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, 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

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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. [ADD EXAMPLES?] Lastly, we show that a public health insurance scheme, funded by flat-income tax, could go a long way in decreasing the inequality. xx
Keywords: Health Inequality, Technological Progress, Health Insurance
JEL Classification: I12, I13, I14, O11

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. 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

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[1]Mean income for top income group was $256,000 and $17,000 for the bottom income

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. 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 paper 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. There is stochastic aging in the model. Given that the health shocks can arrive continually, our model brings continuous time methods[3], a popular tool used in macroeconomics and finance, into a problem involving individual's health related decisions. 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 transi-

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

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

tioning 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.
- 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[4]. Thus, he not only ends up spending the same amount as a rich person in any given year, he is also not able to reap the benefits of the medical technological progress that we have witnessed.

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.

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.

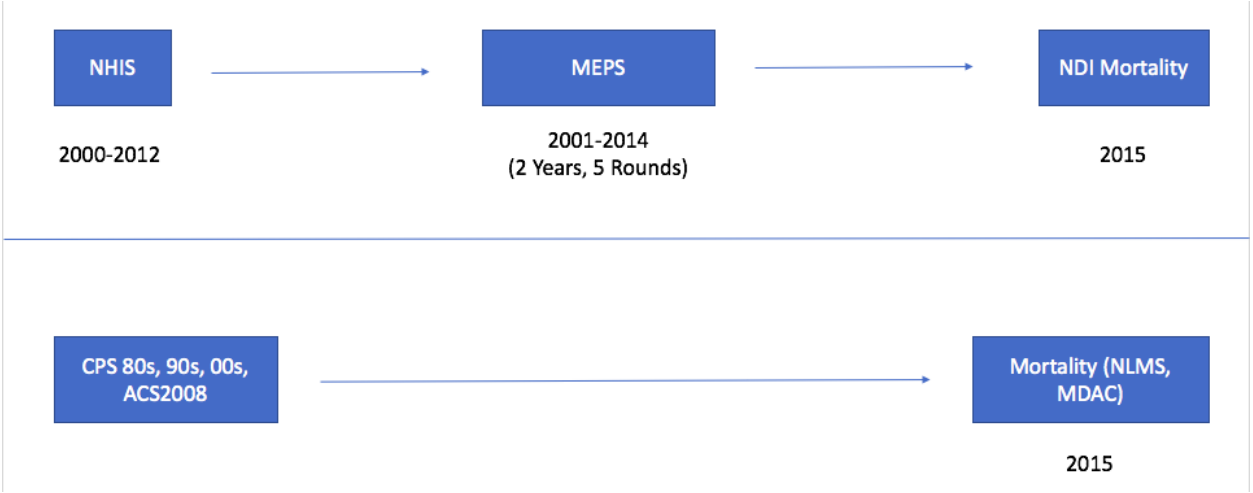
One of the predictions of the model is a significant positive impact of insurance on mortality. In order to cross-validate this results, we perform the following empirical exercise:

[4]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.

- We borrow the evaluation methods used in microeconometrics literature and use the propensity score matching estimator to find the effect of private health insurance on the probability of dying. We find that private insurance reduces the probability of dying in the next 6 years by 15-25% across various NLMS waves as compared to the uninsured (baseline) (Table 14)
- Using state variation in Medicaid eligibility in 2000, we find that among the working age individuals with low family income, Medicaid reduces the probability of dying by 9% (Table 14). This is consistent with a concurrent paper by [ADD MILLER ET AL]

The remaining of the paper is divided as follows: section **??** includes literature review and placing the paper into the literature, section **??** provides the motivating empirical facts, section 2.1 documents some additional aggregate patterns, section **??** describes the model, and section **??** concludes.

2. Data



Our 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). We provide a brief description of the datasets here.

1. National Health Interview Survey (NHIS) - Medical Expenditure Panel Survey (MEPS): We use the recently harmonized 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

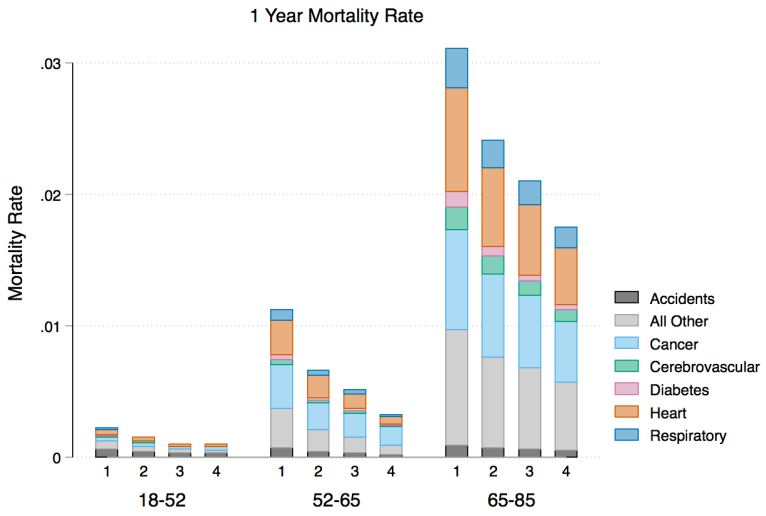
2. National Longitudinal Mortality Survey (NLMS) and Mortality Differentials Across Communities (MDAC): Besides the demographic and socio-economic variables described earlier, NLMS includes detailed date and cause of death across multiple CPS waves from 1980- 2008. Some waves include additional information 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.

2.1 Health outcomes and health spending: a Puzzle

Poor and rich have comparable total medical spending, including private and public insurance, out-of-pocket, but very different outcomes

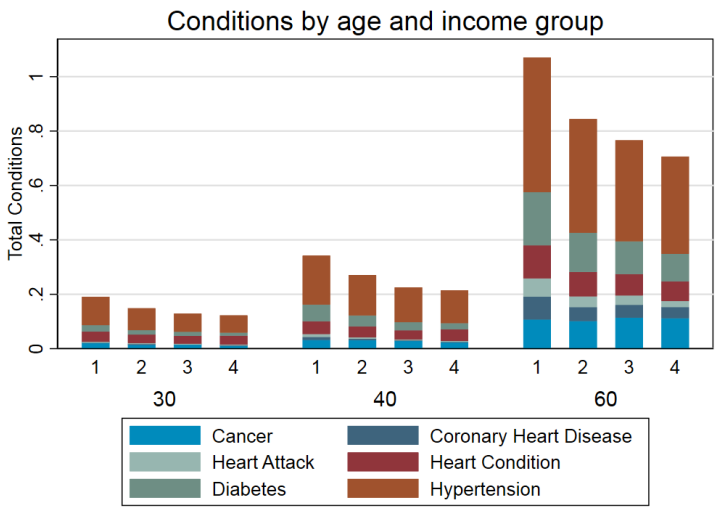
The leading cause of death across the income distribution were cancer and heart conditions based on 2008 year data from MDAC. As shown in figure 1, we see that across all

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



Source: NLMS-MDAC

Figure 2: Conditions by Age and Income

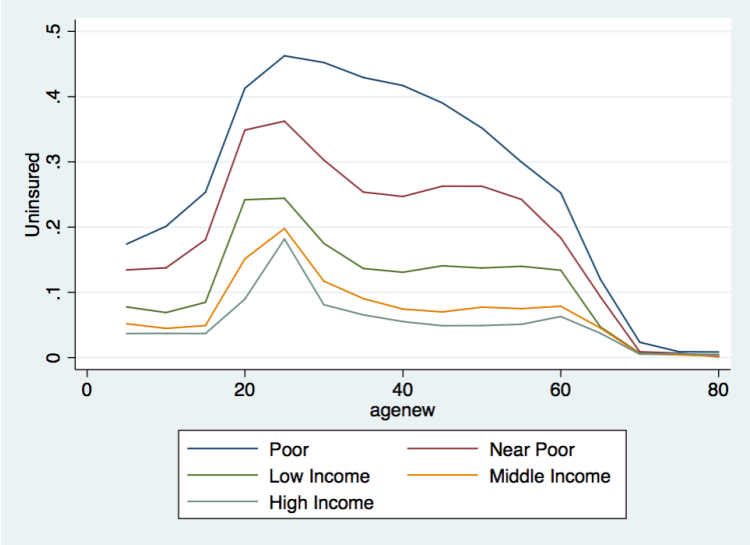


Source: NHIS-MEPS

age groups and cause of death, individuals in fourth quartile of family income distribution[5] have a lower aggregate and cause-specific mortality-rate compared to individuals in first quartile of family income distribution, a pattern that has long been 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.

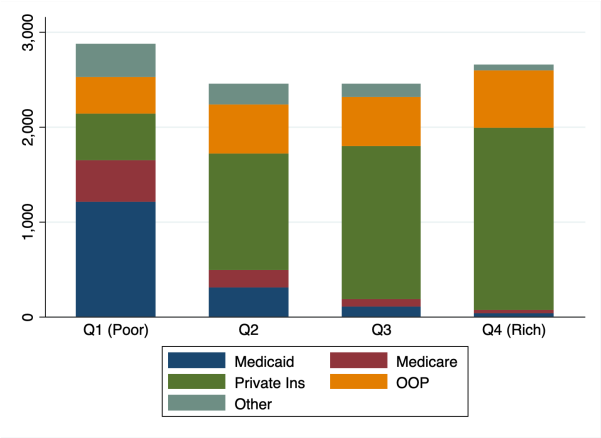
[5]Family income and poverty percent which adjusts for family size is consistently available in both datasets. Thus, we'll use family income quartiles adjusting for family size for the data section to be able to compare similar people across datasets. The measure of quartiles is 10-year age group specific so as to take out the income over the life-cycle pattern. The patterns are very similar when we define the quartiles based on wealth.

Figure 3: Fraction Uninsured by Income and Age



Source: NLMS-MDAC

Figure 4: Medical Expenditure Age 45-55 (IHS transformation)



Source: NHIS-MEPS

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 5. Similar pattern holds for other age groups.

Its 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?

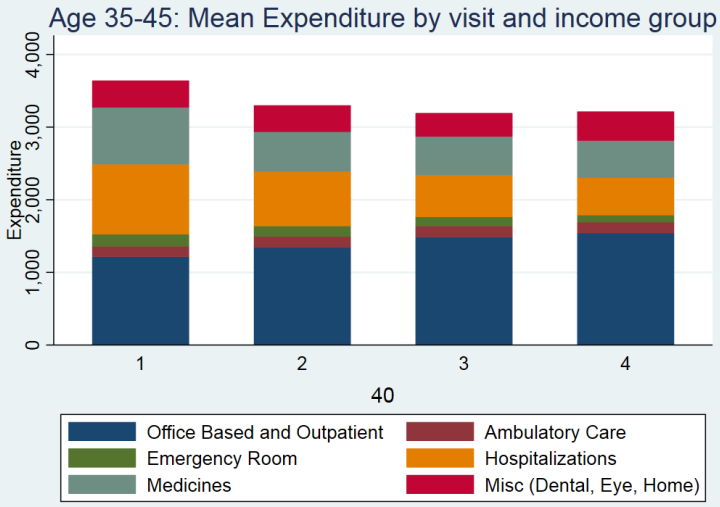
In order to understand the sources, we'll now dig deeper into the data. To the best of our knowledge, the empirical facts in the next section are relatively unexplored in the

literature.

2.2 Empirical Facts

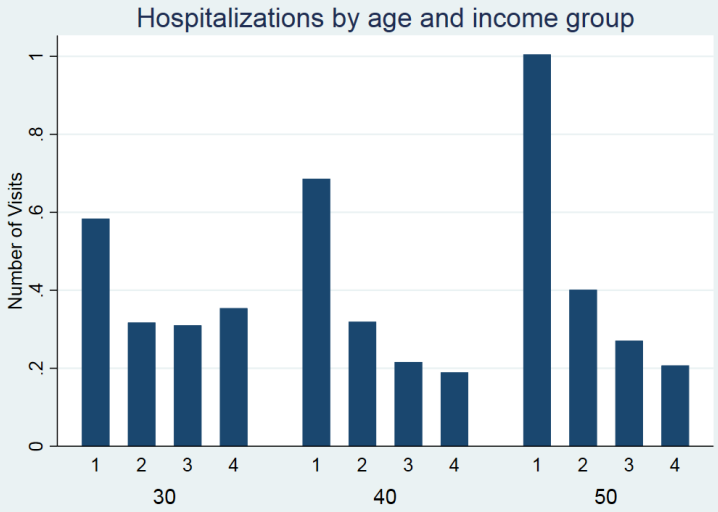
Fact 1. Poor spend more on Hospitalizations and Emergency Rooms while rich spend more on Outpatient visits

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



Source: NHIS-MEPS

Figure 6: Number of Hospitalizations by Age and Income

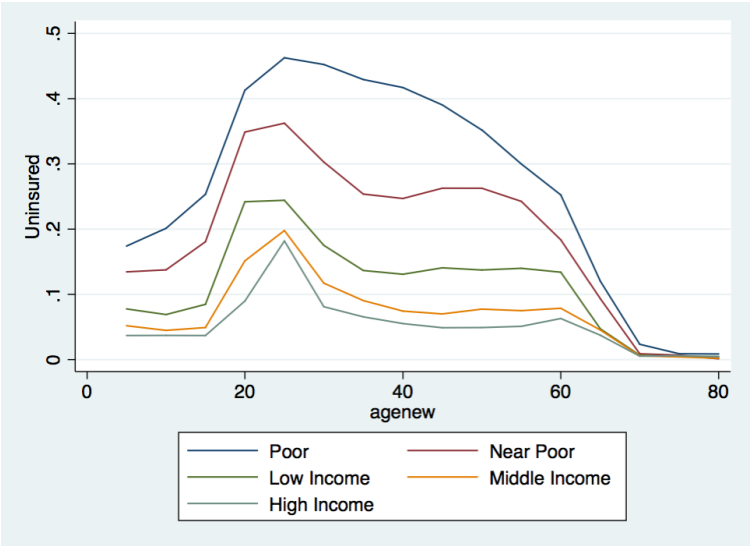


Source: NHIS-MEPS

While the rich and poor[6] spend comparable amounts in total medical expenditures as we saw in the previous section, 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. ($1100 for the first quartile vs $1500 for the top quartile for ages 35-45) 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.

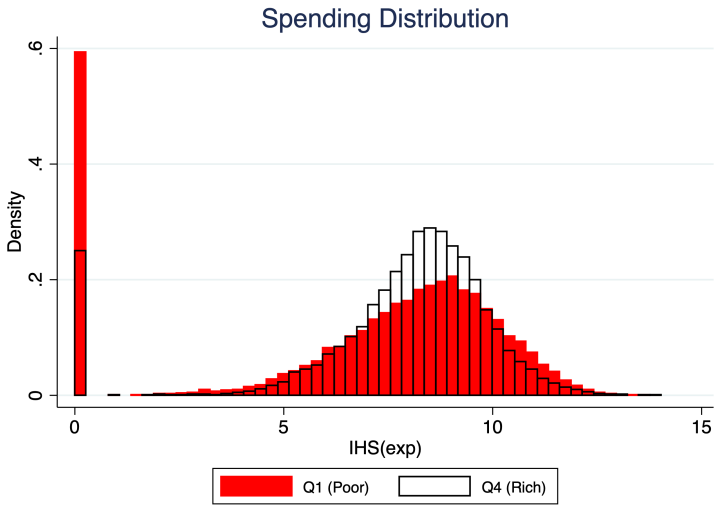
[6]based on family income quartiles, as defined in the previous section

Figure 7: Fraction Uninsured by Income and Age



Source: NLMS-MDAC

Figure 8: Medical Expenditure Age 45-55 (IHS transformation)



Source: NHIS-MEPS

In figure 8, we document the 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 don't 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.

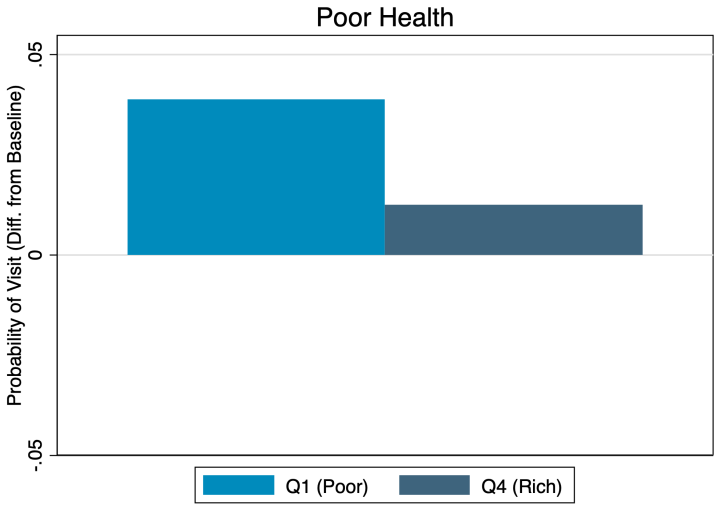
At this time, it is important to point out that a limitation of the spending data, which is commonly used in the literature, is that the prices are not known. It is also important to understand how the spending or expenditure is reported. Spending or expenditure is anything for which the provider was compensated for and thus it does not include uncompensated care[7], 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. One potential concern can be if the insurance providers negotiate a better price for the same quantity and thus the poor get a lower quantity of medical good even after spending the same amount. It is also worth noting that public provisions such as Medicaid, which is available for the poor subject

[7]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

to income 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 8 for those in 45-55 ages, are one of the most efficient negotiators and negotiate some of the lowest prices for the medical services [TO BE ADDED Citation]. 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 optrometrist 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.

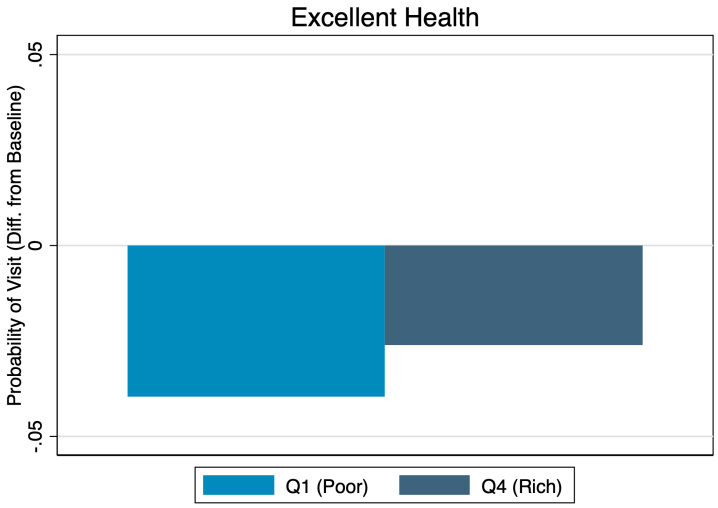
Fact 2. Rich individuals go to the doctor in a much healthier state

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



Source: NLMS-MDAC

Figure 10: Elasticity w.r.to. Health State: Poor vs Rich



Source: NHIS-MEPS

Notes: Includes individual fixed effect; base set to average health in each income group regression

In figure 10 and 9 we 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. The result point out 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 "kills" poor, while improves rich individuals' health

Table 1: Poor: Transition in Health, Age 35-52 No Visit

	Poor	Fair	Good	Very Good	Excellent	Missing
Poor	28.9	31.6	9.2	10.5	0.0	19.7
Fair	4.7	25.8	33.2	11.0	6.6	18.7
Good	1.0	9.5	41.8	20.5	8.7	18.5
Very Good	0.6	3.8	26.1	33.8	17.8	17.9
Excellent	0.5	2.2	16.9	27.3	33.7	19.3
Missing	0.4	8.8	21.1	21.1	17.1	31.6
Total	1.8	8.8	29.3	24.0	16.6	19.5

Source: NHIS-MEPS

Table 2: Poor: Transition in Health, Age 35-52 Visit

	Poor	Fair	Good	Very Good	Excellent	Missing
Poor	38.0	31.7	11.6	2.6	1.5	14.5
Fair	9.8	39.6	27.2	7.2	2.1	14.0
Good	3.9	16.5	41.9	17.6	5.7	14.4
Very Good	1.1	7.1	29.2	33.4	12.4	16.8
Excellent	1.0	6.0	18.9	26.1	33.2	14.8
Missing	9.0	21.6	33.3	11.7	7.2	17.1
Total	8.6	20.6	29.2	17.5	9.2	14.9

Source: NHIS-MEPS

In table 1 and 2 we look at the annual transitions in health for individuals in the first quartile of family income distribution conditional on medical visit. Table 1 shows that amongst the bottom income individuals who reported no medical visit, 10.5% of those in poor health in period 1 had very good health in period 2 while 28.9% of those in poor health stayed in poor health. While among those who reported a medical visit, only 4.1% of those in poor health in period 1 had very good or excellent health in period 2. At the same time, about 38% of those in poor health stayed in poor health.

We then look at the annual transitions in health for individuals in the fourth quartile of family income distribution conditional on medical visit in table 3 and 4. Table 1 shows that amongst the top income individuals who reported a medical visit, 8.5% of those in poor health in period 1 had very good or excellent health in period 2. At the same time, about 21.5% of those in poor health stayed in poor health.

In other words, while going to the doctor improves health for those in top quartile of family income distribution, the effect of medical visit for those in bottom quartile don't seem as much. This along with Fact 6 seems to suggest that those in top income distribution go for medical visit at much healthier state and are also able to transition to

a better health while those in the bottom quartile go at a much worse health state and are not able to improve their health as much.

Table 3: Rich: Transition in Health, Age 35-52 No Visit

	Poor	Fair	Good	Very Good	Excellent	Missing
Poor	33.3	33.3	16.7	0.0	0.0	16.7
Fair	0.0	26.2	28.6	21.4	7.1	16.7
Good	1.1	4.6	31.4	31.1	15.0	16.8
Very Good	0.2	1.6	19.3	41.5	20.4	17.0
Excellent	0.0	0.5	7.3	26.9	46.4	18.9
Missing	0.0	3.7	24.3	20.6	25.7	25.7
Total	0.4	2.7	17.5	31.1	29.8	18.5

Source: NHIS-MEPS

Table 4: Rich: Transition in Health, Age 35-52 Visit

	Poor	Fair	Good	Very Good	Excellent	Missing
Poor	21.5	32.2	22.3	5.0	3.3	15.7
Fair	3.6	25.6	37.6	14.9	4.3	14.0
Good	0.7	6.4	40.4	30.8	9.0	12.6
Very Good	0.4	2.2	19.1	47.4	18.3	12.6
Excellent	0.2	0.8	7.9	28.5	49.9	12.8
Missing	4.0	6.0	25.0	23.0	31.0	11.0
Total	0.8	4.3	20.9	34.7	26.5	12.7

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[8], 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[9]. With time, the survival

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

[9] Note: 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

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

The improvements in heart related causes have contributed the highest gains in life-expectancy, the distributional impact of heart causes have been limited. As shown in table 5, while poor have gained 2.6 years in life-expectancy due to heart related causes, rich have gained 2.7 years in life-expectancy. Malignant neoplasms (cancer) 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 followup 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 5: 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

We first describe the model in which we assume that health is common knowledge at all times. A key consideration of the model is to be able to speak to data as much as possible. Individuals are born young with certain 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. Our health evolution process is a modified birth and death process adjusted to account for mortality, aging and endogenous Poisson intensities. Note, in particular, that we only allow for one step above or below in health transitions. This is because of data limitation: 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 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.

Individuals are born with different initial wealth and initial health. 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[10]. 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

[10]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.

particular, we assume that individuals observe their health capital with/without medical visit. We leave more interesting version in which health capital cannot be observed perfectly, for future research.

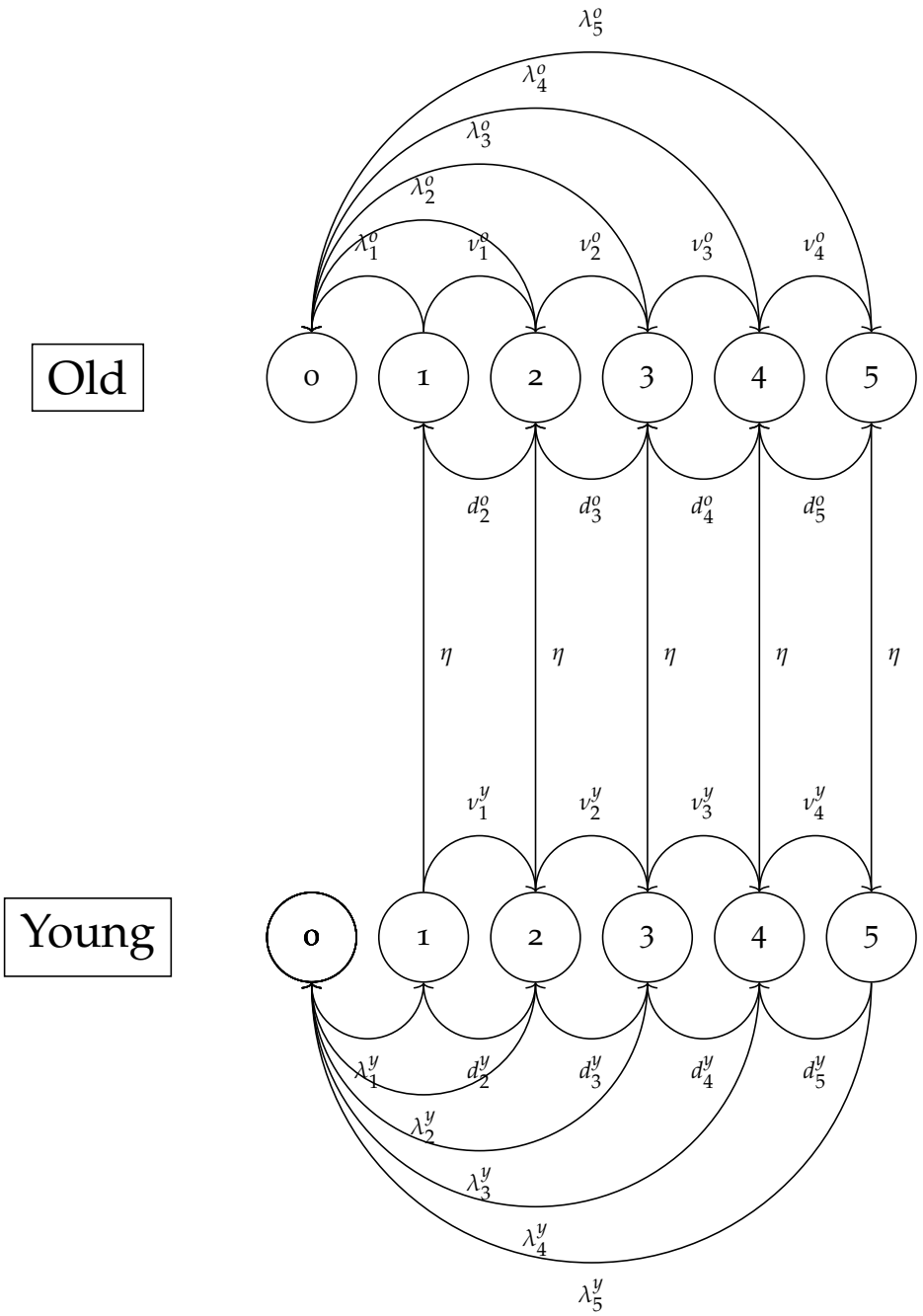


Figure: Illustrative health evolution with two ages

Evolution of health capital

We model health capital h_t in a flexible way and it follows a Poisson process with exogenous intensities d_h^a and endogenous intensity, ν_h^a. Exogenous depreciation is governed by d_h^a, which is the intensity with which a person of age a, goes from state h to $h-1$. Improving ones 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 in health state h and age a die and exit the model with intensity λ_h^a. The intensities are allowed to vary by health, h, and age, a to allow for the fact that healthier individuals would likely die at a much lower rate for the same age individuals in poor or bad health (h = 1 or 2). The formulation is general enough to capture a potential increase in the depreciation of health as individuals age and a reduction in health improvement. Lastly, 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.

To illustrate the evolution of health, lets look at the illustrative figure above. The individuals are born in the state "Young" and are distributed over different health states from 1-5 depicting poor to excellent health. Lets take an 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 nu_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. We assume a terminal age of 85, so individuals who are hit by the aging poisson in the group 75 to 85 also die.

Wealth and income

The budget constraint is standard and given by

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

Where $\theta(h)$ is the labor productivity which could be an increasing function of health, h. Income, $y(e,a)$ is allowed to vary by education, e and age a, c is consumption, p is the health insurance premium

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 and invest in transitioning to a better health state by paying a fixed cost k by investing in their ν.

Individuals can invest in the likelihood of transitioning to a better health, i.e. invest in the Poisson intensity to transition to a better health. They face a fixed cost of going to the doctor and a proportional out-of-pocket cost depending on their insurance status. Thus, individuals optimally choose when to visit the doctor and how much to spend on medical care.

Wealth evolution on Visit

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

Health evolution on Visit

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

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.

Insurance take-up problem

Individuals can decide on insurance take-up problem at random intervals governed by a Poisson process. by intersity ϕ At the time of Poisson realization, individuals are offered a price of the premium, $p(h, a)$ based on their health and age and the premium stays the same until another (random) realization of the Poisson.

Individual's problem

Under the assumptions of at most linear growth and Lipschitz continuity,[11] the individual's problem can be written compactly as,

[11] By Øksendal and Sulem (2005, Theorem 1.19), the solution to Levy SDEs (**??**) exists and is unique

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

Claim: 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 (**??**).

The two branches in equation 1 correspond to continuation region, where the individuals don't do to the doctor and the only decisions are consumption-savings and taking-up private insurance in case of poisson realization and stopping region where individuals go to the doctor and invest in their health capital. As described in equation 1, the individuals continuously and optimally choose which branch they are in by comparing the value in each branch. Lets write down the two branches separately:

Continuation region: $\rho V(w,h,\nu,a,I,p) = \max_c \{u(c,h) + V_w[\theta(h)y(a) + rw - c - p]\}$

$$\underbrace{\eta[V(w,h,\nu,a+1,I,p) - V(.)]}_{\text{aging to } a+1} + \underbrace{\nu[V(w,h+1,\nu_0,a,I,p) - V(.)]}_{\text{transition to } h+1} +$$

$$\underbrace{d(h,a)[V(w,h-1,\nu_0,a,I,p) - V(.)]}_{\text{transition to } h-1} + \underbrace{\lambda^T(h,a)[V^T - V(.)]}_{\text{death}} +$$

$$\underbrace{\phi[\bar{V}(w,h,\nu,a,I',p') - V(.)]}_{\text{insurance choice}}$$

Stopping region: $V(w,h,\nu,a) = V^*(w',h,\nu',a)$ (2)

where, $\bar{V}(w,h,\nu,a,I',p') = max\left\{ \overbrace{V(w,h,\nu,a,1,p(h,a))}^{\text{insurance}}, \overbrace{V(w,h,\nu,a,0,0)}^{\text{no insurance}} \right\}$

$$V^*(w,h,\nu,a) = \max_m V^i(w',h,\nu',a) \quad (3)$$

$$w' = w - k(I_0) - mq(I_0) \quad (4)$$

$$\nu' = \nu_0(a) + Am^{\alpha_m} \quad (5)$$

(6)

In the continuation region, the value includes the flow utility from consumption – augmented with the health state – and captures the idea that individuals may derive more utility from consumption in a healthier 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. The value also incorporates the dynamic effects from aging, transitioning to a better or worse health, likelihood and value from dying and the change in value associated with the insurance choice.

On the other hand, in the stopping region, the individuals problem is given by equations , where the individuals pay a fixed cost, $k(I_0)$ of going to the doctor and a proportional out-of-pocket cost, $q(I_0)m$ and invest in the intensity to go to a better health by optiamlly chooiseing medical spending, m. When they visit they doctor, they choose optimal medical expenditure m_t to invest in their health capital using technology with Total Factor Productivity (TFP) A and intensities α_m of m respectively. Given their decision to invest in health, they choose the medical expenditure m_t which increases ν, i.e. lowers the expected duration of going to the better health state 5 and their wealth as in equation 3. 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. Note that we think of ν as consisting two parts: a natural improvement rate ν_0 to capture the feature of data that individuals transition to a better health state without doctoral visits. Every time 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 uncertainity 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 aren't able to get to a better health state.

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.

- Utility Function

$$u(c,h) = (1+\phi(h))\frac{c^{1-\gamma}-1}{1-\gamma} \tag{7}$$

3.1 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 in bad health below. Because of the fixed cost, there are wealth effects in the vision 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. If one is already goign to get to a better health, the individual wouldnt go to the doctor unless the health depreciates. And this threshold is increasing in wealth. 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 wouldn't. Visit Decision, Age 35-45

Figure 11: Uninsured, Bad Health

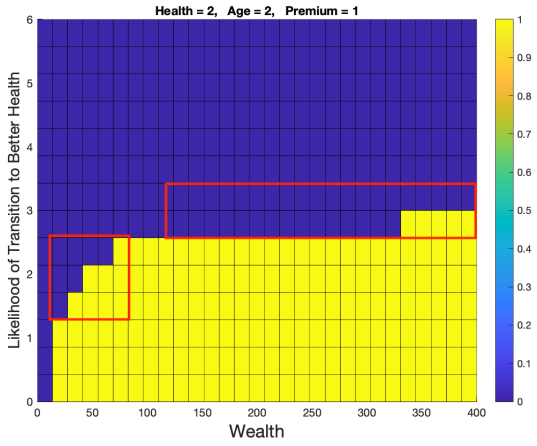
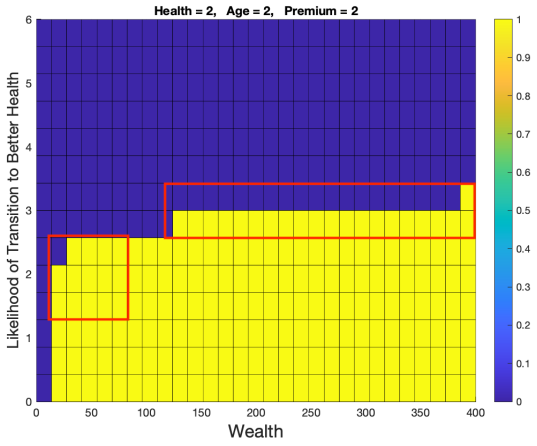


Figure 12: Insured, Bad Health



Continuation (don't go to the doctor)

Stopping (go to the doctor)

4. Estimation

The quantitative model has 5 health states and 6 ages, so as such the number of parameters run in hundreds. 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.

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. In order to reduce the number of parameters to be estimated, we make further simplifying assumptions in the following way:

- Equal depreciation across health states: $d(5,a) = d(4,a) = d(3,a) = d(2,a) = d(a)$

- Depreciation over age: Power function

$$d(a) \quad = \quad d_0 + d_1 age + d_2 age^2$$

- Natural improvement by age: Power function

$$\nu_0(a) = n_0 + n_1 age + n_2 age^2$$

- Utility cost of health: Power function

$$\phi(h) = \phi_0 + \phi_1 h + \phi_2 h^2$$

We simulate the model monthly and take 15-day exit rates to pin down instantaneous mortality rate. The underlying assumption is that the health status doesn't change in this 15 day period and that this is the instantaneous exit rate unaffected by the endogenous objects in the model. Given that not many healthy, young people die in the next 15 days from the interview, we assume proportional increase of mortality rates across by age, i.e. while we estimate $\lambda(h, 6)$ from data for individuals aged 75-85 across health, we assume:

$$\lambda(h, a) = \begin{cases} \lambda(h, 6)/F_{25-35} \text{ if age } \in \{25 - 35\} \\ \lambda(h, 6)/F_{35-45} \text{ if age } \in \{35 - 45\} \\ \lambda(h, 6)/F_{45-55} \text{ if age } \in \{45 - 55\} \\ \lambda(h, 6)/F_{55-65} \text{ if age } \in \{55 - 65\} \\ \lambda(h, 6)/F_{65-75} \text{ if age } \in \{65 - 75\} \end{cases} \tag{8}$$

Table 6: 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

As described earlier, we match instantaneous mortality rates by health for individuals aged 75-85 in the data and 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.

Table 7: Estimated Outside of the Model

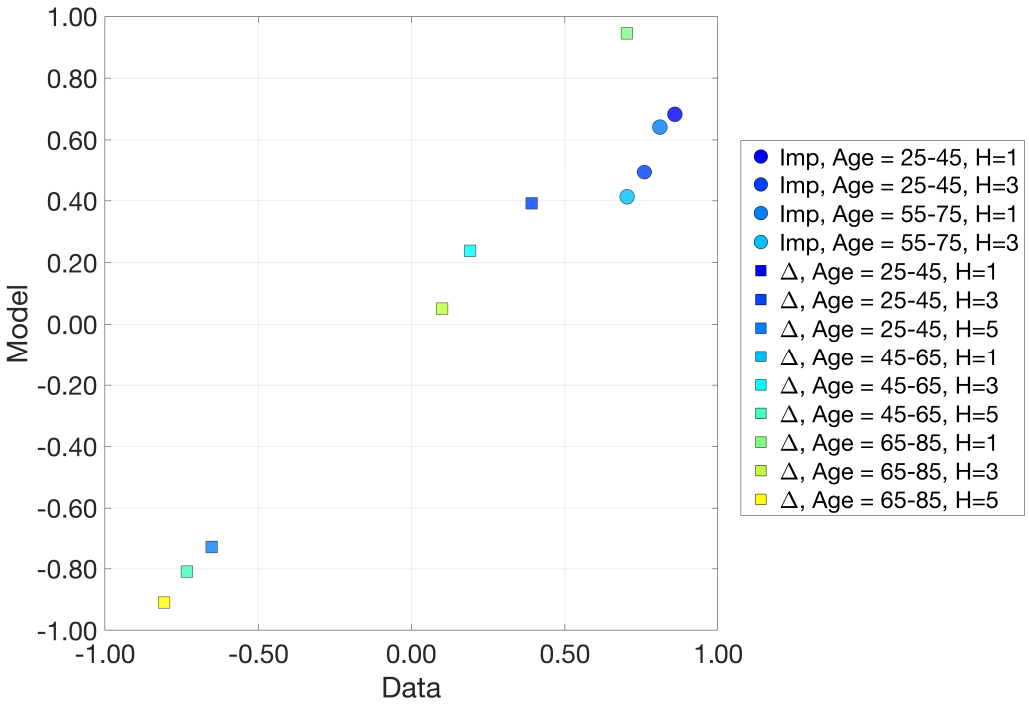
Meaning	Parameter	Value
Mortality Poisson, Age 75-85, h = 1	$\lambda(1,6)$	0.116
Mortality Poisson, Age 75-85, h = 2	$\lambda(2,6)$	0.024
Mortality Poisson, Age 75-85, h = 3	$\lambda(3,6)$	0.0127
Mortality Poisson, Age 75-85, h = 4	$\lambda(4,6)$	0.0057
Mortality Poisson, Age 75-85, h = 5	$\lambda(5,6)$	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)

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 4.

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 **?**.

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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0.00
0.50
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Imp, Age = 25-45, H=3
Imp, Age = 55-75, H=1
Imp, Age = 55-75, H=3
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Δ, Age = 25-45, H=3
Δ, Age = 25-45, H=5
Δ, Age = 45-65, H=1
Δ, Age = 45-65, H=3
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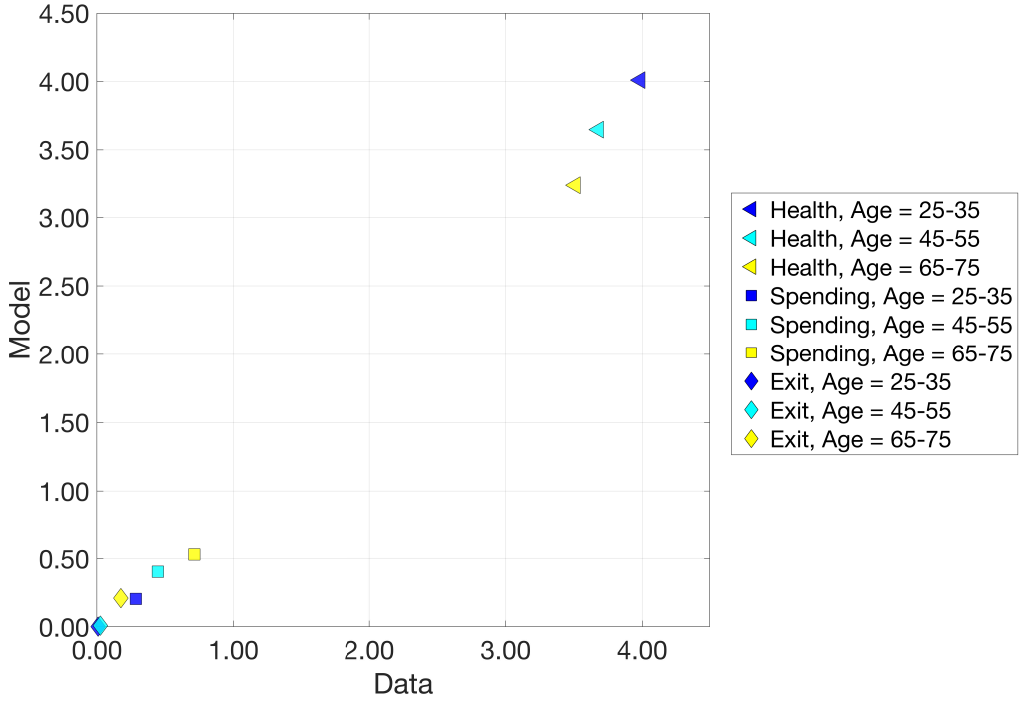
Δ, Age = 65-85, H=3
Δ, Age = 65-85, H=5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4.00
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Health, Age = 45-55
Health, Age = 65-75
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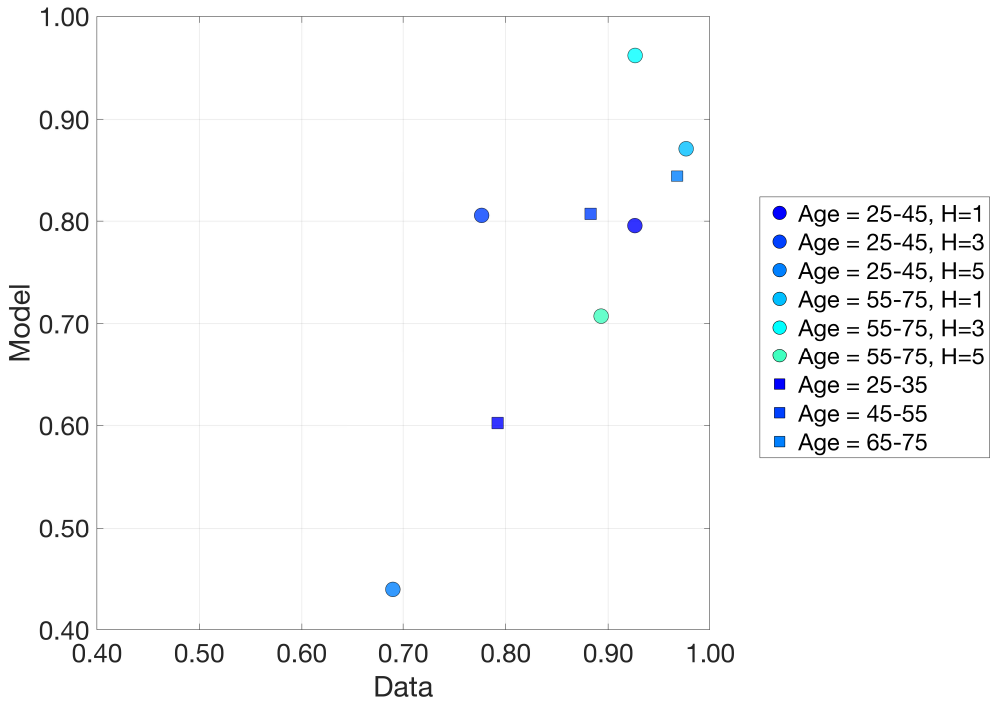
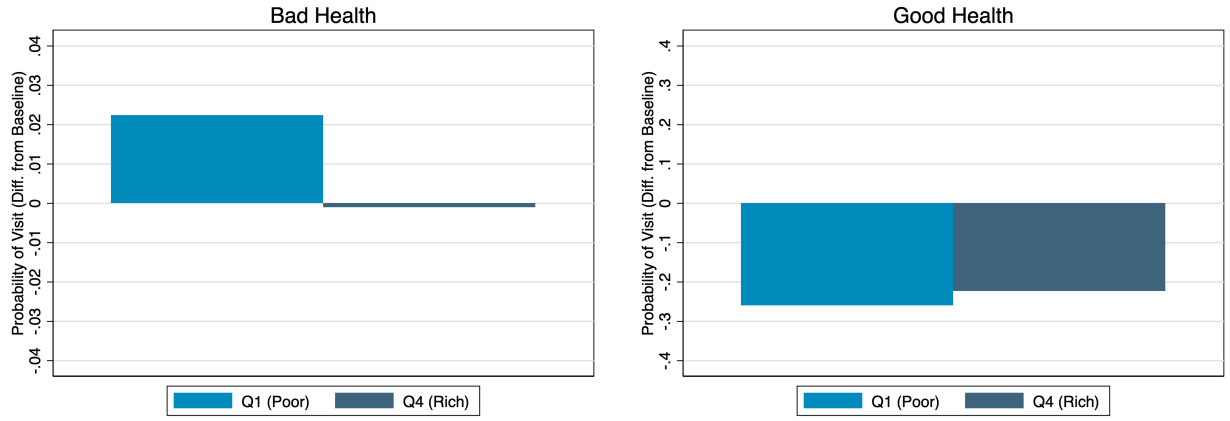
Spending, Age = 45-55
Spending, Age = 65-75
Exit, Age = 25-35
Exit, Age = 45-55
Exit, Age = 65-75


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.



The estimated model implies that lower wealth indivuduals' visit decision is highly elastic w.r.to. their health status. An implication of this is that the poor individuals go to the doctor in a much more unhealthier state than the rich. We do 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 quaterly 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. 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 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 surprizing 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 investing 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- something that is left for future work.

Table 8: 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 9: 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

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, as shown in **??**. This pattern is true across all health states[12]. On the right block of table **??**, we show that this compares well with the medical spending data by family income adjusted for family size and age quartile.[13] Subsequently, they move on to transition to a better health with a higher probability in the next quarter, as we show in 13 where we plot the 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 exericse 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 0,1

[12]It holds for all ages, however, ages 35-45 are shown here for exposition.
[13]Moments by wealth are pending from the data center and will be added in future work.

health as is common in the literature [CITE DENARDI] and also a multinomial logit with similar results.

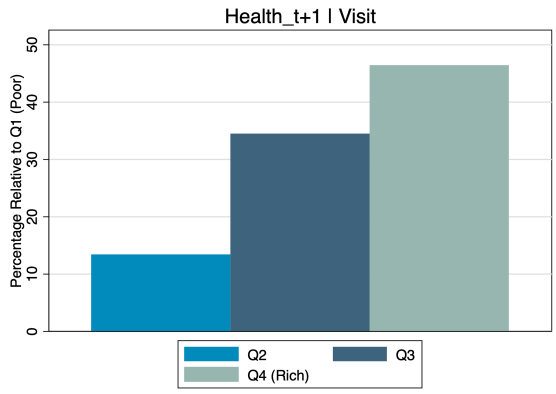


Figure 13: Model (by Wealth)

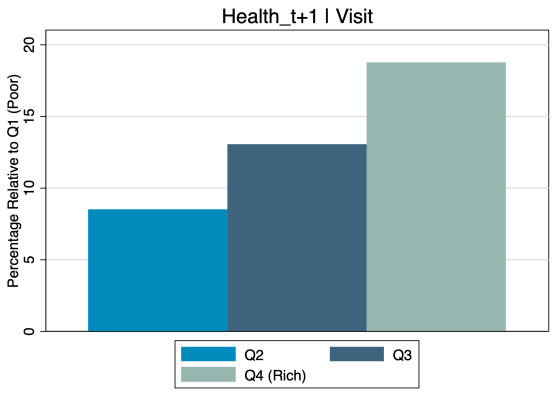


Figure 14: Data (by Family Income)

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

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 10. 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 10: 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 11: 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

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 15. 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 folks exiting the sample. Its 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.

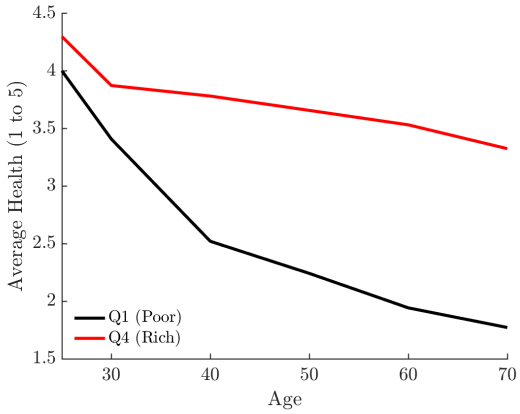


Figure 15: Model

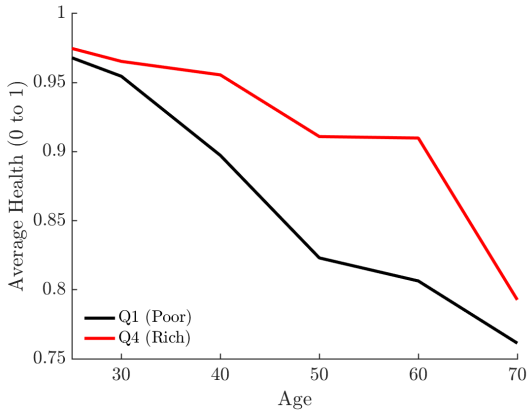


Figure 16: Data Analogue in PSID

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 untarted 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 12: 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 13: Data

	Wealth Quartiles			
	Q1	Q2	Q3	Q4
Life-Expectancy	1.00	1.05	1.10	1.14
Mean Spending 35-45	1.00	1.01	1.03	1.12
Mean Spending 45-55	1.00	0.92	0.94	0.96
Mean Spending 55-65	1.00	1.11	1.05	1.14
100 x Mortality 35-45	1.00	0.86	0.91	0.58
100 x Mortality 45-55	1.00	0.88	0.75	0.56
100 x Mortality 55-65	1.00	0.65	0.56	0.44

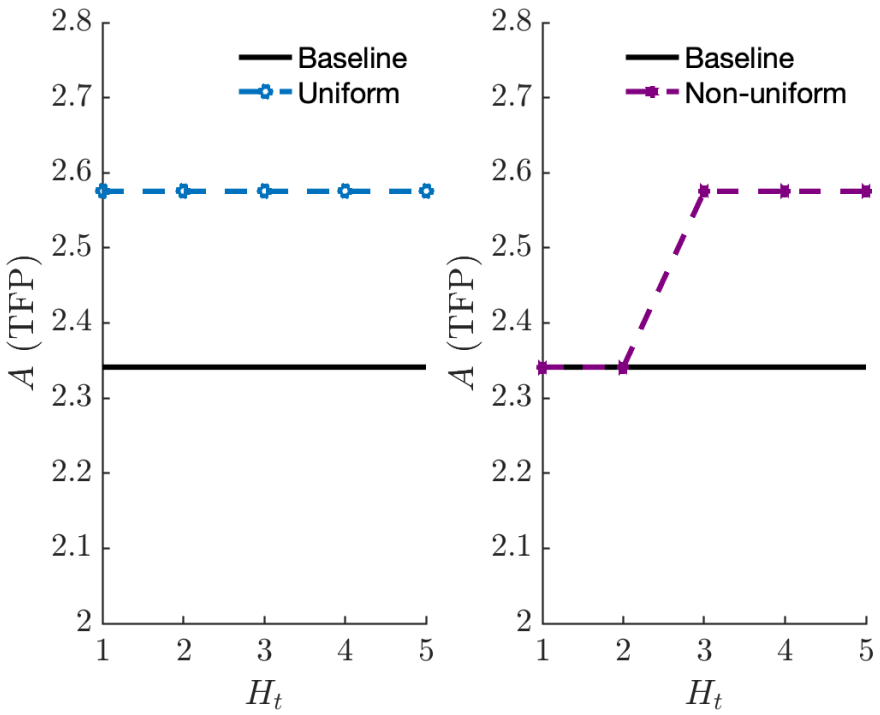
6. Quantitative Experiments

6.1 Technology

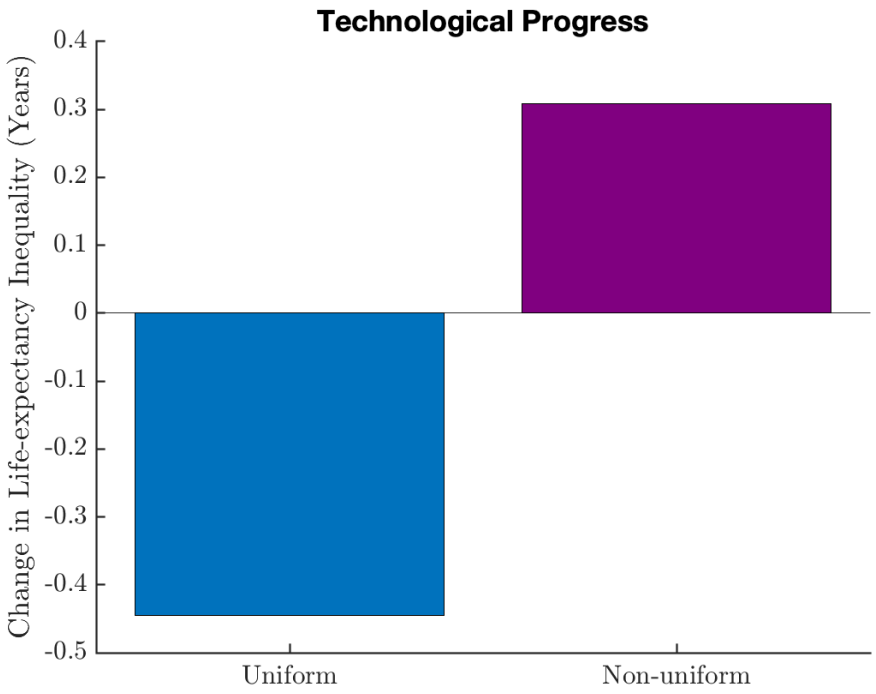
In order to understand the role of technological progress in the rising health ineqaulity in the US, we perform two counterfactuals:

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 by increasing the life-expectancy of the poor more than the improvements for the rich- 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, 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 17 and 18. 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 woul lead to a modest reduction in inequality between the two and the bottom quartiles.

Figure 17: Good Health

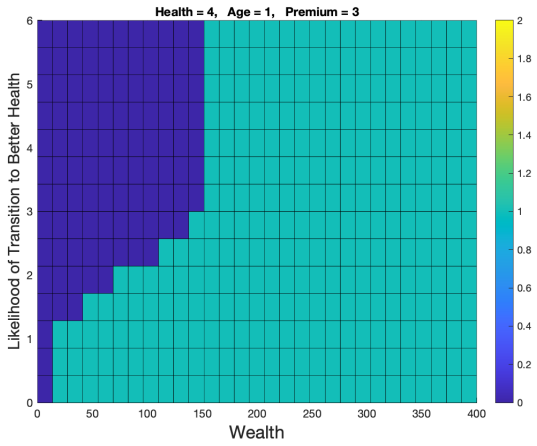
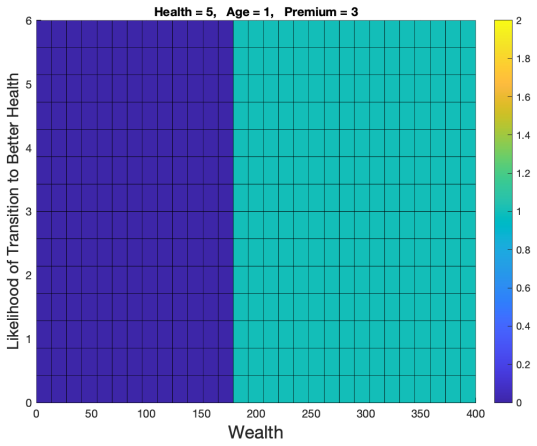


Figure 18: Excellent Health

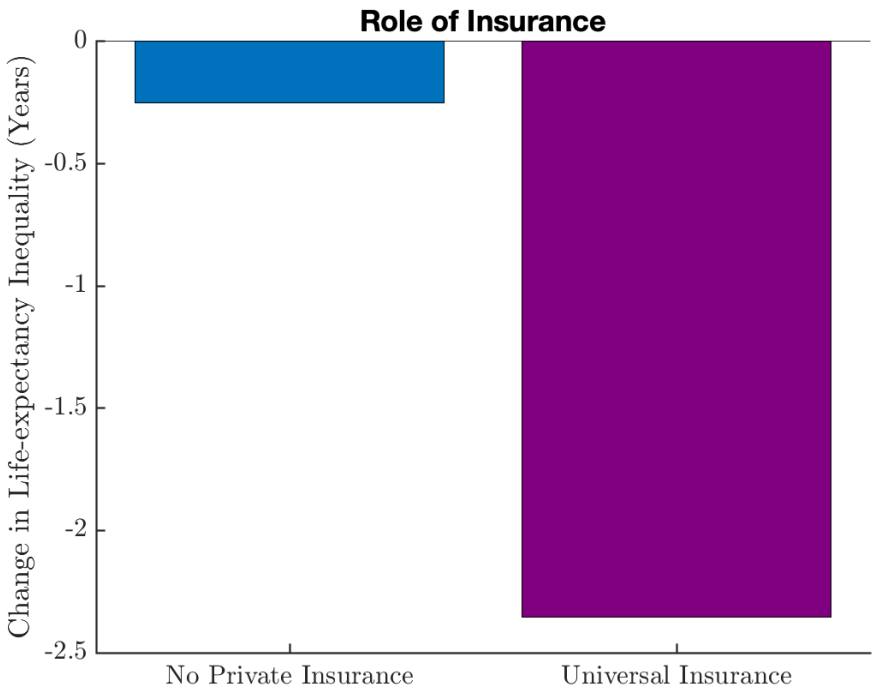


Two experiments:

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 may be missing general equilibrium effects though the insurance firms since who takes up private insurance would be different depending on whether or not insurance firms are allowed to cream-skim by charing 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

National Longitudinal Mortality Survey (NLMS)

National Longitudinal Mortality Survey (NLMS) is a longitudinal survey to study the differentials in mortality rates by socio-economic status and demographics. We use the Public Use Microdata Sample (PUMS) which is a multi-stage stratified sample of non-institutionalized population of the U.S. It is uniquely important for our purposes because it matches subsample of Census Bureau data from Current Population Surveys (CPS) with death certificate information to identify the mortality status and cause of death. In

NLMS-PUMS version 5, 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.

In summary, there are 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.

Effect of Medicaid on Mortality

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:

$$\alpha^{RD}(z^*) = \frac{P(Y_{t+6} = 1|z = 2) - P(Y_{t+6} = 1|z = 1)}{P(Medicaid = 1|z = 2) - P(Medicaid = 1|z = 1)} \tag{9}$$

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 14).

Table 14: 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 14 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)[14]. 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[15]. 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:

$$\alpha_{PSM}^{ATT} = E_{P(X)|D=1}\{E[P(Y_{t+6} = 1)|D = 1, P(X)] - E[P(Y_{t+6} = 0)|D = 0, P(X)]\} \quad (10)$$

We use nearest-neighbor matching and check for common support assumption in figure 33, 34 and 35 and leave out the bins without overlap to ensure that common support assumption is not violated. Our propensity score specification is the following:

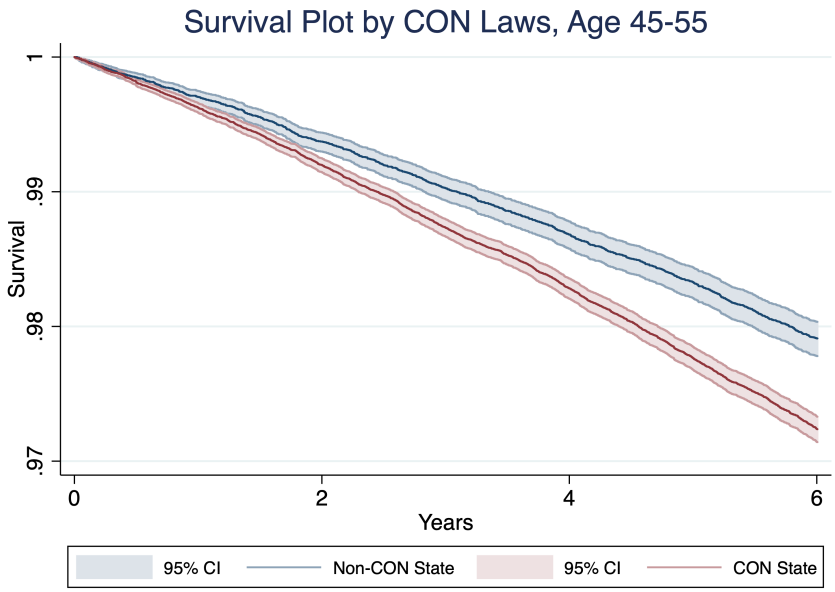
$$P(D = 1|age, sex, income) = \beta_0 + \beta_1 \text{ x } age + \beta_2 \text{ x } sex + \beta_3 \text{ x } income + \beta_4 \text{ x } education \quad (11)$$

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 14, 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.

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

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

Figure 19: Survival Plot: CON vs Non-CON States, Age 45-55



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.

$$I(w_0, h_0, x_0, p_0) = E[\int_0^\tau e^{-rs} p_0 ds + e^{-r\tau}(-m(w, h, x, p_0))] \tag{12}$$

subject to:

$$\begin{aligned} dh_t &= -\delta(e)hdt + \sigma^A h_t(1-h_t)dZ_t^A - (1-\delta(x))h_t dN_t && (13)\\ dx_t &= \sigma^B dZ_t^B && (14)\\ dw_t &= [\theta_i y(1-e-l) + rw_t - c_t - p_0]dt && (15)\\ (\lambda(x), \delta(x)) &= \begin{cases} \lambda^H, \delta^H \text{ if } x \geq \bar{x} \\ \lambda^L, \delta^L \text{ if } x < \bar{x} \end{cases} && (16) \end{aligned}$$

By Feynman-Kac, in between two treatments, the firm's value function follows,

$$rI(w, h, x, p_0) = p_0 + I_w[\theta_i y + rw - c - p_0] + I_h[-\delta(e)h] + \frac{1}{2} I_{hh}\sigma^2 h^2(1-h)^2 + \frac{1}{2} I_{xx}\sigma_B^2 \tag{17}$$

$$+ \lambda(x)[I(w, h\delta(x), x) - I(w, h, x))] \quad + \lambda^H(h)[0 - I(w, h, x))]$$

$I(w, h, x, p_0)$ 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, symptoms is x. Value matching condition at exogenous stopping time for the firm is:

$$\lim_{w,h,x} I(w, h, x, p_0) = -m(w, h, x, p_0) \tag{18}$$

Free entry condition: $I(w_0, h_0, x_0, p_0) = 0$ determines p_0 for each level of initial w_0, h_0 and x_0 which is binding until the next stopping time.

Since the firm is not choosing stopping time optimally, there would be no smooth pasting condition.

$$\rho F(w,h,\nu,a,I,p) = p + \underbrace{\eta[F(w,h,\nu,a+1,I,p) - F(.)]}_{\text{aging to } a+1} +$$

$$\underbrace{\nu[F(w,h+1,\nu_0,a,I,p) - F(.)]}_{\text{transition to } h+1} + \underbrace{d(h,a)[F(w,h-1,\nu_0,a,I,p) - F(.)]}_{\text{transition to } h-1} +$$

$$\underbrace{\lambda^T(h,a)[0 - F(.)]}_{\text{death}} + \underbrace{\phi[\bar{F}(w,h,\nu,a,I',p') - F(.)]}_{\text{insurance choice from individual's problem}}$$

$$\bar{F}(w,h,\nu,a,I',p') = \begin{cases} 0, \text{ if } I^* = 0 \\ F(w,h,\nu,a,I,p(h,a)) \text{ if } I^* = 1 \end{cases}$$

$\lim_{\tau \to 1} F(.) = -mq(I) + F(w',h',\nu',a,I,p)$

Insurance firms 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

For without exit and utility from health

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

Guess,

$$V^D(w) = \frac{(y^D + rw)^{1-\gamma}}{r(1-\gamma)} \left(\frac{\rho - r(1-\gamma)}{r\gamma} \right)^{-\gamma} \tag{20}$$

let $c_1 = \left(\frac{\rho - r(1-\gamma)}{r\gamma} \right)^{-\gamma}$

$$V^D(w) = \frac{(y^D + rw)^{1-\gamma}}{r(1-\gamma)} c_1 \tag{21}$$

$$V_w^D(w) = (y^D + rw)^{-\gamma} c_1 \tag{22}$$

$$c = (y^D + rw) c_1^{-1/\gamma} \tag{23}$$

Substituting in HJB:

$$\rho\frac{(y^D+rw)^{1-\gamma}}{r(1-\gamma)}c_1 = \frac{(y^D+rw)^{1-\gamma}c_1^{-(1-\gamma)/\gamma}}{1-\gamma}+(y^D+rw)^{-\gamma}c_1(y^D+rw)(1-c_1^{-1/\gamma}) \quad (24)$$

$$\rho\frac{1}{r(1-\gamma)}c_1 = \frac{c_1^{-(1-\gamma)/\gamma}}{1-\gamma}+c_1(1-c_1^{-1/\gamma}) \quad (25)$$

$$\frac{\rho c_1}{r(1-\gamma)} = \frac{c_1^{(\gamma-1)/\gamma}}{1-\gamma}+c_1-c_1^{(\gamma-1)/\gamma} \quad (26)$$

$$\frac{\rho c_1}{r(1-\gamma)}-c_1 = c_1^{(\gamma-1)/\gamma}\left(\frac{1}{1-\gamma}-1\right) \quad (27)$$

$$c_1\left(\frac{\rho-r(1-\gamma)}{r(1-\gamma)}\right) = c_1^{(\gamma-1)/\gamma}\frac{\gamma}{1-\gamma} \quad (28)$$

$$c_1\left(\frac{\rho-r(1-\gamma)}{r}\right) = c_1^{(\gamma-1)/\gamma}\gamma \quad (29)$$

$$\left(\frac{\rho-r(1-\gamma)}{\gamma r}\right) = c_1^{-1/\gamma} \quad (30)$$

$$c_1 = \left(\frac{\rho-r(1-\gamma)}{\gamma r}\right)^{-\gamma} \quad (31)$$

$$(32)$$

Standard Guess and Verify argument gives,

$$V^D(w)=\frac{(y^D+rw)^{1-\gamma}}{r(1-\gamma)}\left(\frac{\rho-r(1-\gamma)}{r\gamma}\right)^{-\gamma} \quad (33)$$

For the version with exit and utility from health,

$$\rho V^D(w,h^D)=\max_c\{u(c,h^D)+V_w^D[y^D+rw-c]\}+\lambda^D(V^T-V^D) \quad (34)$$

$$V^D(w,h^D)=\frac{(y^D+rw)^{1-\gamma}}{r(1-\gamma)}\left(\frac{(\rho+\lambda^D)-r(1-\gamma)}{r\gamma}\right)^{-\gamma}+\left(\frac{1}{\rho+\lambda^D}\right)\left(\omega\frac{h^{D^{1-\sigma}}}{1-\sigma}+\lambda^D V^T\right) \quad (35)$$

7. 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. [ADD EXAMPLES?] Lastly, we show that a public health insurance scheme, funded by flat-income tax, could go a long way in decreasing the inequality.

References

Abadie, Alberto and Guido W Imbens (2016), "Matching on the estimated propensity score." *Econometrica*, 84, 781–807.

Achdou, Yves, Jiequn Han, Jean-Michel Lasry, Pierre-Louis Lions, and Benjamin Moll (2017), "Income and wealth distribution in macroeconomics: A continuous-time approach." Technical report, National Bureau of Economic Research.

Ales, Laurence, Roozbeh Hosseini, and Larry E Jones (2012), "Is there" too much" inequality in health spending across income groups?" Technical report, National Bureau of Economic Research.

American College of Physicians-American Society of Internal Medicine (1999), "No health insurance? it's enough to make you sick: Scientific research linking the lack of health coverage to poor health." *Philadelphia, Pa: American College of Physicians-American Society of Internal Medicine*.

Arcaya, Mariana C and José F Figueroa (2017), "Emerging trends could exacerbate health inequities in the united states." *Health Affairs*, 36, 992–998.

Baicker, Katherine, Amy Finkelstein, Jae Song, and Sarah Taubman (2014), "The impact of medicaid on labor market activity and program participation: Evidence from the oregon health insurance experiment." *The American economic review*, 104, 322–328.

Baicker, Katherine, Sarah L Taubman, Heidi L Allen, Mira Bernstein, Jonathan H Gruber, Joseph P Newhouse, Eric C Schneider, Bill J Wright, Alan M Zaslavsky, and Amy N Finkelstein (2013), "The oregon experiment?effects of medicaid on clinical outcomes." *New England Journal of Medicine*, 368, 1713–1722.

Becker, Gary S, Tomas J Philipson, and Rodrigo R Soares (2005), "The quantity and quality of life and the evolution of world inequality." *American Economic Review*, 95, 277–291.

Blundell, Richard and Monica Costa Dias (2009), "Alternative approaches to evaluation in empirical microeconomics." *Journal of Human Resources*, 44, 565–640.

Broaddus, Matthew, Shannon Blaney, Annie Dude, Jocelyn Guyer, Leighton Ku, and Jaia Peterson (2002), "Expanding family coverage: States? medicaid eligibility policies for working families in the year 2000." *Washington, DC: Center on Budget and Policy Priorities*, 17–19.

Caliendo, Marco and Sabine Kopeinig (2008), "Some practical guidance for the implementation of propensity score matching." *Journal of economic surveys*, 22, 31–72.

Card, David, Carlos Dobkin, and Nicole Maestas (2008), "The impact of nearly universal insurance coverage on health care utilization: evidence from medicare." *American Economic Review*, 98, 2242–58.

Card, David Edward, Carlos Dobkin, Nicole Maestas, et al. (2007), *The Impact of Health Insurance Status on Treatment Intensity and Health Outcomes*. RAND.

Chen, Li-Shiun, Ping Wang, and Yao Yao (2017), "Smoking, health capital, and longevity: Evaluation of personalized cessation treatments in a lifecycle model with heterogeneous agents." Technical report, National Bureau of Economic Research.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler (2016), "The association between income and life expectancy in the united states, 2001-2014." *Jama*, 315, 1750–1766.

Cole, Harold L, Soojin Kim, and Dirk Krueger (2016), "Analyzing the effects of insuring health risks."

Currie, Janet and Jonathan Gruber (1996), "Health insurance eligibility, utilization of medical care, and child health." *The Quarterly Journal of Economics*, 111, 431–466.

Curto, Vilsa, Liran Einav, Amy Finkelstein, Jonathan D Levin, and Jay Bhattacharya (2017), "Healthcare spending and utilization in public and private medicare." Technical report, National Bureau of Economic Research.

De Nardi, Mariacristina, Svetlana Pashchenko, and Ponpoje Porapakkarm (2017), "The lifetime costs of bad health." Technical report, National Bureau of Economic Research.

Dobkin, Carlos, Amy Finkelstein, Raymond Kluender, and Matthew J Notowidigdo (2016), "The economic consequences of hospital admissions." Technical report, National Bureau of Economic Research.

Einav, Liran, Amy Finkelstein, Stephen P Ryan, Paul Schrimpf, and Mark R Cullen (2013), "Selection on moral hazard in health insurance." *The American economic review*, 103, 178–219.

Finkelstein, Amy, Nathaniel Hendren, and Erzo FP Luttmer (2015), "The value of medicaid: Interpreting results from the oregon health insurance experiment." Technical report, National Bureau of Economic Research.

Finkelstein, Amy, Nathaniel Hendren, and Mark Shepard (2017a), "Subsidizing health insurance for low-income adults: Evidence from massachusetts."

Finkelstein, Amy, Erzo FP Luttmer, and Matthew J Notowidigdo (2013), "What good is wealth without health? the effect of health on the marginal utility of consumption." *Journal of the European Economic Association*, 11, 221–258.

Finkelstein, Amy, Neale Mahoney, and Matthew J Notowidigdo (2017b), "What does (formal) health insurance do, and for whom?" Technical report, National Bureau of Economic Research.

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P Newhouse, Heidi Allen, Katherine Baicker, and Oregon Health Study Group (2012), "The oregon health insurance experiment: evidence from the first year." *The Quarterly journal of economics*, 127, 1057–1106.

Gilleskie, Donna B (1998), "A dynamic stochastic model of medical care use and work absence." *Econometrica*, 1–45.

Glied, Sherry and Adriana Lleras-Muney (2008), "Technological innovation and inequality in health." *Demography*, 45, 741–761.

Goodman-Bacon, Andrew (2013), "Public insurance and mortality: evidence from medicaid implementation." *University of Michigan*.

Grossman, Michael (1972), "On the concept of health capital and the demand for health." *Journal of Political economy*, 80, 223–255.

Hai, Rong and James J Heckman (2015), "A dynamic model of health, education, and wealth with credit constraints and rational addiction."

Hall, Robert E and Charles I Jones (2007), "The value of life and the rise in health spending." *The Quarterly Journal of Economics*, 122, 39–72.

Hatzenbuehler, Patrick L, Jeffrey M Gillespie, and Carol E O'Neil (2012), "Does healthy food cost more in poor neighborhoods? an analysis of retail food cost and spatial competition." *Agricultural and Resource Economics Review*, 41, 43–56.

Heckman, James J, Hidehiko Ichimura, and Petra Todd (1998), "Matching as an econometric evaluation estimator." *The review of economic studies*, 65, 261–294.

Kronick, Richard (2009), "Health insurance coverage and mortality revisited." *Health services research*, 44, 1211–1231.

Manuelli, Rodolfo et al. (2017), "Natural disasters and growth: The role of foreign aid and disaster insurance." In *2017 Meeting Papers*, 1118, Society for Economic Dynamics.

McGinnis, J Michael and William H Foege (1993), "Actual causes of death in the united states." *Jama*, 270, 2207–2212.

Mehta, Nitin, Jian Ni, Kannan Srinivasan, and Baohong Sun (2017), "A dynamic model of health insurance choices and healthcare consumption decisions." *Marketing Science*.

Mokdad, Ali H, James S Marks, Donna F Stroup, and Julie L Gerberding (2004), "Actual causes of death in the united states, 2000." *Jama*, 291, 1238–1245.

Murphy, Kevin M and Robert H Topel (2006), "The value of health and longevity." *Journal of political Economy*, 114, 871–904.

Myerson, Rebecca, Darius Lakdawalla, Lisandro D Colantonio, Monika Safford, and David Meltzer (2017), "Effects of expanding health screening on treatment–what should we expect? what can we learn?"

Nakajima, Makoto and Didem Tuzemen (2016), "Health-care reform or labor market reform? a quantitative analysis of the affordable care act."

Niu, Xiaoling, Lisa M Roche, Karen S Pawlish, and Kevin A Henry (2013), "Cancer survival disparities by health insurance status." *Cancer medicine*, 2, 403–411.

Øksendal, Bernt (2003), "Stochastic differential equations." In *Stochastic differential equations*, 65–84, Springer.

Øksendal, Bernt Karsten and Agnes Sulem (2005), *Applied stochastic control of jump diffusions*, volume 498. Springer.

Ozkan, Serdar (2014), "Preventive vs. curative medicine: A macroeconomic analysis of health care over the life cycle." *Unpublished. https://sites. google. com/site/serdarozkan/Ozkan_2014. pdf*.

Poterba, James M, Steven F Venti, and David A Wise (2017), "Longitudinal determinants of end-of-life wealth inequality." Technical report, National Bureau of Economic Research.

Prados, Marıa José et al. (2012), "Health and earnings inequality over the life cycle: The redistributive potential of health policies." *Manuscript, Columbia University, New York, NY*.

Schneider, Andy, Risa Elias, and Rachel Garfield (2003), "Medicaid eligibility." *The Medicaid Resource Book*, 17–18.

Scholz, John Karl and Ananth Seshadri (2011), "Health and wealth in a life cycle model."

Skinner, Jonathan and Weiping Zhou (2004), "The measurement and evolution of health inequality: evidence from the us medicare population." Technical report, National Bureau of Economic Research.

Sommers, Benjamin D, Katherine Baicker, and Arnold M Epstein (2012), "Mortality and access to care among adults after state medicaid expansions." *New England Journal of Medicine*, 367, 1025–1034.

Sommers, Benjamin D, Atul A Gawande, and Katherine Baicker (2017), "Health insurance coverage and health?what the recent evidence tells us."

Taubman, Sarah L, Heidi L Allen, Bill J Wright, Katherine Baicker, and Amy N Finkelstein (2014), "Medicaid increases emergency-department use: evidence from oregon's health insurance experiment." *Science*, 343, 263–268.

Todd, Petra (1999), "A practical guide to implementing matching estimators." Technical report, mimeo.

Walker, Gary V, Stephen R Grant, B Ashleigh Guadagnolo, Karen E Hoffman, Benjamin D Smith, Matthew Koshy, Pamela K Allen, and Usama Mahmood (2014), "Disparities in stage at diagnosis, treatment, and survival in nonelderly adult patients with cancer according to insurance status." *Journal of Clinical Oncology*, 32, 3118–3125.

Wilper, Andrew P, Steffie Woolhandler, Karen E Lasser, Danny McCormick, David H Bor, and David U Himmelstein (2009), "Health insurance and mortality in us adults." *American journal of public health*, 99, 2289–2295.

Appendix: Tables

Table 15: (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 16: (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 17: 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

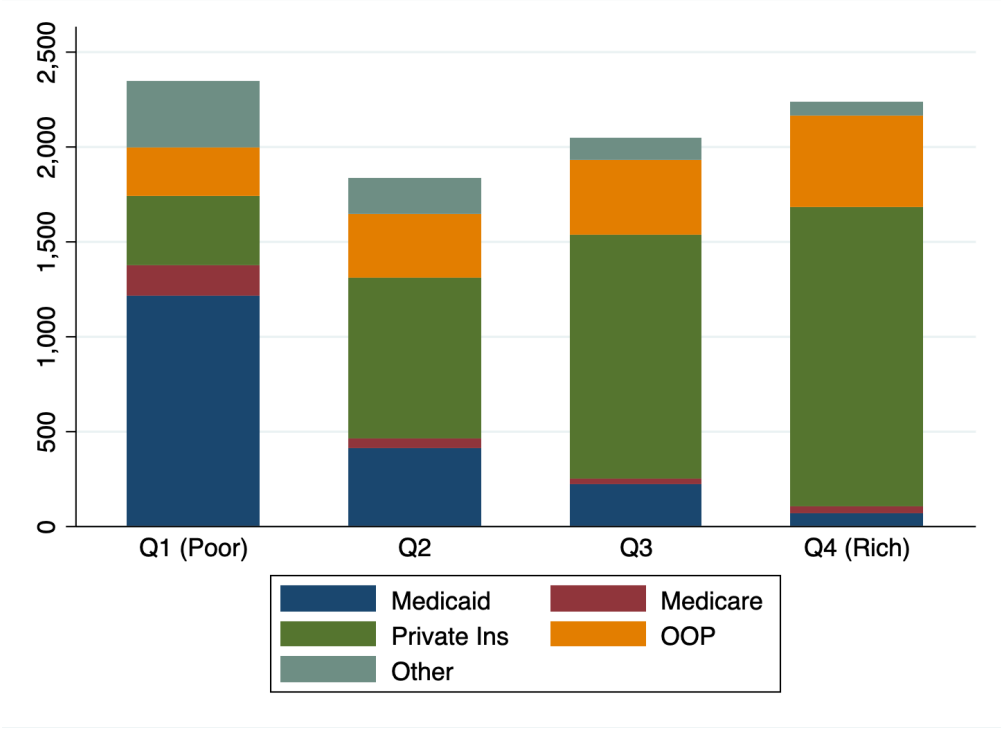
Source: NHIS-MEPS

Table 18: 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

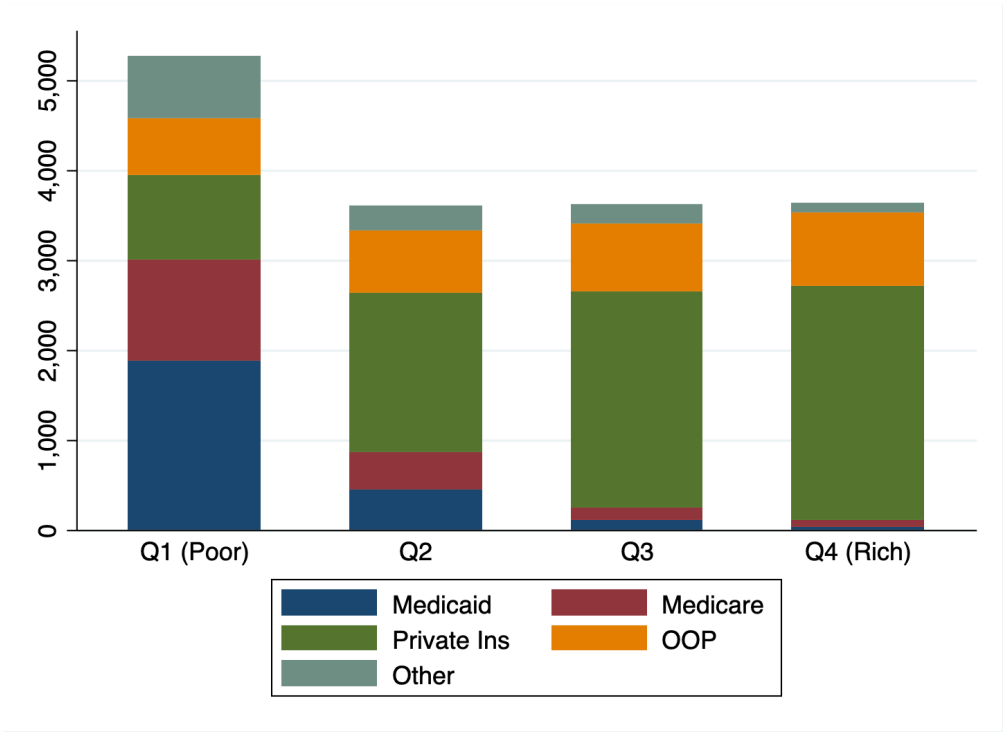
Figure 20: Mean Medical Investment: Age 25-35



Source: NHIS-MEPS

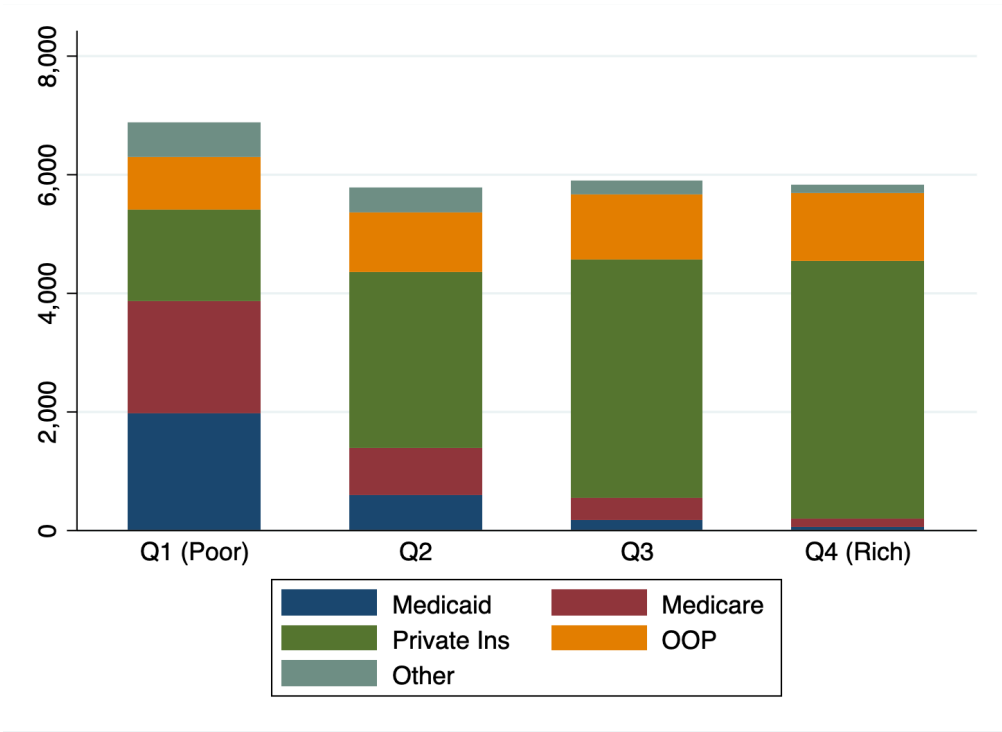
Appendix: Figures

Figure 21: Mean Medical Investment: Age 45-55



Source: NHIS-MEPS

Figure 22: Mean Medical Investment: Age 55-65



Source: NHIS-MEPS

Figure 23: Mean Medical Investment: Age 65-75

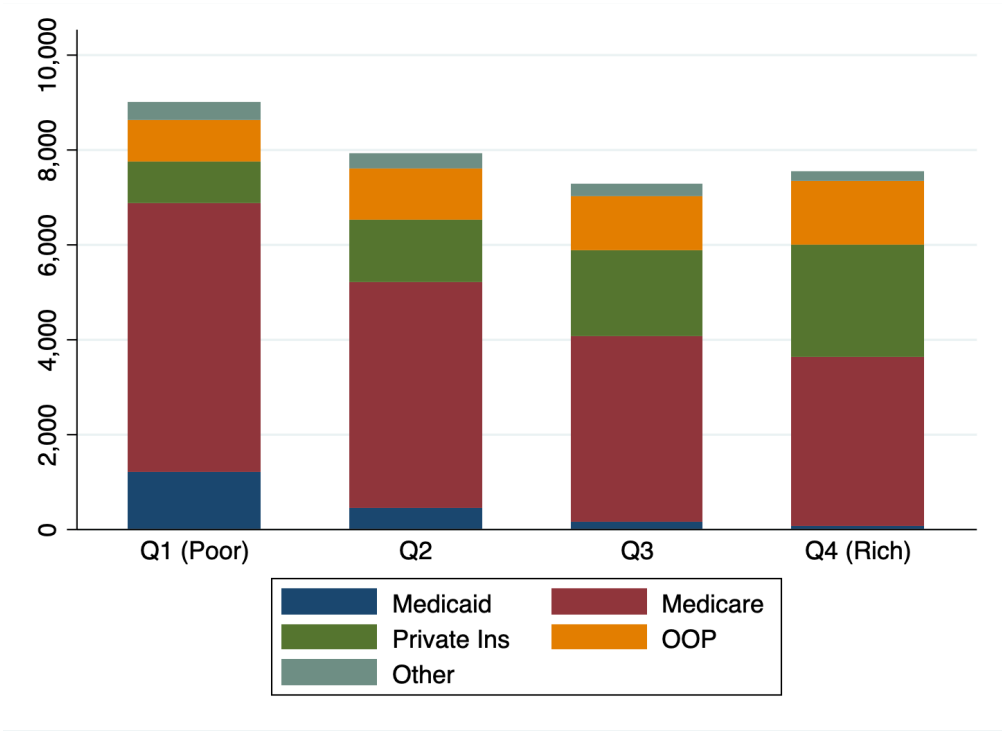
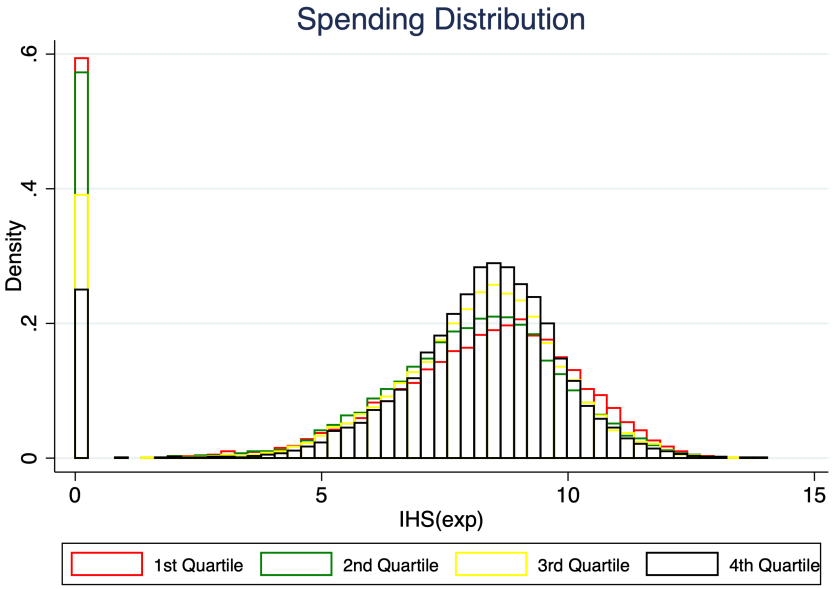
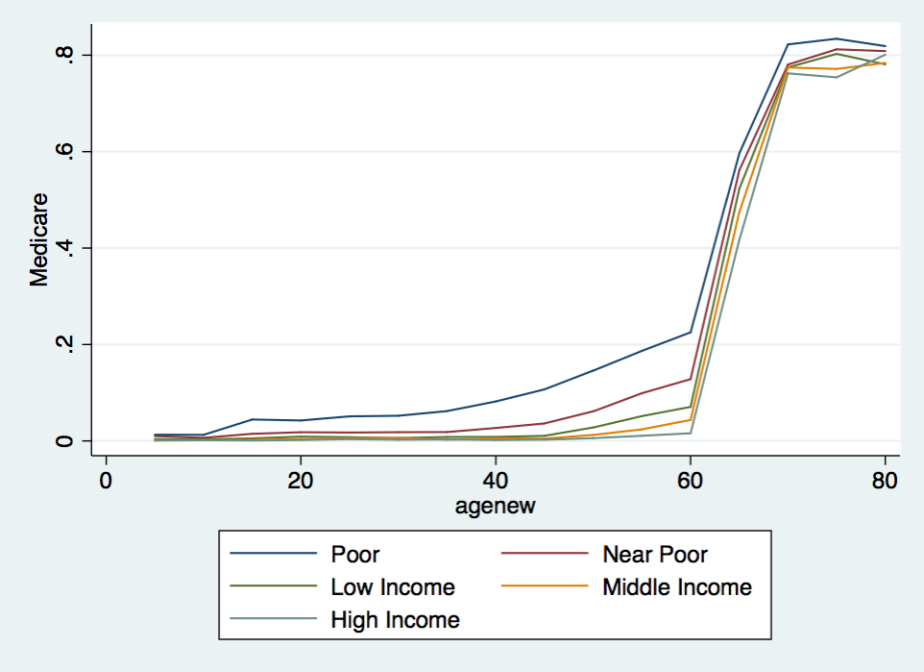


Figure 24: Medical Investment Distribution, Age 45-55



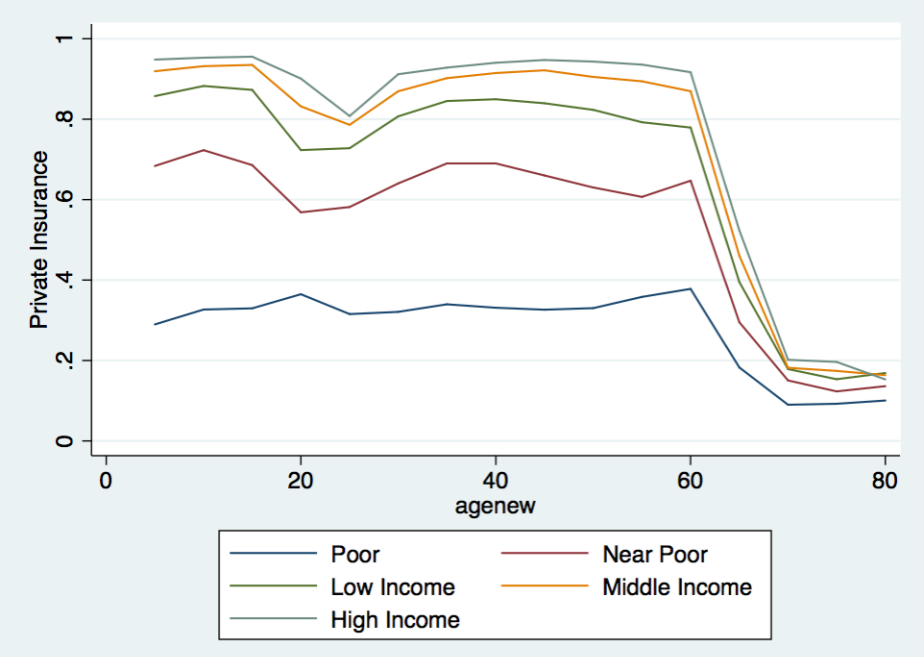
Notes: Inverse Hyperbolic Sine (IHS) Transformation

Figure 25: Fraction with Medicaid by Income



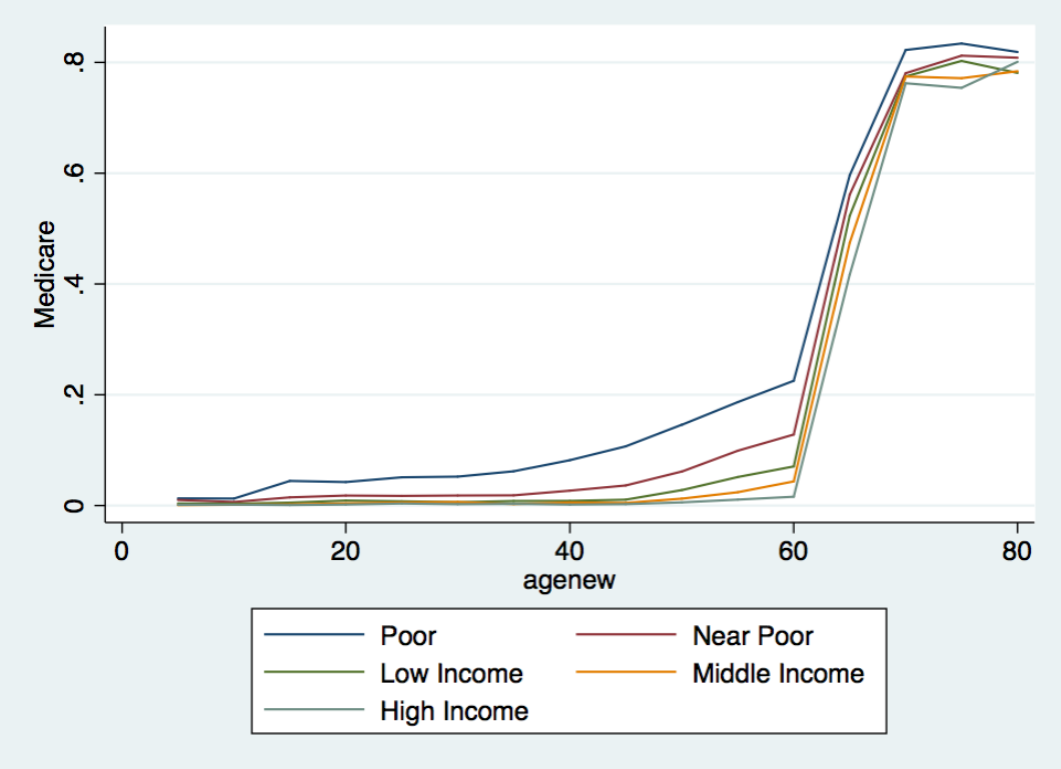
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 26: Fraction with Private Insurance by Income and Age



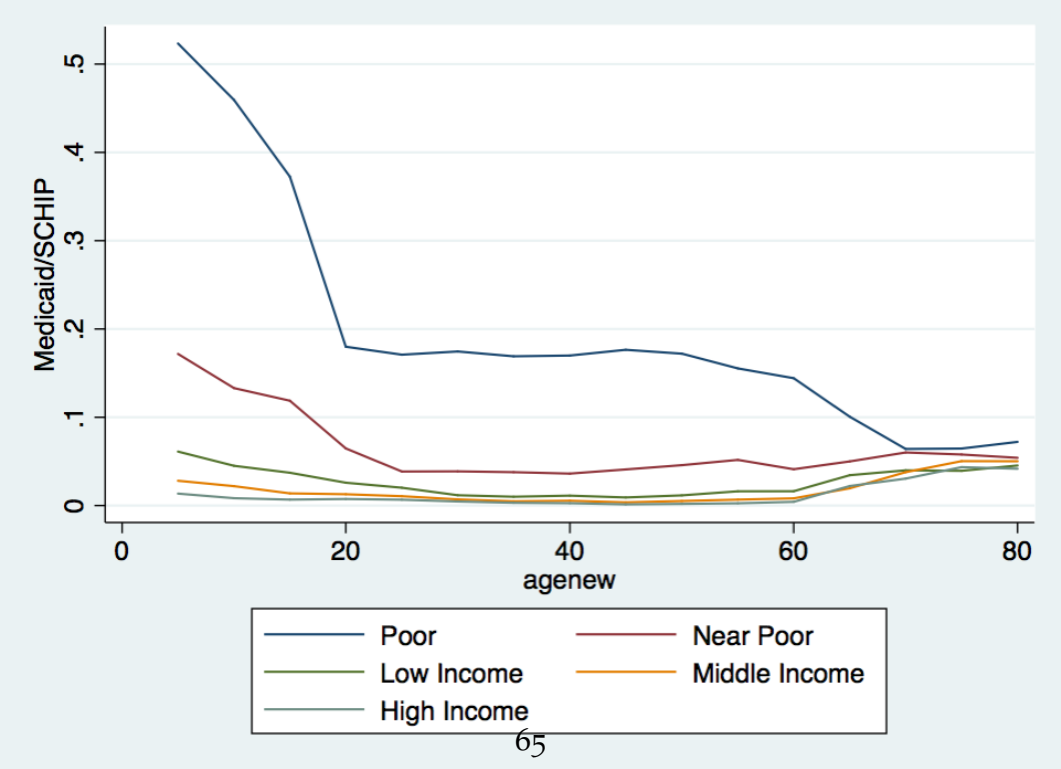
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 27: Fraction with Medicare by Income



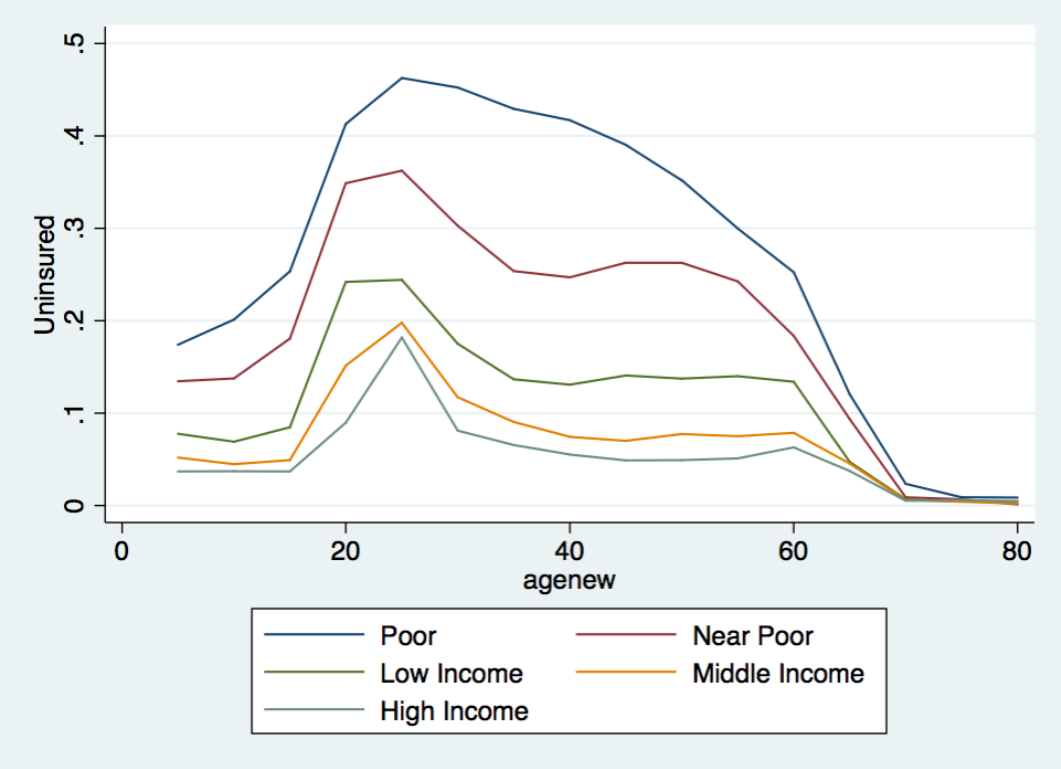
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 28: Fraction with Medicaid and SCHIP by Income and Age



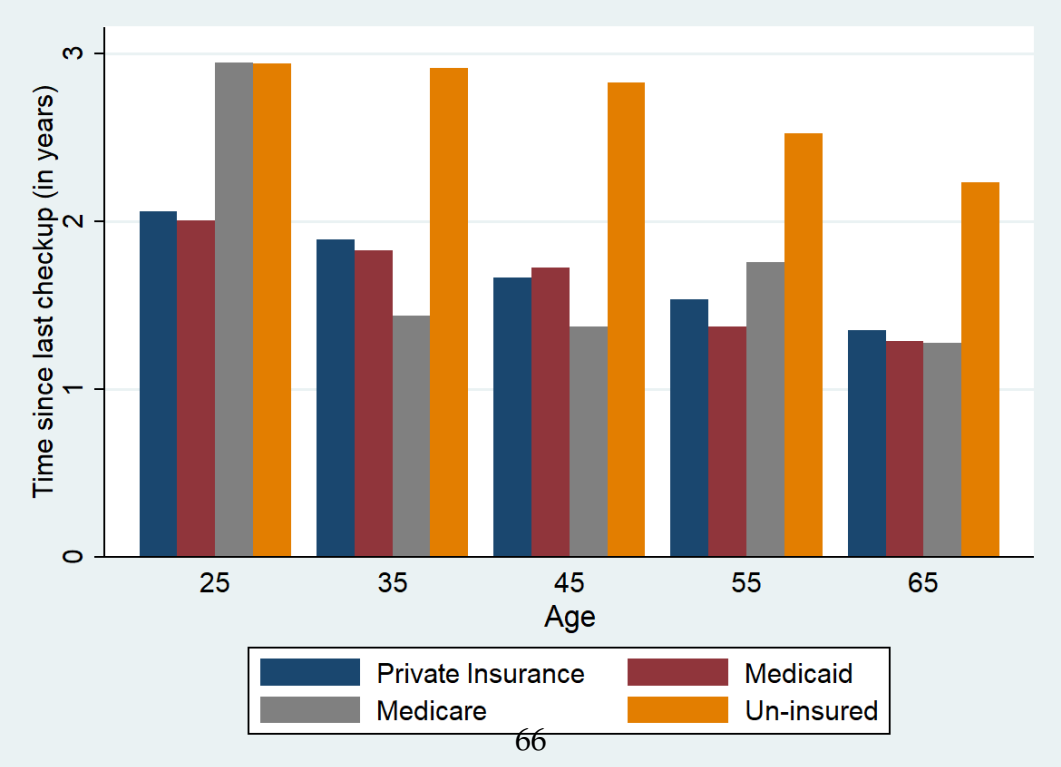
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 29: Fraction Uninsured by Income and Age



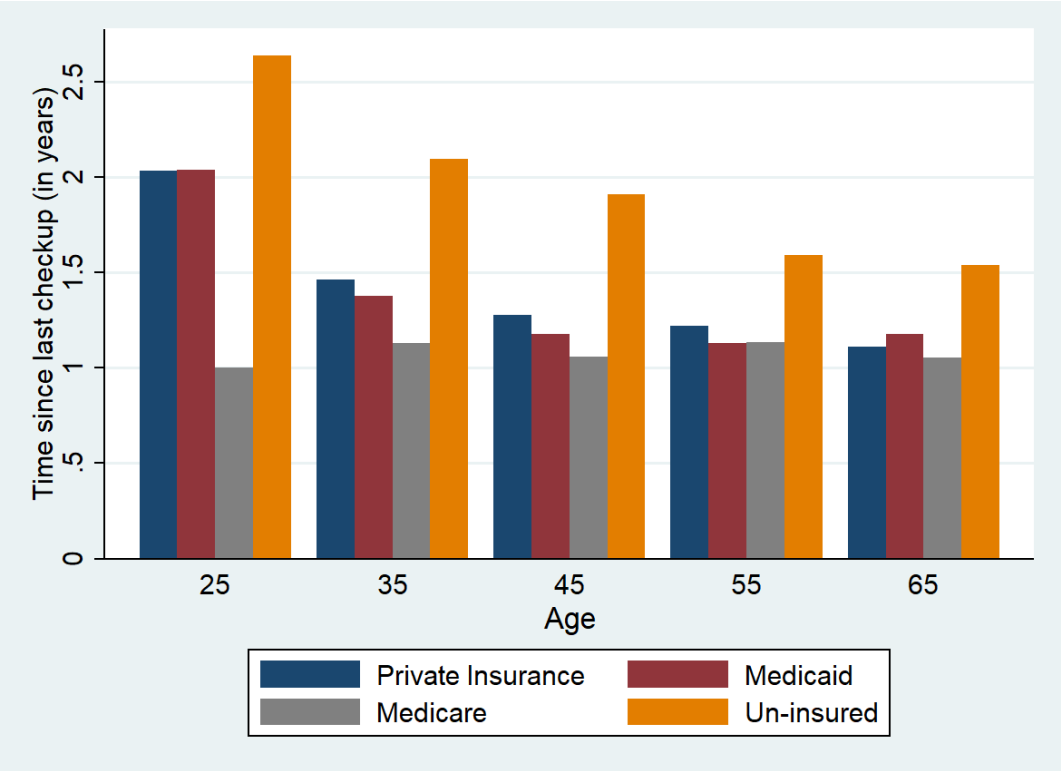
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 30: Time Since Checkup (in years)



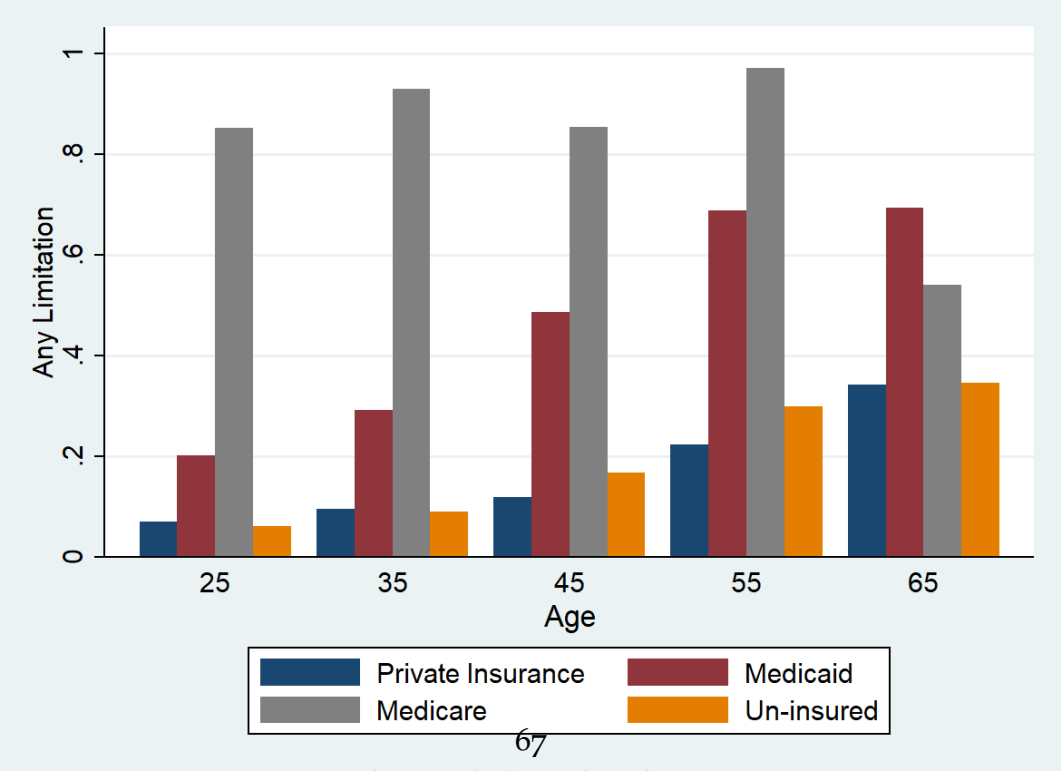
Source: Author's Calculation based on MEPS Data

Figure 31: Time Since Cholesterol Checkup (with pre-existing condition)



Source: Author's Calculation based on MEPS Data

Figure 32: Any Limitation by Age and Insurance Status



Source: Author's Calculation based on MEPS Data

Figure 33: Support for Propensity Score Matching, Wave 6a

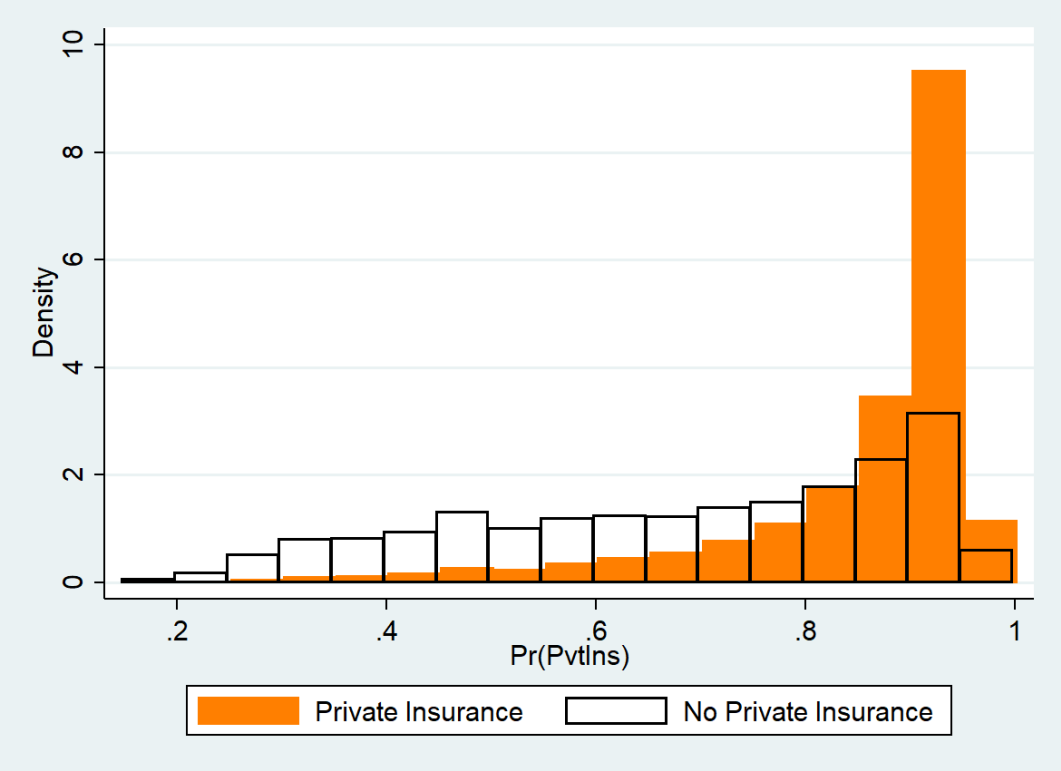


Figure 34: Support for Propensity Score Matching, Wave 6b

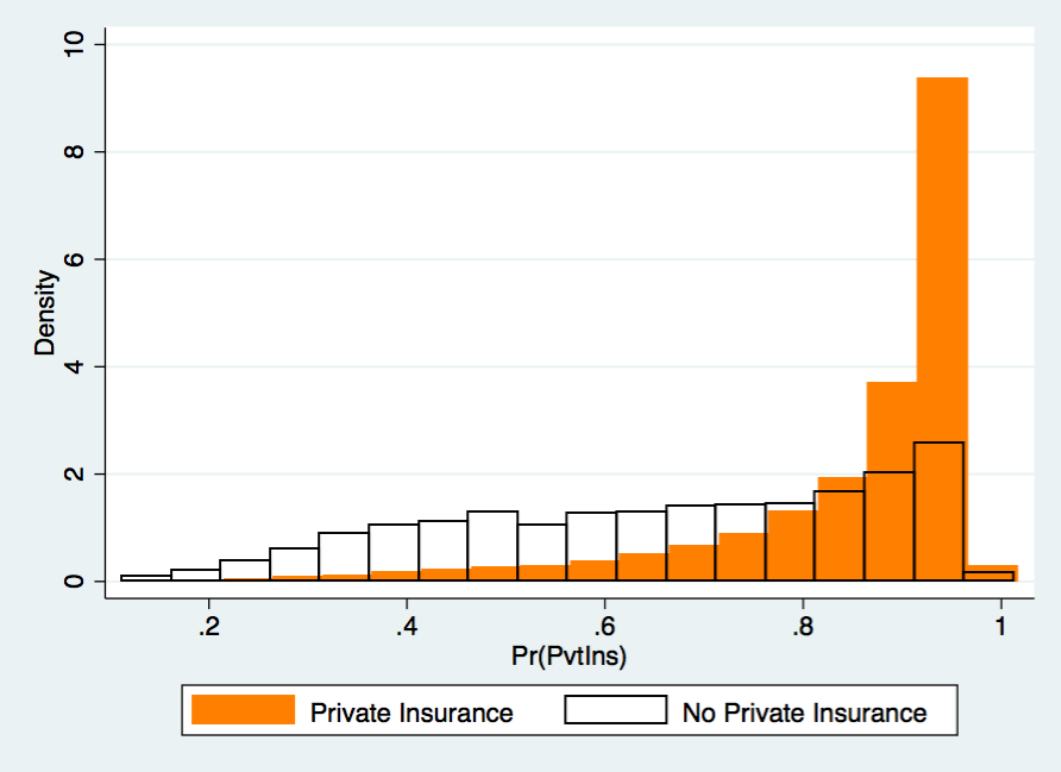


Figure 35: Support for Propensity Score Matching, Wave 6c