-0.1	-0.1
Heart	2.2	2.4	2.2	2.2
Respiratory	0.0	0.0	-0.1	0.1
Unknown	-0.0	-0.0	-0.0	0.0
By age group:				
20-40	0.0	0.0	-0.0	0.1
40-60	1.5	1.4	1.4	1.5
60-80	1.0	1.1	1.1	1.7
80+	0.1	0.5	0.3	0.5

Life-expectancy conditional on surviving until age 20.

Table 12: (Robustness) Gains in Life-expectancy, Age8: 1983 to 2003

	0-25%	25-50%	50-75%	75-100%
Life-expectancy 1983	71.2	74.0	75.2	76.4
Total Change (1983 - 2003)	2.4	2.7	2.7	3.0
By cause of death:				
Accident	0.3	0.1	0.2	0.2
Other	-0.3	0.0	0.1	0.1
Malignant neoplasms	0.4	0.5	0.5	0.8
Cerebrovascular	0.3	0.2	0.2	0.2
Diabetes	-0.1	-0.1	-0.0	-0.0
Heart	1.8	1.9	1.8	1.6
Respiratory	0.0	0.1	0.0	0.1
Unknown	-0.0	-0.0	-0.0	-0.0
By age group:				
20-30	0.1	0.0	0.0	-0.0
30-40	0.0	0.0	0.1	0.1
40-50	0.3	0.3	0.2	0.5
50-60	0.7	0.9	0.8	0.8
60-70	0.9	0.9	0.9	0.9
70-80	0.2	0.4	0.5	0.6
80-90	0.0	0.1	0.2	0.2

Life-expectancy conditional on surviving until age 20.

Table 15: Parameter Estimates

Meaning	Parameter	Value	Std. Errors*
TFP	A	2.34	(0.007)
Elasticity w.r.to. m	α_m	0.10	(0.002)
Fixed Cost	k	0.0213	(0.00011)
Depreciation Poisson-1	d_0	0.86	(0.0007)
Depreciation Poisson-2	d_1	0.23	(0.0005)
Depreciation Poisson-2	d_2	-0.026	(0.0007)
Natural Improvement-1	n_0	0.48	(0.005)
Natural Improvement-2	n_1	-0.022	(0.0004)
Natural Improvement-3	n_2	-0.028	(0.0009)
Utility parameter-1	ϕ_0	1.26	(0.0019)
Utility parameter-2	ϕ_1	1.016	(0.00029)
Utility parameter-3	ϕ_2	0.036	(0.0054)

Table 13: Expenditure by Income: Age 35-45

	p1	p25	p50	p75	p99
1st Quintile	0	0	261	1663	40771
2nd Quintile	0	0	409	1662	30136
3rd Quintile	0	104	602	2091	27274
4th Quintile	0	195	768	2263	26763

Source: NHIS-MEPS

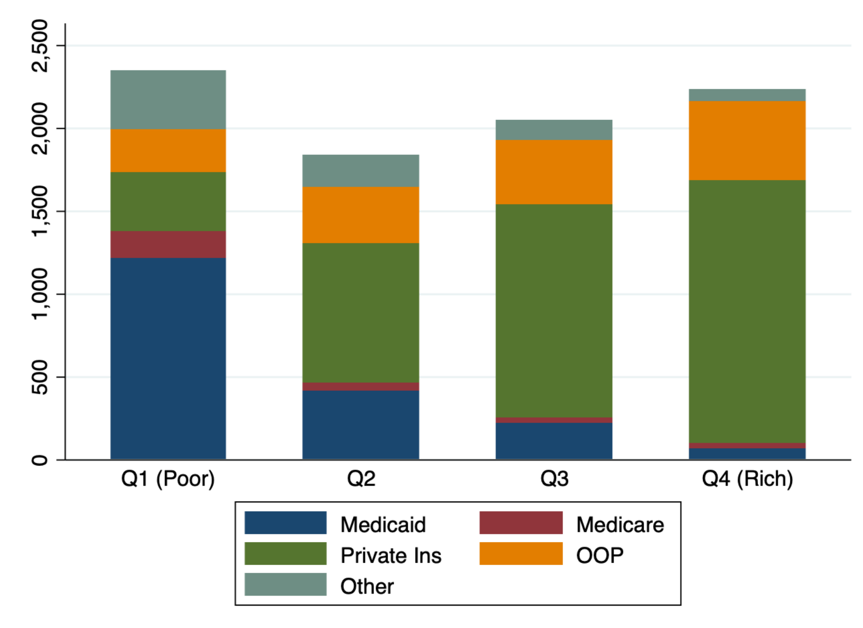
Table 14: Expenditure w/o 0 by Income: Age 35-45

	p1	p25	p50	p75	p99
1st Quintile	10	239	838	3158	51506
2nd Quintile	13	284	855	2520	36688
3rd Quintile	24	328	958	2714	29267
4th Quintile	26	373	1035	2741	28800

Source: NHIS-MEPS

Moment	Data	Model
Fraction Visit, Poor Health Age 55-75	0.97	0.80
Fraction Visit, Average Health Age 55-75	0.92	0.80
Fraction Visit, Excellent Health Age 55-75	0.89	0.43
Fraction Visit, Poor Health Age 25-45	0.92	0.87
Fraction Visit, Average Health Age 25-45	0.77	0.96
Fraction Visit, Excellent Health Age 25-45	0.69	0.70
Improvement Poor Health, Age 55-75	0.79	0.68
Improvement Average Health, Age 55-75	0.70	0.50
Improvement Poor Health, Age 25-45	0.86	0.64
Improvement Average Health, Age 25-45	0.75	0.41
Change in Health, Poor Health, Age 25-45	1.07	1.16
Change in Health, Average Health, Age 25-45	0.39	0.39
Change in Health, Excellent Health, Age 25-45	-0.65	-0.72
Change in Health, Poor Health, Age 45-65	0.80	1.09
Change in Health, Average Health, Age 45-65	0.20	0.23
Change in Health, Excellent Health, Age 45-65	-0.72	-0.80
Change in Health, Poor Health, Age 65-85	0.72	0.94
Change in Health, Average Health, Age 65-85	0.10	0.05
Change in Health, Excellent Health, Age 65-85	-0.80	-0.90
Average investment, Age 25-35	0.28	0.20
Average investment, Age 45-55	0.44	0.40
Average investment, Age 65-75	0.71	0.53
Average Health, Age 45-55	3.68	3.64
Average Health Age 25-35/Average Health, Age 45-55	1.08	1.09
Average Health Age 65-75/Average Health, Age 45-55	0.95	0.88
Fraction Visit, Age 25-35	0.79	0.60
Fraction Visit, Age 45-55	0.88	0.80
Fraction Visit, Age 65-75	0.96	0.84

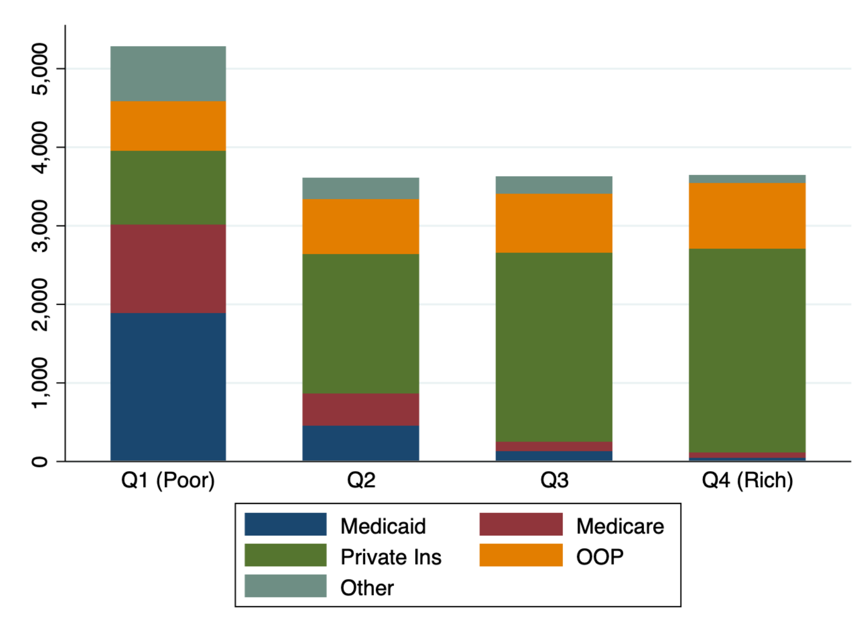
Figure 22: Mean Medical Investment: Age 25-35



Source: NHIS-MEPS

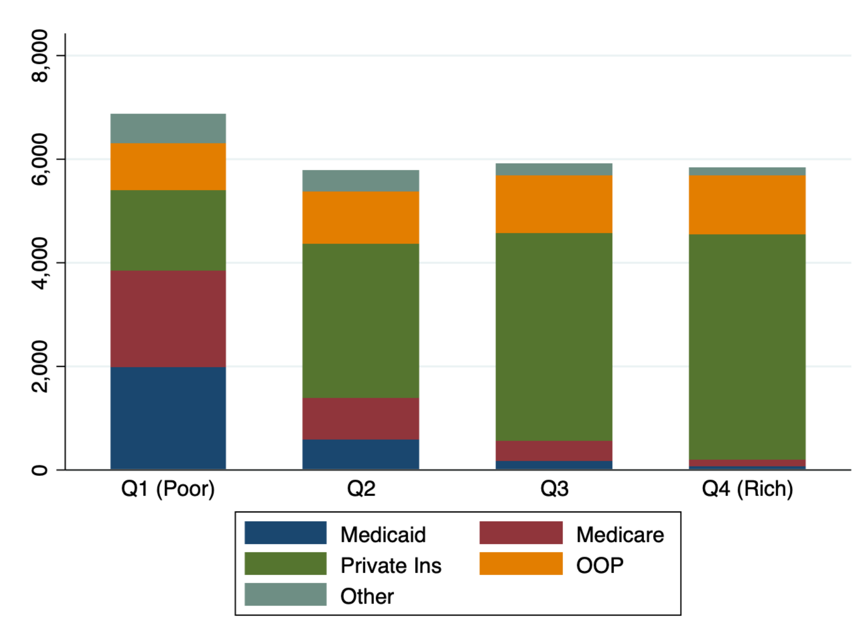
Appendix: Figures

Figure 23: Mean Medical Investment: Age 45-55



Source: NHIS-MEPS

Figure 24: Mean Medical Investment: Age 55-65



Source: NHIS-MEPS

Figure 25: Mean Medical Investment: Age 65-75

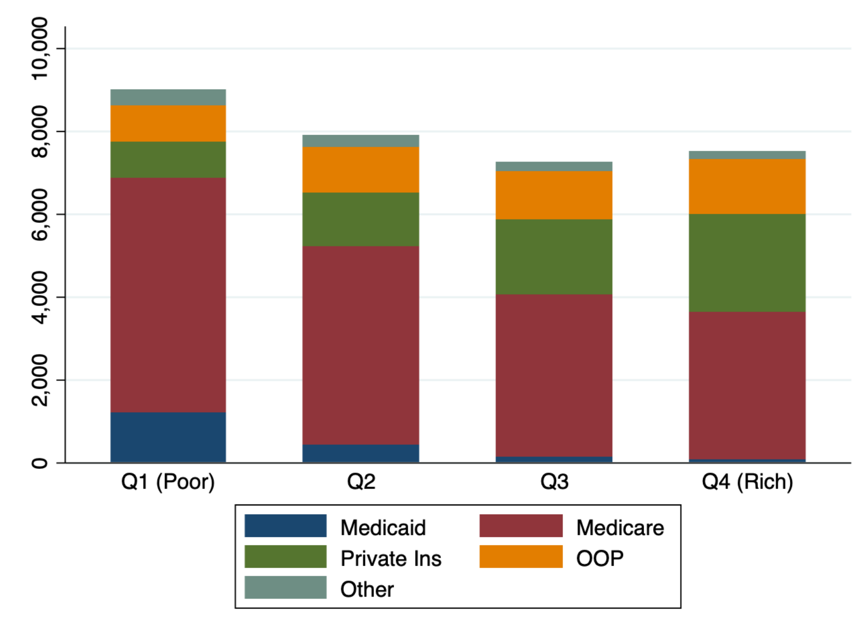
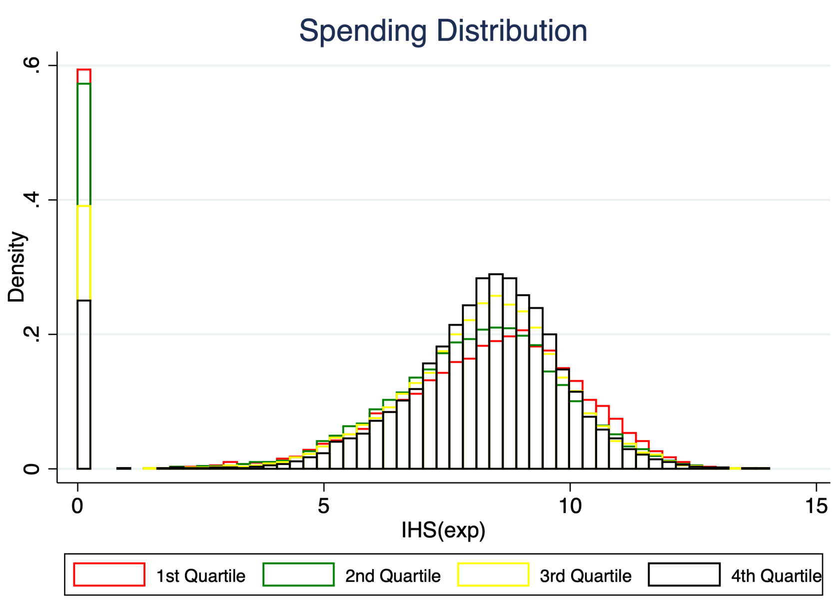
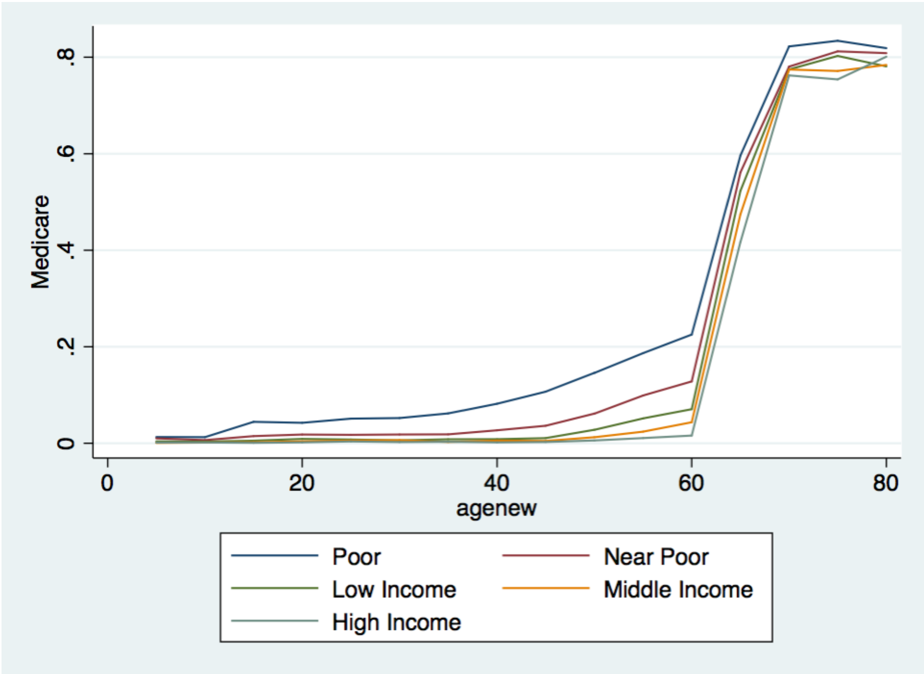


Figure 26: Medical Investment Distribution, Age 45-55



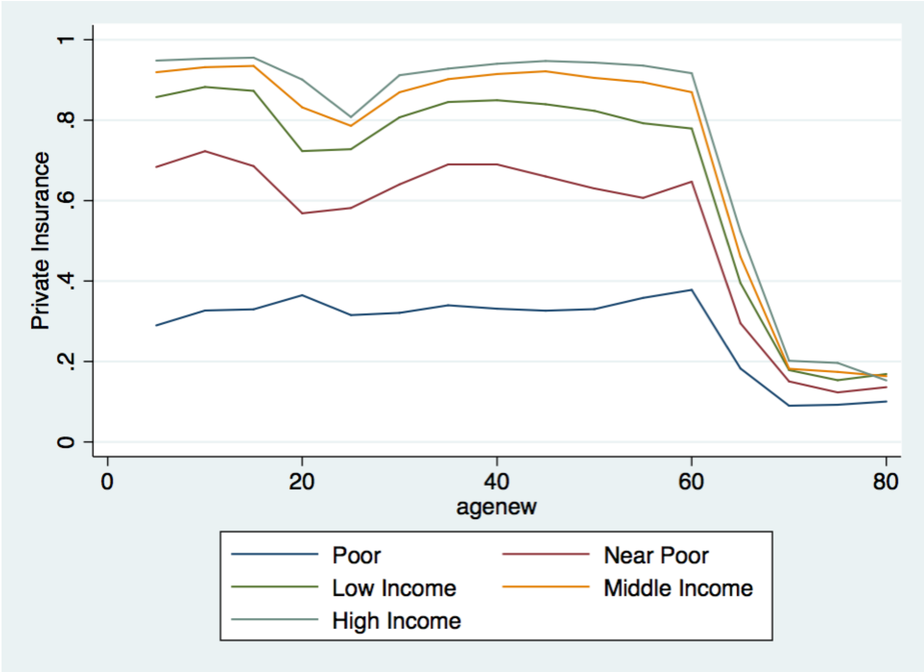
Notes: Inverse Hyperbolic Sine (IHS) Transformation

Figure 27: Fraction with Medicaid by Income



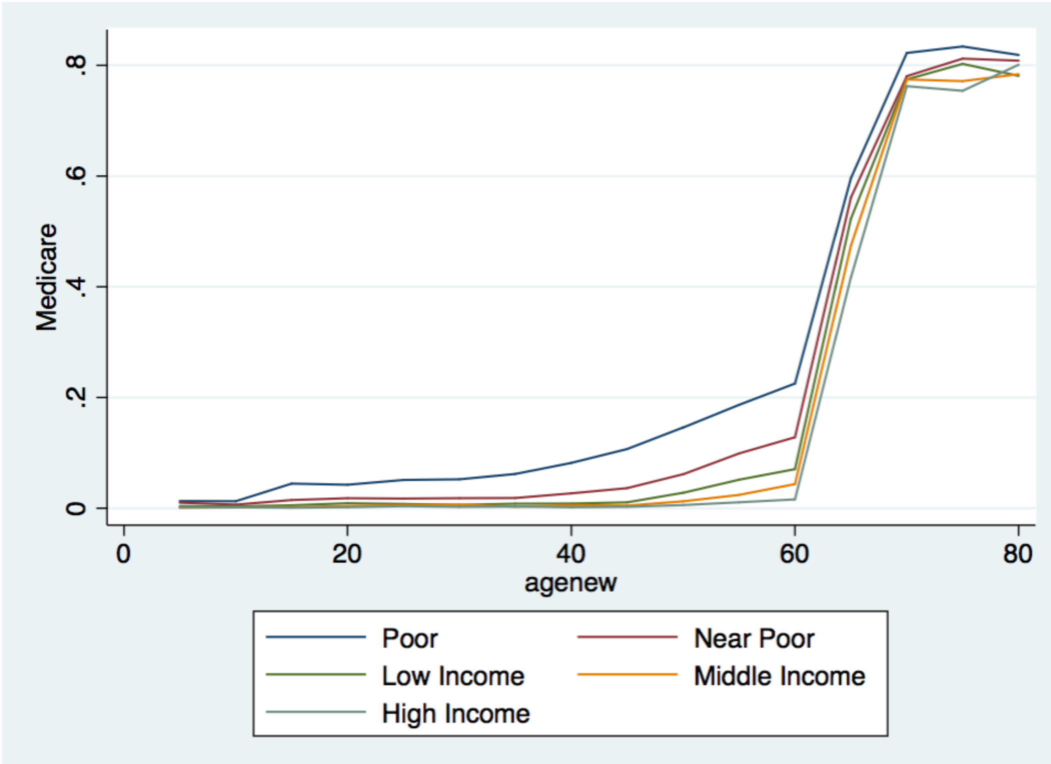
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 28: Fraction with Private Insurance by Income and Age



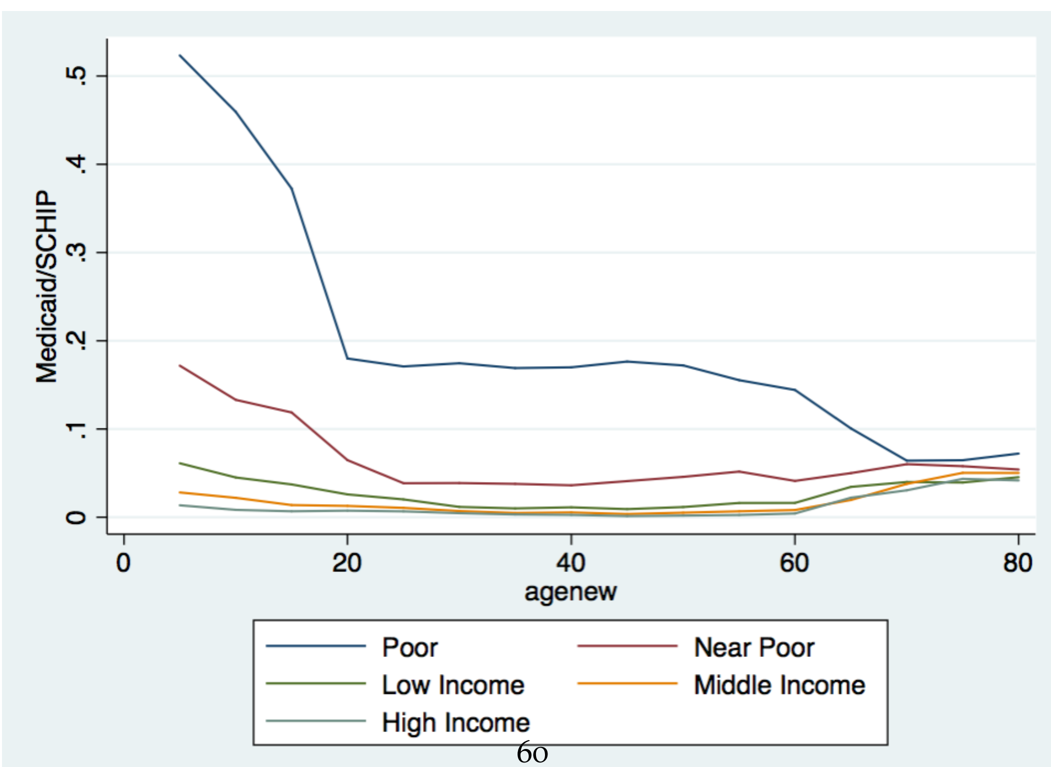
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 29: Fraction with Medicare by Income



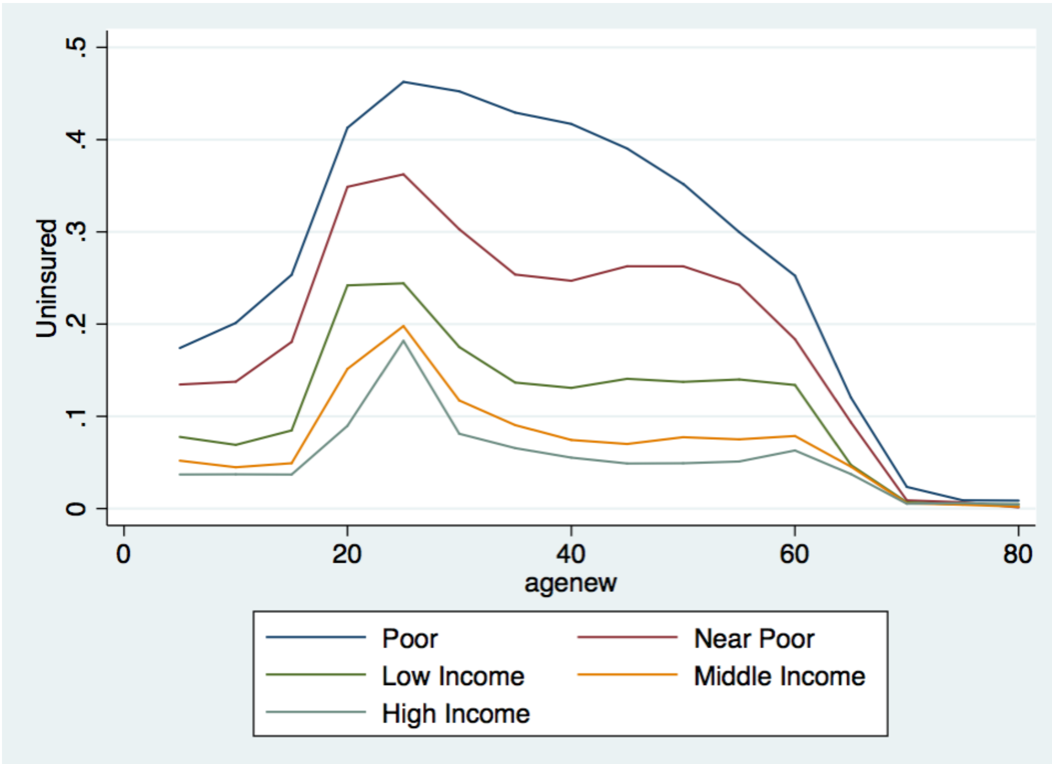
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 30: Fraction with Medicaid and SCHIP by Income and Age



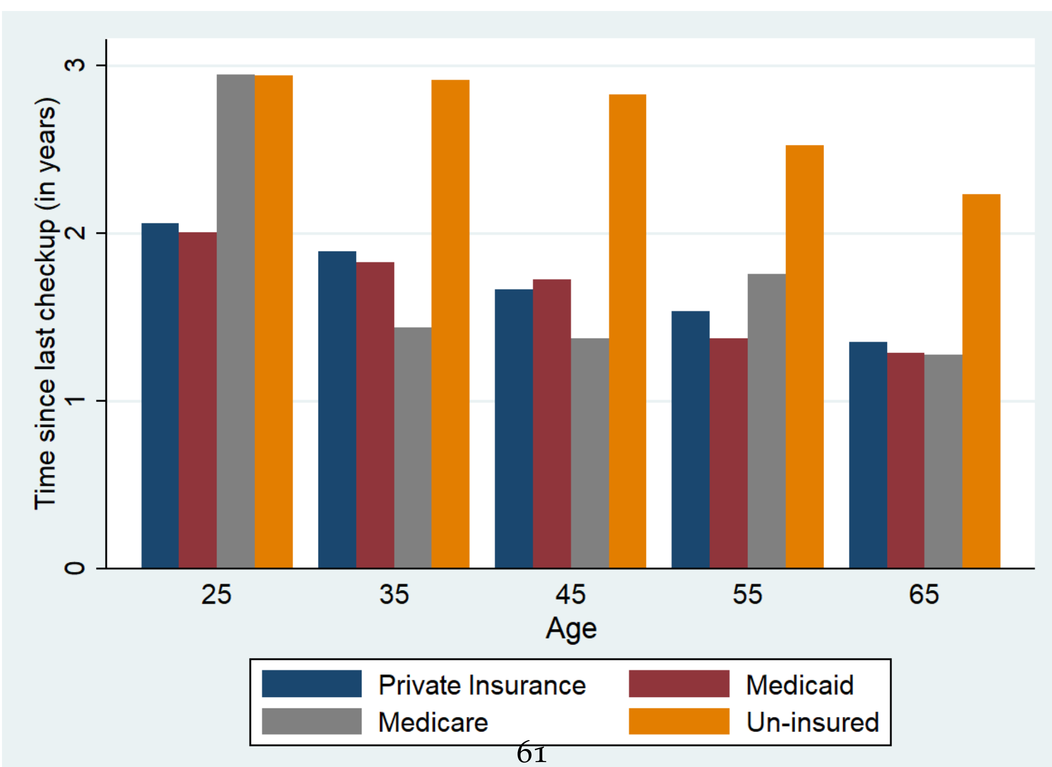
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 31: Fraction Uninsured by Income and Age



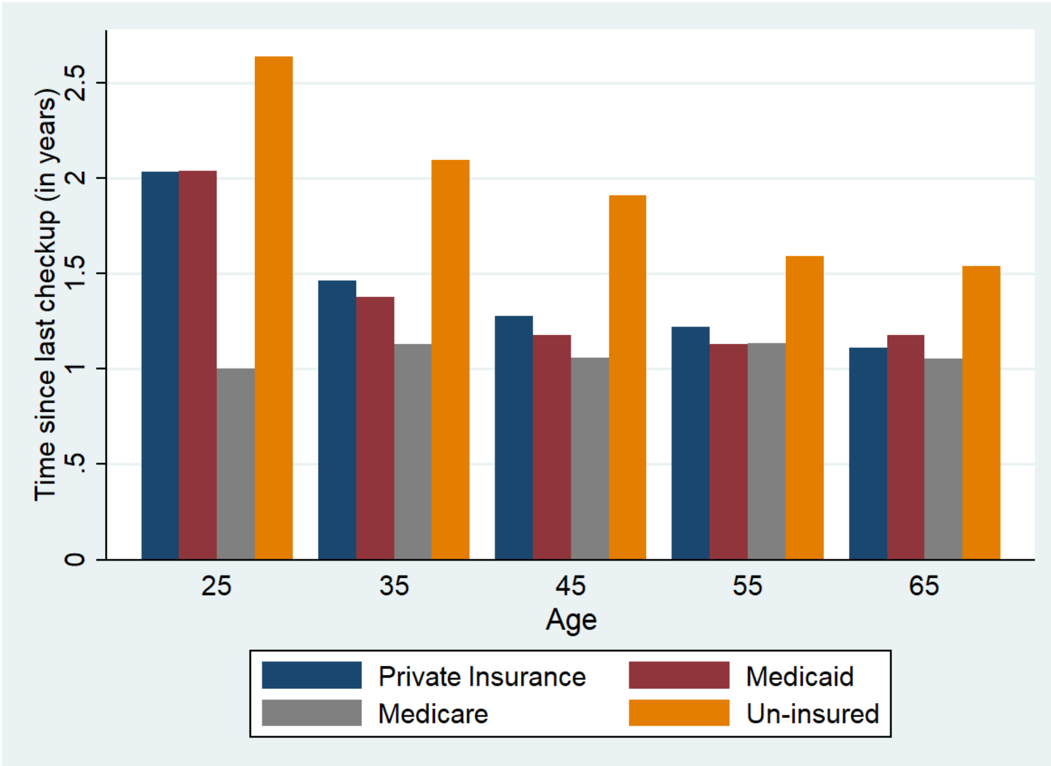
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 32: Time Since Checkup (in years)



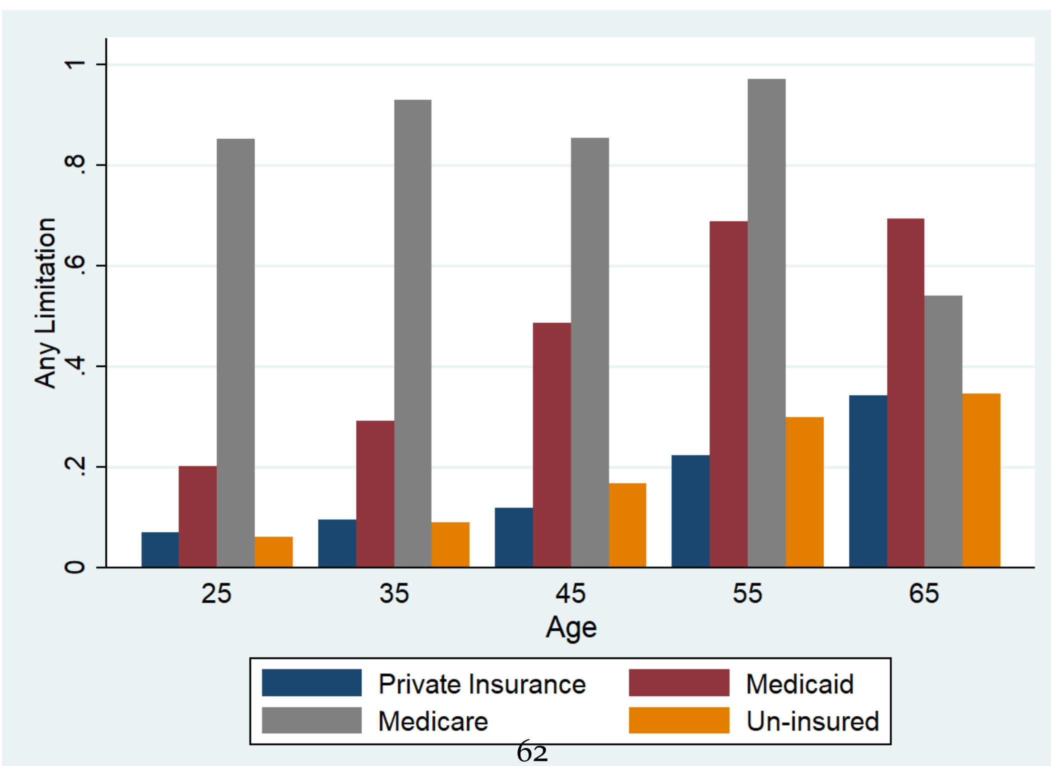
Source: Author's Calculation based on MEPS Data

Figure 33: Time Since Cholesterol Checkup (with pre-existing condition)



Source: Author's Calculation based on MEPS Data

Figure 34: Any Limitation by Age and Insurance Status



Source: Author's Calculation based on MEPS Data

Figure 35: Support for Propensity Score Matching, Wave 6a

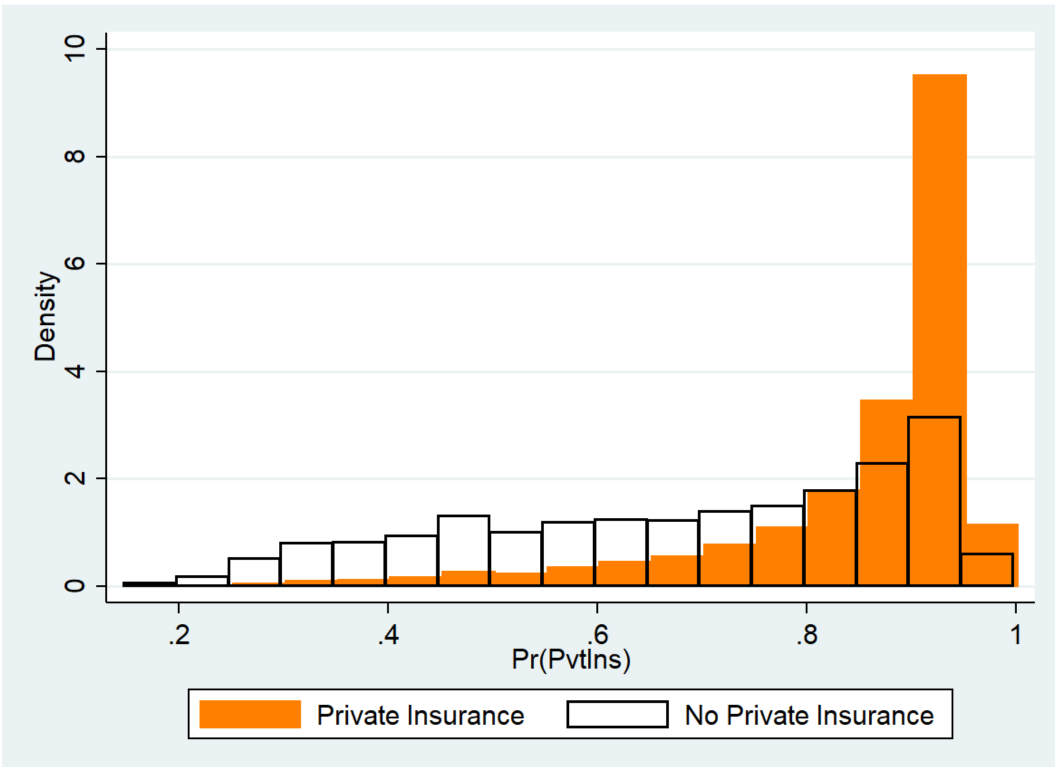


Figure 36: Support for Propensity Score Matching, Wave 6b

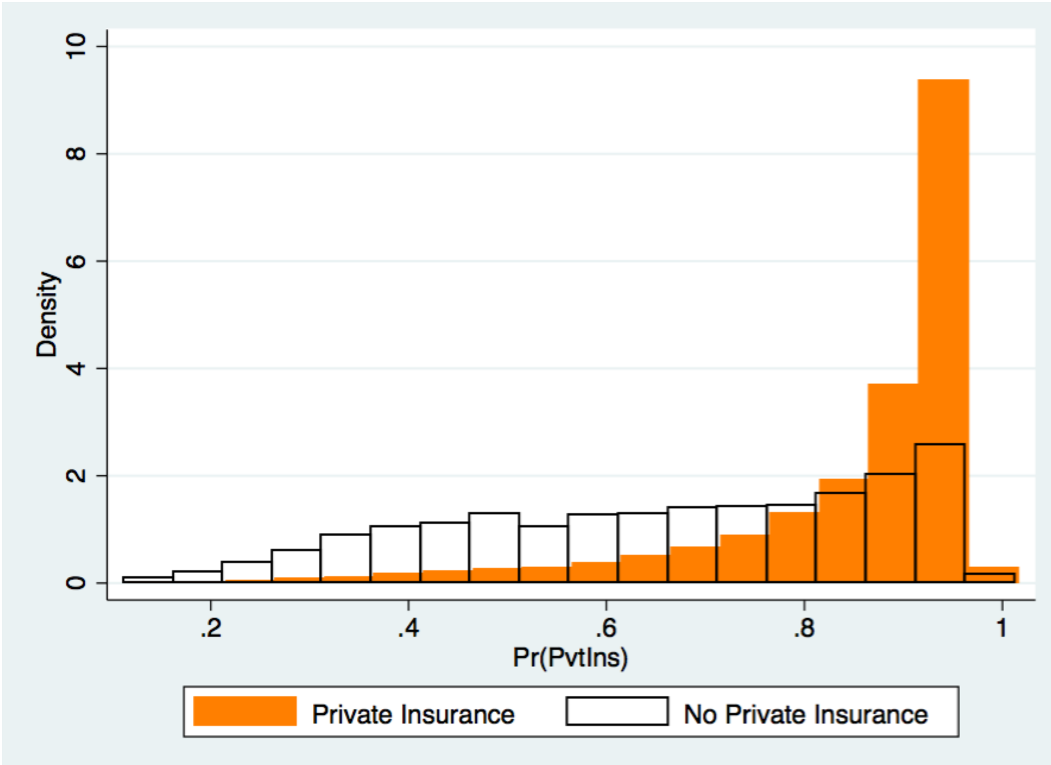


Figure 37: Support for Propensity Score Matching, Wave 6c

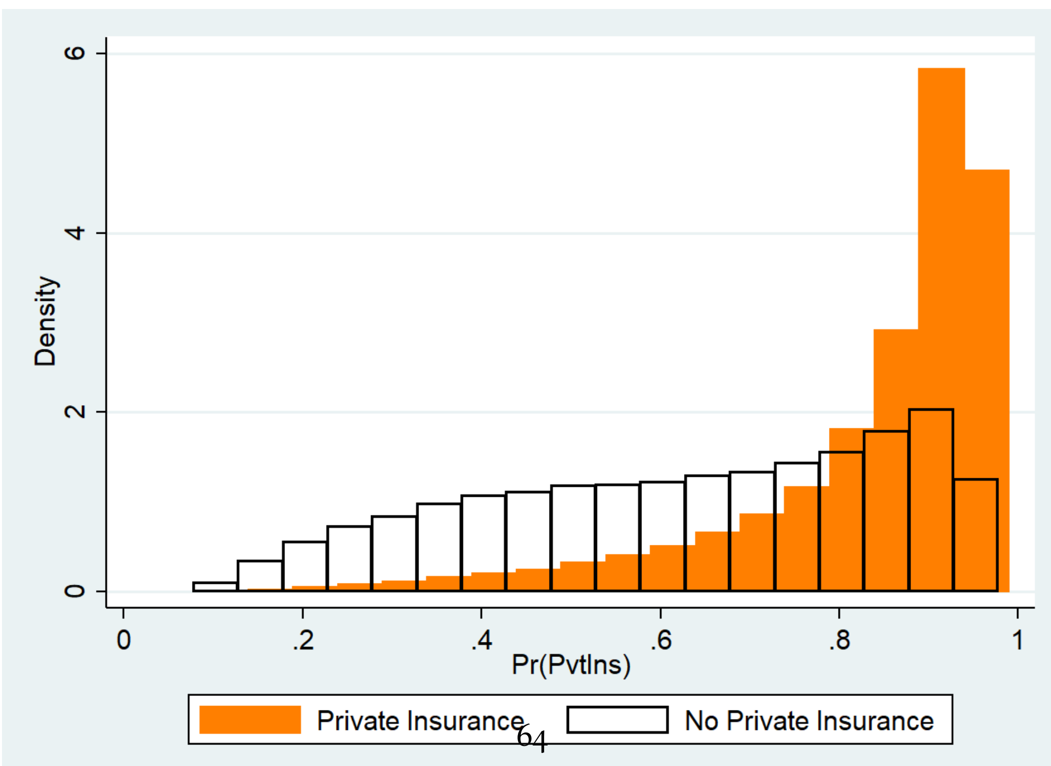
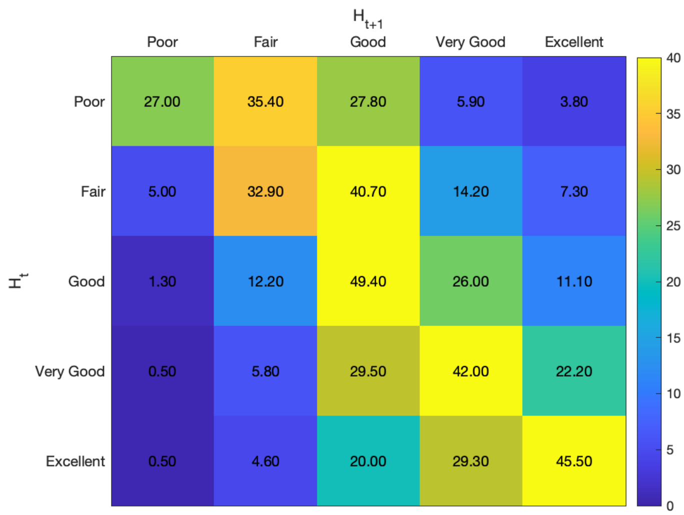
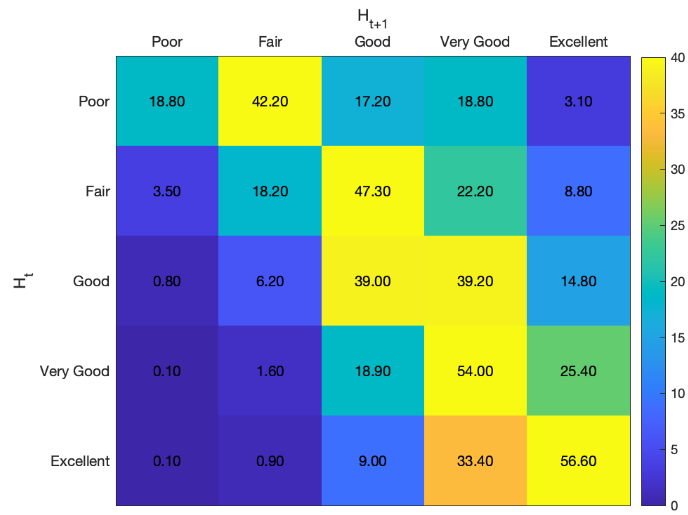


Figure 38: Transition matrix | visit: Poor age 25-35



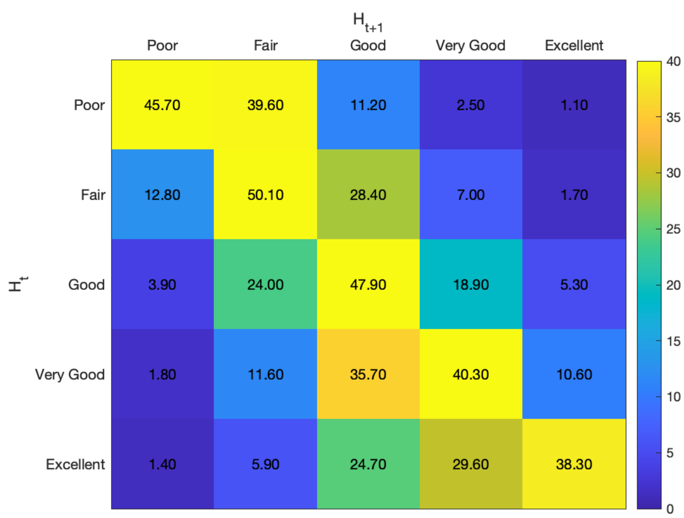
Source: NHIS-MEPS

Figure 39: Transition matrix | visit: Rich aged 25-35



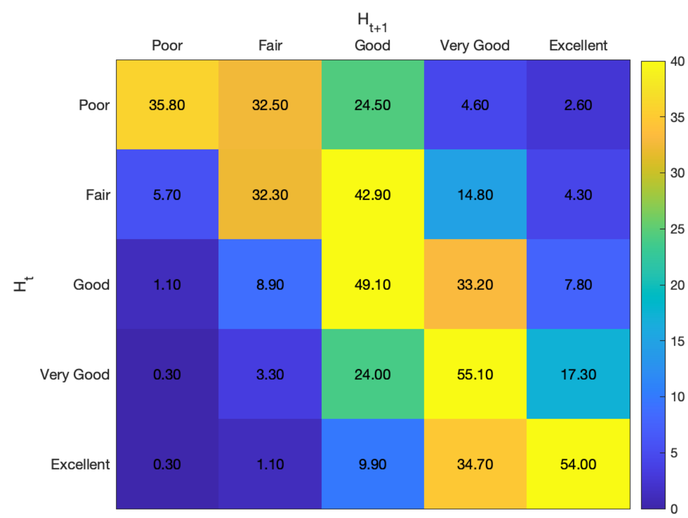
Source: NHIS-MEPS

Figure 40: Transition matrix | visit: Poor age 45-55



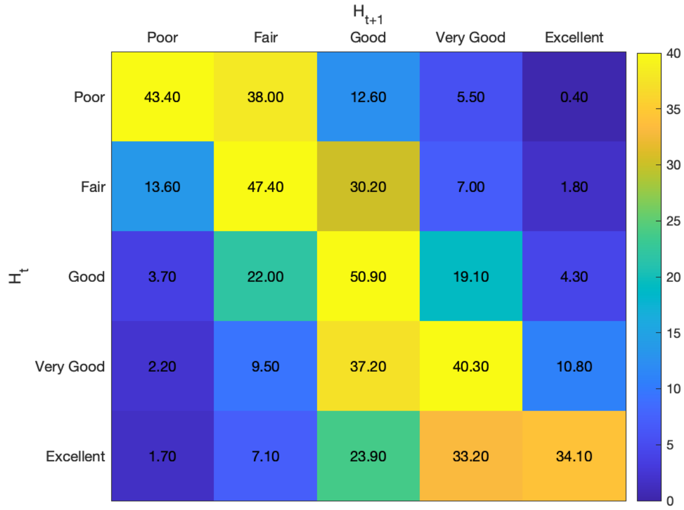
Source: NHIS-MEPS

Figure 41: Transition matrix | visit: Rich aged 45-55



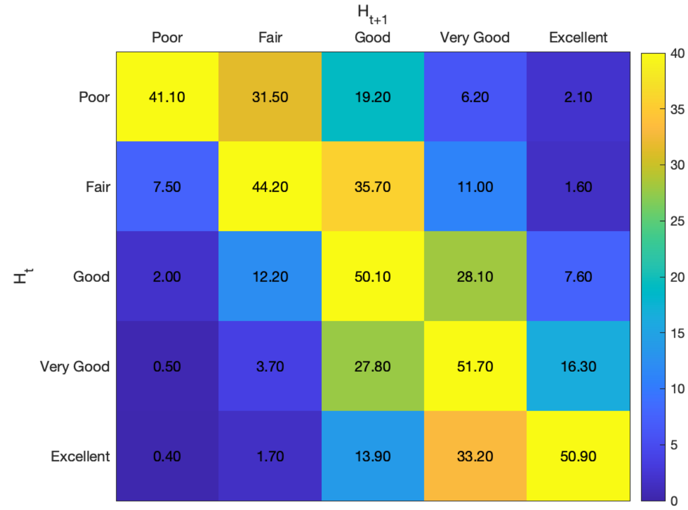
Source: NHIS-MEPS

Figure 42: Transition matrix | visit: Poor age 55-65



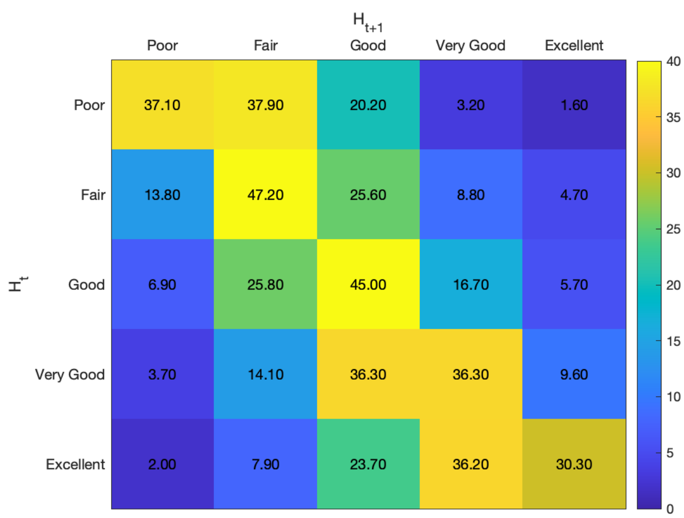
Source: NHIS-MEPS

Figure 43: Transition matrix | visit: Rich aged 55-65



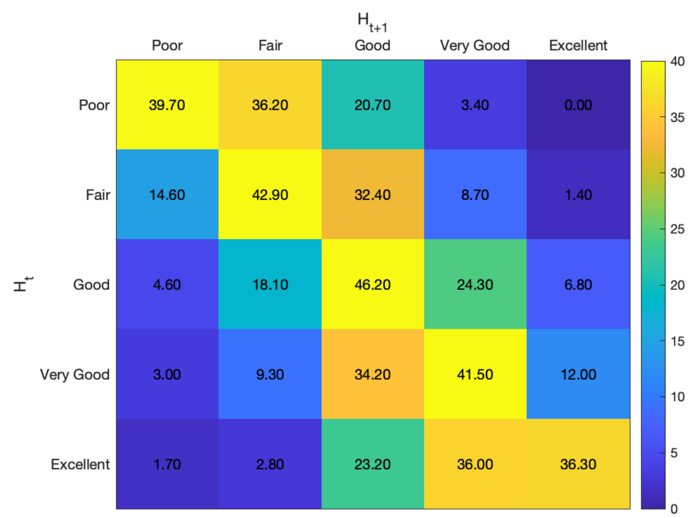
Source: NHIS-MEPS

Figure 44: Transition matrix | visit: Poor age 65-75



Source: NHIS-MEPS

Figure 45: Transition matrix | visit: Rich aged 65-75



Source: NHIS-MEPS