Health Inequality: The Role of Insurance and Technological Progress

Siddhartha Sanghi *†

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Abstract

The paper investigates the role of insurance and technological progress on rising health inequality across income/wealth groups. Using large scale federal survey datasets, I document new findings which suggest that the timing of healthcare spending is a key channel behind increased health disparities. I then develop a dynamic stochastic life-cycle model of an economy where individuals choose the timing of healthcare spending and insurance take-up. Consistent with my data findings, model estimates show that while rich and poor have comparable healthcare spending, there are substantial differences in their timing. This, in turn, is a significant factor in accounting for differences in health outcomes — the estimated model is able to explain about half of the gap in life expectancy across income/wealth groups. Technological innovation and insurance interacts with the timing of healthcare spending and have a first-order effect on health disparities. While a non-uniform increase in the productivity of the medical sector — where there are improvements in treating early stages of cancer for example, but none for stage 4 cancer — can lead to an increase in inequality in life expectancy, a uniform increase in the productivity can lead to a reduction. While Medicaid alleviates health inequality, private insurance exacerbates it by almost twice as much. Finally, a comprehensive public health insurance, financed by a flat income tax, would not only reduce health inequality, it could also lower existing income inequality.

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†Research Division, Federal Reserve Bank of St. Louis. Email: sid.sanghi@stls.frb.org

1. Introduction

There is a huge disparity in health outcomes across income groups in the US. The richest 1% are expected to live 12.3 more years than the poorest 1%, and this gap has been increasing over time (Chetty et al., 2016). However, the growing inequality in health outcomes is puzzling, given that the rich and poor have comparable total healthcare spending[1] in any given year (see, e.g., Ales, Hosseini, and Jones (2012) and Skinner and Zhou (2004)). Furthermore, these trends are in stark contrast to other developed countries, which have seen convergence in life expectancy.[2]

Motivated by these puzzling observations, this paper seeks to answer the following three questions: (i) Why do health outcomes differ across the rich and poor, despite their comparable healthcare spending? (ii) What is the role of technological innovations in the healthcare sector in increased health disparities? (iii) What is the impact of private insurance and Medicaid on health inequality?

In order to answer these questions, I focus on one key mechanism: the timing of healthcare spending. I start by documenting several new stylized facts on healthcare spending and outcomes in the US, using a merged panel dataset of health, healthcare spending, and health outcomes, complemented by large-scale federal datasets on mortality. First, I document that the impact of technological improvement in healthcare has been unequal with some innovations benefiting all equally, while others benefiting only the rich. For example, heart-related technological improvements are the biggest contributors to the increased life expectancy over the past few decades – poor and rich alike have gained about 4 years of life expectancy due to heart-related innovations. On the other hand, one of the largest contributors to the increased disparity in health outcomes is differences in the reduction of mortality from cancer, where the rich have gained more than a year in their life expectancy but the poor have only gained three months. Second, about 60% of poor individuals (vs. 22% of rich individuals) do not make any healthcare spending in a given year.[3] Conditional on having positive healthcare spending, the spending distribution of poor individuals has a thicker tail compared to that of the rich, i.e., the poor also have very high expenditures. I also find that while the poor spend more on hospitalizations and emergency rooms, the rich spend more on outpatient vis-

[1] I use healthcare spending, investments and expenditures interchangeably throughout the paper.

[2] For example, Canada, which spends 10.7 % of their GDP on healthcare (vs. 17.7% for the US) and has seen a convergence in inequality (see for e.g., Baker et al. (2021)) and have better health outcomes (life expectancy of 82 years vs. 79 years in the US)

[3] The second fact has been documented in the literature such as Ozkan (2014).

its. Third, poor individuals' visit and spending decisions are very responsive to their health status, i.e., they do not go for regular checkups when their health is good and only visit the doctor once their health has deteriorated considerably. In contrast, rich individuals go to the doctor more in all health states and their decision to visit the doctor is less responsive to their health state. Fourth, I find that likely because of how they time their doctor visits, poor individuals are less likely to transition to a better health state even when they do go to the doctor.

The empirical findings suggest that the timing of healthcare spending is a key channel behind increased health disparities.Specifically, when the rich visit the doctor, they are in much better health than poor are when they visit the doctor. Therefore, I develop a dynamic stochastic life-cycle model with incomplete markets, where I explicitly model that individuals choose the timing of healthcare spending and insurance take-up. Individuals enter the model at age 25, with heterogeneity in their education, wealth and health. There are 5 key model ingredients: first, individuals face health shocks that can arrive continuously. Flow utility of consumption, productivity in the labor market, disability rate and death rate is affected by how healthy they are. Second, individuals can invest in the likelihood of transitioning to a better health state. The health production function features dynamic complementarities: if one invests in their health when it is very low, their health is less likely to improve substantially compared to those who invest when it is not very low.[4] Third, they face a fixed cost (such as doctor co-pay or search and travel costs) associated with healthcare spending, that lead to a stopping time component where individuals decide on the timing of doctor visits. During their lifetime, individuals differ across many dimensions: their income (affected by education, potential experience in the labor market and health), health state, wealth, age, the intensity to go to a better health (based on their previous healthcare spending), insurance status (based on their previous choices) and disability status. Fourth, individuals can change their insurance once annually, on average, and choose between paying a fixed cost associated with Medicaid, if they are eligible, or paying the monthly premium associated with private insurance. This leads to a selection into Medicaid and private insurance where only the unhealthy or the wealthy take up private insurance. Fifth, markets are incomplete and individuals face borrowing constraints. This means that individuals can-

[4]In general, one may view the benefit of healthcare spending as being greater when the patient is sick. However, this view ignores the dynamic pathway by which an earlier visit can forestall the transition into the bad state of the world; catching a cancer when it is stage 1 yields better outcomes than when it presents as stage 4 cancer.

not borrow against their future income or future healthcare spending funded by public provisions (such as Medicaid and Medicare).

I use a rich panel dataset on health, spending and outcomes[5] along with large-scale federal datasets on mortality[6] to estimate the model using Simulated Methods of Moments. The summary of the identification strategy is as follows: i) I use the transitions in health with and without visits along with the healthcare spending ratio between rich and poor of same health to estimate the health production function. ii) Fixed costs in visit decision and Medicaid take-up are estimated from the corresponding choices of visit decision and Medicaid take-up. iii) Observable variation by age and health estimates the remaining parameters.

There are four key findings from the estimated model, which are consistent with the data. First, while total healthcare spending across income groups is similar, the timing of the spending is very different for the rich and poor. For poor individuals, the decision to visit a doctor is more responsive to their health state, particularly if they are in poor health. Second, fixing health, the rich have higher healthcare spending over the next year, thus transitioning to better health with a higher probability. Third, health inequality starts off low at the beginning of the working life and increases substantially by age 45. Fourth, when a poor uninsured individual defers getting treatment until their health has deteriorated significantly, they are not able to improve their health by spending the same amount of money on their health as a rich person does, i.e. they don't get the same bang for their buck. This is because of the effective complementarities in health production where investing early is better than investing later. An example to provide intuition for this: $1,000 on physician visit, MRI and a small surgery is likely to have better outcomes than $5,000 in chemotherapy.

The effect of difference in timing of healthcare spending on health outcomes can be illustrated through an example of an uninsured individual in average health with low wealth and income. They face financial constraints and cannot borrow against their future income. Hit by a health shock, they face two possible scenarios: i) They wait to accumulate savings before going to the doctor, as a result of the steep out-of-pocket cost (without insurance) ii) They wait and take-up Medicaid (if eligible) or private insurance before going to the doctor. As a result of the delay their health might deteriorate further. Given the complementarities in health production, where $1 in average health is better

[5] Merged National Health Interview Survey (NHIS) and Medical Expenditure Panel Survey (MEPS)

[6] National Longitudinal Mortality Survey (NLMS) and Mortality Differentials in American Communities (MDAC) Survey

than \$1 in worse health, the spending at a lower health state is less likely to result in a transition to good health. It may also result in a transition into long-term-disability at a younger age after which Medicare starts paying for them. It is also important to point out that this feeds into the income and wealth accumulation: poor health decreases labor income[7], making wealth accumulation slower. On the other hand, a rich insured individual in average health — when faced with a health shock — would visit the doctor without any delay, invest in their health and transition to a better health state. This would result in comparable healthcare spending but significant differences in health outcomes.

In order to understand the role of insurance, I perform three counterfactual experiments: in the first, I eliminate Medicaid; in the second, I shut down both Medicaid and private insurance; and in the third, I implement a comprehensive public health insurance (not unlike proposals for Medicare-for-all) financed by a flat income tax. My findings are: i) Medicaid alleviates health inequality, and without it, the gap in life expectancy between the bottom and top quartiles would go up by about 10%; ii) Private insurance exacerbates inequality by almost twice as much. This increase in inequality is due to the fact that private insurance overwhelmingly is taken up by the relatively wealthy — who face a lower effective price of goods and consume more. iii) Comprehensive public health insurance, with fixed costs and co-pays, can reduce the gap in life expectancy between the bottom and top quartiles by about 20%. Public health insurance illustrates a key trade-off in the policy making: while the inequality in health outcomes would go down, the public health insurance would have to be financed by income taxes.

Motivated by my empirical findings on technological innovation, I consider two types of innovations. First, uniform broad-based Total Factor Productivity (TFP) improvements in the healthcare sector and second, a non-uniform productivity increase in early treatments but not in terminal illnesses. I find that the type of technological progress and its interaction with the visit decision is one of the key determinants of increased health disparities. A uniform 13% broad-based increase in productivity of the healthcare sector (which leads to an overall increase in life expectancy by 5 months) lowers health inequality by 2.5 months while a 20% non-uniform increase (where there are improvements in early care, but not in late treatments, leading to same overall gains in life expectancy of 5 months) increases the disparity by 1.5 months. An example to build intuition for

[7]My model only models labor income, but one can think that this comes from two channels: either due to fewer hours worked or lower wage. See, for example, Hosseini et al. (2021b)

this result: suppose that two decades ago medical technology was such that only stage 1 cancer could be treated. Now suppose that due to technological progress in cancer treatments, the medical technology today is such that cancer until stage 2 can be treated. While the rich, frequently going to see the doctor, visit the doctor and invest in their health at cancer stage 1, the poor defer treatment and only visit the doctor and invest in their health at cancer stage 3.[8] Thus, the poor not only end up spending the same amount as a rich person in any given year, they also end up unable to reap the benefits of medical technological progress.[9]

I use my model to quantify the dollar value of the two types of innovations in the healthcare sector discussed above. My findings can be summarized as follows. First, I find that society puts a large dollar value[10] on medical innovations, nearly 1.5 times average income per capita. Second, the value of an innovation depends on whether it is uniform broad-based or limited to certain types. The value of a non-uniform improvement in the productivity of the health sector is $69,000 per individual (1.58 times average income per capita in the model) compared to $64,000 per individual (1.45 times average income per capita) for uniform broad-based improvements.

Lastly, I use my model to quantify the role played by health in exacerbating existing income inequality, as measured by 90/10 income ratio (≈ 3.65 in the baseline). I find that private insurance exacerbates existing income inequality by about 5%, whereas a comprehensive public health insurance — financed by a flat income tax — reduces income inequality by 9%.

Related Literature The literature modeling health as health capital dates back to Grossman (1972). I brings the timing of healthcare spending, such as Gilleskie (1998), into life-cycle models with endogenous health and wealth accumulation. My paper endogenizes the evolution of health, largely assumed exogenous in the literature (such as in Hosseini et al. (2021a), Attanasio et al. (2011), Palumbo (1999), Michaud and Wiczer

[8]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 the basis for our example here.

[9]It is consistent with the fact that the type of cancer for which the survival rates have converged the most for the affluent and less affluent over the past 2 decades is Hodgkin lymphoma, for which the survival rate is relatively flat across cancer stages, while the cancer for which the survival rates have diverged the most is oesophageal cancer, which has a steep one-year mortality rate across cancer stages Source: UK Cancer Cancer Research UK-1, Accessed: April 2021 Cancer Research UK-2, Accessed April 2021

[10]Difference in wealth equivalent of value in utils, i.e., the present discounted value of utility, computed using an individual in average health.

(2018), Poterba et al. (2017), De Nardi et al. (2017), Nakajima et al. (2018), Conesa et al. (2018) and Nakajima and Tuzemen (2016)), and builds onto recent work with endogenous health (such as, De Nardi et al. (2010), Cole et al. (2016), Ozkan (2014), Scholz and Seshadri (2011), Hai and Heckman (2015) and Halliday et al. (2019)).

The closest work to the present paper is Ozkan (2014) and Hong, Pijoan-Mas, and Rios-Rull (2015). The key innovation with respect to these papers is that I explicitly model the timing of healthcare spending, which is crucial in understanding the empirical facts I document. Also, neither of those papers focuses on increased health disparities over time.

This work complements the literature focusing on other aspects such as smoking (for example, Darden (2017), Adda and Cornaglia (2006), Hai and Heckman (2015) and Chen et al. (2017)) or race (such as Schwandt et al. (2021)). Other forms of health investments such as nutrition, exercise and smoking and not smoking, are not explicitly modeled in this paper. Recent literature (such as Schwandt et al. (2021)) point out the *convergence* in inequality across race, consistent with my findings across race.[11]

The existing literature hasn't focused on the causes of increased health disparities over time. An exception is Glied and Lleras-Muney (2008) who look at the role of education in increased health disparities over time. I complement their work by showing that even for individuals with college education or higher, there is divergence in life expectancy by family income quartile over the past few decades, suggesting that education may not be enough to explain increased health disparities across these groups. Their work also doesn't analyze healthcare spending or its comparability across rich and poor. Unlike the previous literature, this paper looks at the flatness in spending, cross-sectional differences in outcomes, *and* increased health disparities over time.

On the methodological side, this paper brings continuous time tools to questions relating to health in a life-cycle model allowing better characterization of the visit decision, complementing the models of daily frequency such as Agarwal et al. (2019), who model the arrival process in the context of kidney exchange and Gilleskie (1998), who model daily visit decisions for the sick patients. It also contributes to the literature using continuous time tools for questions relating to income and wealth inequality, such as Achdou et al. (2017).

It also contributes to the empirical literature documenting changes in life expectancy over time (such as Cutler et al. (2006), McGinnis and Foege (1993), Becker et al. (2005),

[11]See Appendix A.10.

Chetty et al. (2016), Case and Deaton (2015), and most recently, Schwandt et al. (2021)). Unlike previous literature, this paper documents the change in life expectancy over the past few decades by cause of death across income groups, à la Becker et al. (2005).

It also contributes to the literature on the value of health and healthcare innovation (such as Murphy and Topel (2006), Jones and Klenow (2016), Hamilton et al. (2018), Hall and Jones (2007) Chandra and Skinner (2012), Acemoglu and Finkelstein (2008)).

The paper also relates to the literature on healthcare reforms (such as, Miller et al. (2021), Finkelstein et al. (2012), Baicker et al. (2013), Sommers et al. (2017), Wilper et al. (2009), Sommers et al. (2012), Kolstad and Kowalski (2012), Ho (2006) and Finkelstein et al. (2018)). The estimates also relate to the literature estimating the marginal utility of consumption in the presence of health, such as Finkelstein et al. (2013), and contributes to the literature on health insurance (such as, Handel and Kolstad (2015), Handel (2013) and Einav et al. (2013)).

Lastly, it also contributes to the work quantifying the role of health in income and welfare (such as, Hosseini et al. (2021b), Prados et al. (2012), Miller and Bairoliya (2017) and De Nardi et al. (2017)); although in most of these papers, health is assumed exogenous. I find that by endogenously investing in their health, individuals are able to partly offset the consequences of bad health shocks.

The remainder of the paper is divided as follows: section 2 provides the new facts; section 3 describes the model; section 4, 5 and 6 present estimation strategy, results and policy experiments, respectively; and section 7 concludes.

2. Data

The merged National Health Interview Survey (NHIS) and Medical Expenditure Panel Survey (MEPS) dataset, as detailed in Appendix section A.9, is a rotating panel of nationally representative dataset of health, income and wealth from 2000 to 2014. It consists of measures of health (including diagnostic and procedure codes), individual and family income, wealth, insurance, health expenditures by type of visit and source of payment for 5 interview waves over 2 years along with detailed mortality status and cause of death until 2015. I augment this data with large-scale federal survey datasets National Longitudinal Mortality Survey (NLMS) and Mortality Differentials in American Communities (MDAC) Survey including cross-sectional information merged with mortality status of over 9 Million individuals to decompose the long-term changes in life expectancy.

Due to absence of life-cycle panels of individuals, I use family income or wealth adjusted for family size as a proxy for permanent income. Quartiles are determined by family income or wealth distribution for age decade (25-35, 35-45, and so on). Amongst these two measures, family income is consistently available across all datasets relative to wealth and therefore, this is the measure I primarily use for analysis. I conduct robustness checks with wealth. If family income or wealth is not observed for some datasets (such as NLMS-MDAC), I use poverty percent which adjusts for family size [12]. Note that in order to account for the life-cycle pattern in income and wealth, the quartile cut-offs are based on age decade (25-35, 35-45, and so on). Unless otherwise stated, the bottom quartile will be referred to as poor and top quartile as rich.

2.1 Health outcomes and health spending: a puzzle

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

The leading cause of death across the income distribution were cancer and heart conditions based on one-year crude mortality from MDAC. As shown in Figure 1, I see that across all age groups and cause of death, individuals in fourth quartile of family income distribution[13] have a lower aggregate and cause-specific mortality-rate compared to individuals in first quartile of family income distribution. This pattern has been well documented in the literature including Chetty et al. (2016). For those in 52-65 age group, the mortality-rate of top quartile of income is less than half of the mortality-rate of the bottom quartile of income.

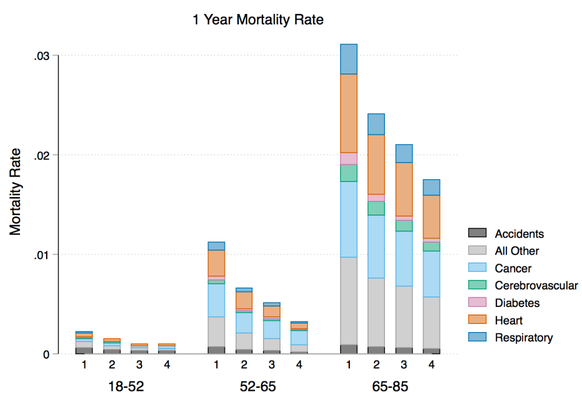
As documented by Ales et al. (2012), the mean total medical spending including the portion covered by private insurance, Medicaid, Medicare, and out-of-pocket looks comparable across family income distribution. For instance, for ages 35-45, individuals in bottom quartile of the family income distribution 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 2. Similar pattern holds for other age groups, as shown in Appendix. A detailed discussion on charge and expenditures is provided in appendix section A.9. Breaking down the spending by source of payment reveals that very low fraction of poor individual's total medical spending comes from private insurance.

A natural question that arises from looking at the two facts documented in the litera-

[12]Details on poverty variable here: https://usa.ipums.org/usa-action/variables/POVERTY

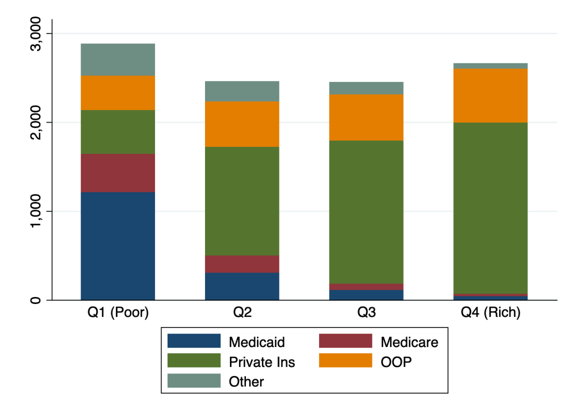
[13]The patterns are very similar when I define the quartiles based on wealth.

Figure 1: 1-Year Mortality Rate by Age and Inc



Source: MDAC

Figure 2: Medical Spending Age 35-45



Source: NHIS-MEPS

ture 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?

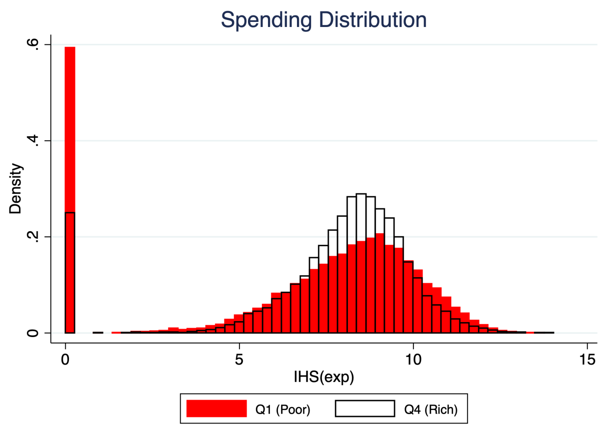
In order to understand the sources, I will now dig deeper into the data. To the best of my knowledge, the empirical facts 2-4 in the next section are relatively unexplored in the literature.

2.2 Facts

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

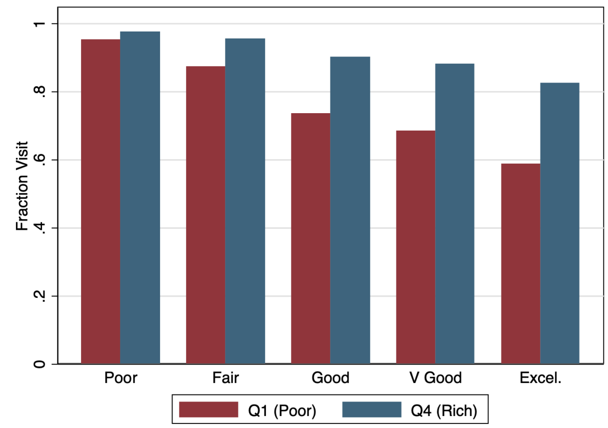
In figure 3, I document the inverse hyperbolic sine (IHS) transformation of the distribution of medical expenditures for 1st and 4th quartile based on family income. I observe that while larger fraction of poor have zero medical spending, they also have thicker tails in expenditure distribution, which suggests that while they are less likely to go for a doctoral visit in any given year, if they do, they end up spending more than the rich who are going for doctoral visits. Those in bottom quartile of the distribution spend significantly more on hospitalizations and emergency room while those in top quartile of the distribution spend more on office based and outpatient visits, as detailed in the appendix A.10. These findings are consistent with the literature (for e.g. Ozkan (2014).

Figure 3: (IHS) Medical Expenditure Age 45-55



Source: NHIS-MEPS

Figure 4: Timing of Spending by Health State



Source: NHIS-MEPS

The next three findings are relatively unexplored in the literature.

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

In figure 4, I document fraction who visit the doctor by health and wealth. I find that rich individuals visit the doctor more in all health states. The fraction of rich who visit the doctor ranges from close to 1 for poor health individuals to 0.83 for those in excellent health. On the other hand, poor individuals visit decision is very responsive to their health status: it goes from 0.95 in poor health to less than 0.6 for excellent 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.

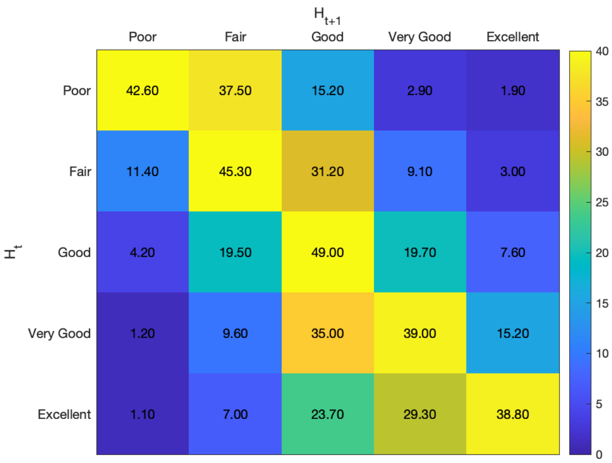
In addition, I also do a fixed effect regression[14] where the variation comes from the panel component where I observe an individual and its doctoral visit decision on their health status. The findings are similar and I present them in appendix A.10.

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

In Figure 5 and 6, I compare the annual transitions in health for individuals in the first quartile and fourth quartile of family income distribution conditional on medical visit

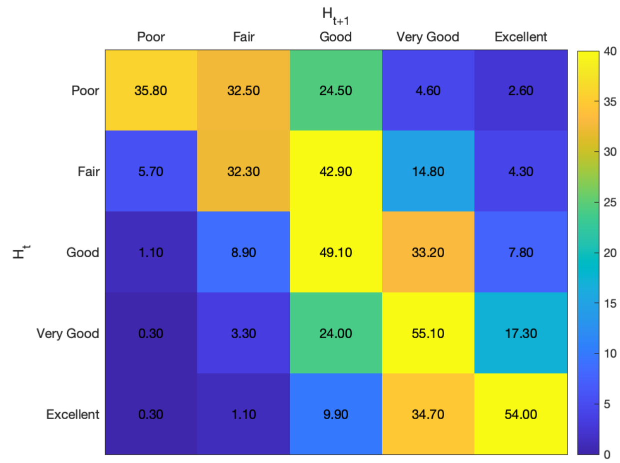
[14] For this analysis, I do not need the self-report status to be comparable across income groups since the coefficients are identified off of the *change* in health status

Figure 5: Transition matrix | visit: Poor aged 35-45



Source: NHIS-MEPS

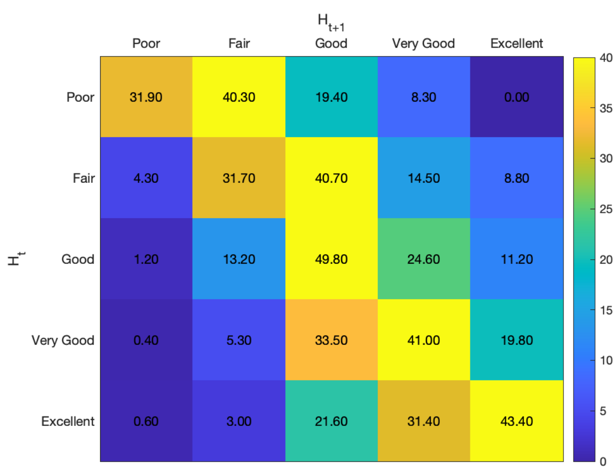
Figure 6: Transition matrix | visit: Rich aged 35-45



Source: NHIS-MEPS

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

Figure 7: Transition matrix | no visit: Poor aged 35-45



Source: NHIS-MEPS

for ages 35-45 years. For those in poor health in time t, 42.6% of poor remain in poor health while compared to 35.8% for rich. Similarly, more than 56% of poor in fair health remain in poor or fair health compared to 37% for the rich. The pattern is similar across age groups, as shown in the appendix.

This is also a good place to emphasize the need to model the visit decision – if I compare the transition matrix of those who didn't go to the doctor for the poor, as shown in figure 7 with those who did in 5, I see that those who didn't go to the doctor transitioned to a better health with a higher probability. Simply put, those whose health got better were also the ones who didn't demand any healthcare, i.e. didn't need to go to the doctor. Thus, modeling visit decision is crucial to understand health outcomes.

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

I find that, conditional on surviving until age 20, there is a gap of about 8.5 years in life expectancy, for the top and bottom quartile of the family income distribution. From 1983 to 2015, those in bottom quartile have gained about 2 years and 11 months, those in top quartile have gained 5 years and 5 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, I do a decomposition by age and cause specific mortality across four family income groups adjusted for family size[15], à la Becker et al. (2005). In appendix , I describe the exercise along with providing robustness across different thresholds, samples and an analysis by race, where we have witnessed convergence in life expectancy.

While the improvements in heart related causes have contributed the highest gains in life expectancy, their distributional impact have been limited. As shown in Table 1, while poor have gained 4.1 years in life expectancy due to heart related causes, rich have gained 4.3 years in life expectancy. It is malignant neoplasms (cancer) that have contributed significantly to the rising health inequality across rich and poor over the two decades from 1983 to 2015. 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

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

contributed to the rise in health inequality across income groups[16].

Table 1: Gains in Life Expectancy: 1980s to 2010s

	Q1 (Poor)	Q2	Q3	Q4 (Rich)
Life-expectancy 1980s	68.9	72.5	75.7	77.4
Total Change (1980s - 2010s)	2.9	3.7	3.9	5.4
By cause of death:				
Heart	4.1	4.3	4.4	4.3
Cancer	0.3	0.5	0.7	1.1
Diabetes	-0.2	-0.1	0.0	0.0
Respiratory	-0.1	0.1	0.0	0.3
Cerebrovascular	0.7	0.6	0.6	0.8
Accidents	0.0	0.0	0.0	0.1
Alzheimer's	-0.3	-0.3	-0.4	-0.4
Suicide	-0.0	-0.0	-0.0	-0.0
Kidney Disease	-0.1	-0.1	-0.0	-0.0
All Other	-0.9	-0.9	-0.8	-0.6

Life expectancy conditional on surviving until age 20.
1980s is computed by NLMS 6a wave 6 year average mortality rates; 2010s is computed by MDAC 2008 wave 6 year average mortality rates

The empirical findings suggest that the timing of healthcare spending might play a key role in the increased health disparities.

3. Model

I then develop a dynamic stochastic life-cycle model of an economy where individuals choose insurance, timing of spending into their health capital, consumption, and savings.

[16]Note that drug-overuse (for e.g., Case and Deaton (2015)) is attributed in accidents. For aggregate trends on cause of deaths, see CDC Report. Category others include Alzheimer's and other forms of dementia, whose occurrence has gone up in the recent decades.

The model brings continuous time methods, a popular tool used in macroeconomics and finance, into a problem involving individual's health related decisions, and is set up based on data availability.

3.1 Setup

Timeline

Individuals enter the model at age 25 with initial wealth (w), initial health (h) and education. 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[17]. Individuals' transition from one health to another as governed by the Poisson intensities. They age when hit by age Poisson η and die when hit by death Poisson $\lambda(h, a)$. The stochastic evolution of health can be thought of as consisting five parts: a) deterioration governed by intensities d_h^a as a function of health, h and age, a, b) improvement governed by intensities ν_h^a,c) sudden illnesses which could lead to long-term disability, κ_h^a or d) mortality governed by intensities λ_h^a and e) stochastic aging governed by intensity η[18]. Other than the standard consumption-saving decisions, individuals face two crucial decisions: whether or not to buy private insurance at a price based on their age or Medicaid if they are eligible and subsequently, given their insurance status and wealth, when to go for a medical visit and invest in their health.

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

Evolution of health capital

An alternative way to think about the health evolution process is that it is a modified birth and death process adjusted to account for mortality, aging and endogenous Poisson intensities. The evolution of health capital follows a Poisson process with an exogenous

[17] An alternative is to use construct health indices such as Poterba et al. (2017) or Hosseini et al. (2021a). However, some of the questions literature use include questions about disease diagnosis (such as cancer and diabetes), which suffer from selection in the context of my model as they require doctoral visits. Therefore, I use the self-reported measure, which doesn't suffer from this bias.

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

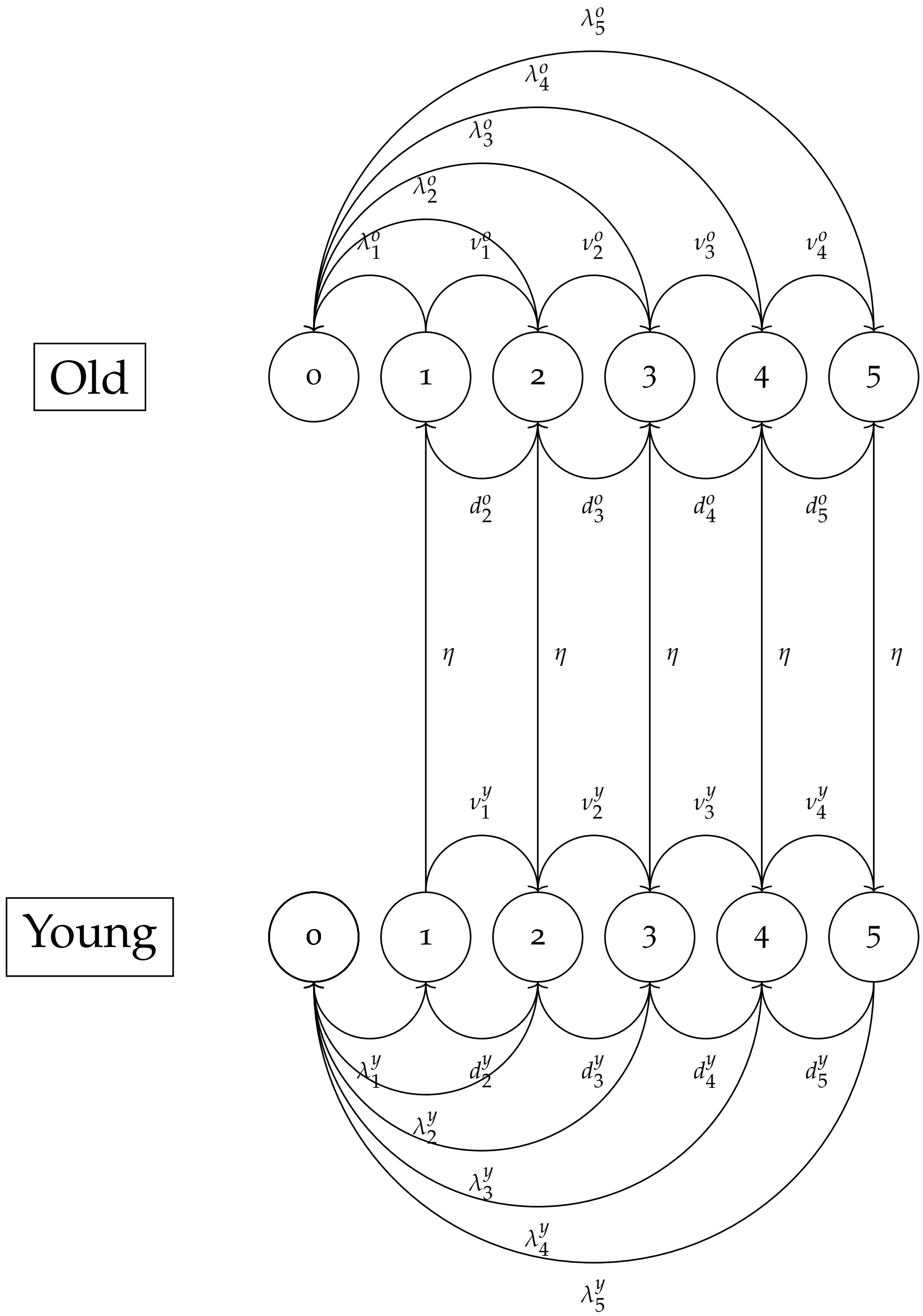


Figure 8: Illustrative health evolution with two ages

depreciation, which is governed by d_h^a, and endogenous appreciation, which is governed by ν_h^a. d_h^a is the intensity with which a person of age a, goes from state h to $h-1$. Improving one's health is governed by intensity ν_h^a, which is the intensity with which a person of age a goes from state h to $h+1$. Individuals age at a rate η which is set to match the interval of 10 years in each age state., i.e. on average, a person stays in an age group for 10 years before aging and transitioning to the next age group. Note that upon aging, the health and wealth of the individual remains the same; as individuals age, the health depreciates at a higher intensity. Individuals in health state h and age a transition to an absorbing state of long-term disability with intensity κ_h^D or die and exit the model with intensity λ_h^a. All the intensities are allowed to vary by health, h, and age, a to allow for the fact that healthier individuals are more like to become disabled or die at a much lower rate compared to individuals in poor or bad health at the same age. Disability or long-term-disability is an absorbing state where individuals get a constant disability income and their healthcare expenses are paid for my Medicare.

To fix ideas, consider a setting with only two age groups young (y) and old (o) and no long-term-disability. Figure 8 illustrates the evolution process for two age groups - 'Young' and 'Old'. Consider a young individual born in good health state, i.e. in node 4 for the figure. He can transition to average health, i.e. node 3, with intensity d_4^y, transition to a better health state, i.e. node 5, intensity ν_4^y, get hit by the aging Poisson with intensity η and transition to node 4 of state 'Old' or be hit by the mortality shock λ_4^y and exit the model.

The formulation is general enough to capture a potential increase in the depreciation of health as individuals age and a reduction in health improvement. Due to data limitations, I only allow for one step above or below in health transitions. Given that I only observe five snapshots for the two years the individual is observed in data, I do not know the exact time the individual stayed in a particular health state or the transition path of health followed. For example, I observe that an individual is in health state 4 in quarter 1 and health state 2 in quarter 2, I won't be able to see if he transitioned directly from 4 to 2 or he went from 4 to 2 via 3 or even 1 for that matter. Therefore, this is an identifying restriction that I need to impose to be able to pin down the Poisson intensities. Since I observe the exact duration of exit in our data, I 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 I typically have to put stronger restrictions on when the choices can be made.

Healthcare spending

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

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

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

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

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

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

Wealth and Income

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

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

Utility Function

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

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

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

Insurance take-up problem

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

At the time of Poisson realizations, individuals can take-up Medicaid if they are eligible by paying a fixed cost f. This leads to selection into Medicaid take-up problem. Note that private insurance is the same as Medicare after 65 where individuals pay a highly subsidized premium, which I estimate from data.

Long-term Disability Stage

Long-term-disability is modeled as an absorbing state, where exit rate is given by $\lambda^D a$, health is given by h^D and disability income is given by y^D. Given that long-term disability makes one eligible for Medicare, it can be modeled at these individuals needing $\bar{m}$ spending continually – such as dialysis treatment for end-stage renal failure, which comes from Medicare.

Thus, the HJB becomes:

$$\begin{aligned} \rho V^D(w, h^D, a) &= \max_c \{u(c, h^D) + V^D_w[y^D + rw - c]\} \\ &\quad + \eta[V^D(w, h, \nu, a+1) - V^D(w, h^D, a)] + \lambda^D(a)(V^T - V^D(w, h^D, a)) \end{aligned} \tag{2}$$

3.2 Individual's Problem

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

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

$$
\begin{aligned}
&\rho V(w,h,\nu,a,I,p) = \max_c\{u(c,h) + V_w[\theta(h)y(a) + rw - c - p]\} \\
&\underbrace{\eta[V(w,h,\nu,a+1,I,p) - V(.)]}_{\text{aging to } a+1} + \underbrace{\nu[V(w,h+1,\nu_0,a,I,p) - V(.)]}_{\text{transition to } h+1} + \\
&\underbrace{d(h,a)[V(w,h-1,\nu_0,a,I,p) - V(.)]}_{\text{transition to } h-1} + \underbrace{\lambda^T(h,a)[V^T - V(.)]}_{\text{death}} + \\
&\underbrace{\phi[\bar{V}(w,h,\nu,a,I',p') - V(.)]}_{\text{insurance choice}} + \underbrace{\kappa^D(h,a)[V^D - V(.)]}_{\text{disability}}
\end{aligned}
\tag{3}
$$

where, $\bar{V}(w,h,\nu,a,I',p') = max\left\{ \overbrace{V(w,h,\nu,a,1,p(h,a))}^{\text{insurance}}, \overbrace{V(w,h,\nu,a,0,0)}^{\text{no insurance}}, \overbrace{V(w-f,h,\nu,a,2,0)}^{\text{Medicaid}} \right\}$

On the other hand, in the stopping region, given their decision to invest in health, they choose medical expenditure m_t which increases ν, i.e. lowers the expected duration of going to the better health state, according to equation (7). The cost of medical expenditure depends on the fixed cost of going to the doctor k and out-of-pocket cost $mq(I_0)$. The impact on wealth is given by equation (6). The stopping region Γ^S is described as follows:

$$V(w,h,\nu,a) = V^*(w',h,\nu',a) \tag{4}$$

$$\text{where, } V^*(w,h,\nu,a) = \max_m V^i(w',h,\nu',a) \tag{5}$$

$$w' = w - k - mq(I_0) \tag{6}$$

$$\nu' = \nu_0(a) + Am^{\alpha_m} \tag{7}$$

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

Thus, under the assumptions of at most linear growth and Lipschitz continuity,[19] the individual's problem can be written compactly as,

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

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

or

$$
\min\left\{\Gamma^C, \Gamma^S\right\} = 0 \quad (9)
$$

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

Following Theorem 3.2 in Øksendal and Sulem (2005) Integrovariational Inequality for Optimal Stopping, the maximization problem is same as solving the following HJBII in (9).[20]

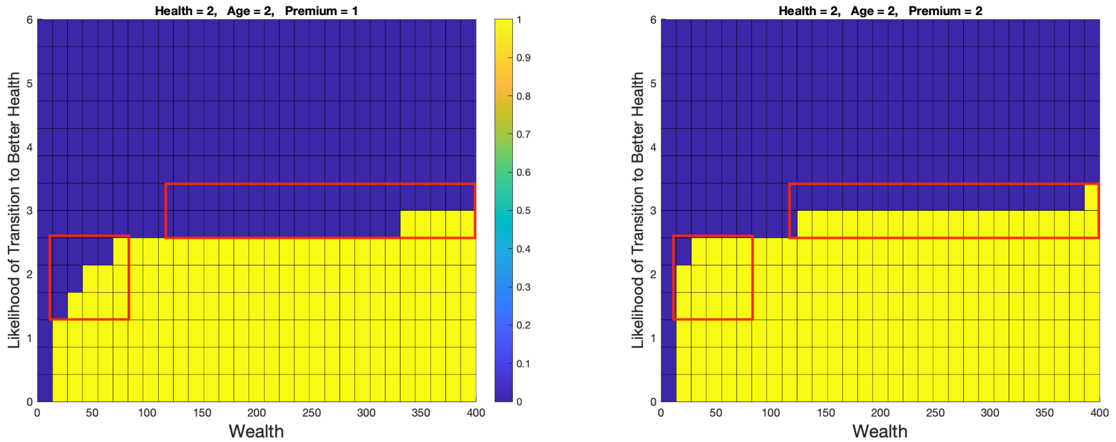
3.3 Policy Function: Doctoral visit

To provide a description of one of the key choices of the model, I look at the visit decision for an individual at age 35-45 in bad health[21] (Figure 9). I plot the decision to visit the doctor as a function of their wealth and improvement intensity, fixing age and health status. As a result of the fixed cost, there are wealth effects in the visit decision. I see that as wealth increases, more individuals go to the doctor, fixing the likelihood of going to a better health state before going to the doctor (y axis). For each level of wealth, there is cutoff in improvement intensity below which the individual goes for the doctoral visit and health spending. It is also clear that rich individuals go to the doctor much earlier (at a higher improvement intensity) as compared to those who are poor. On the other hand, comparing insured and uninsured, there are states of the world where insured individuals would go to the doctor while uninsured individuals would not.

[20]See for example, Achdou et al. (2017) and Phelan and Eslami (2021) on computational methods on solving continuous time models.

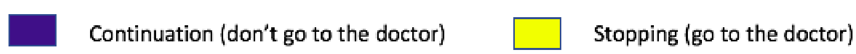
[21]The whole policy function is a multi-dimensional object, I look at some cross-sections of this multi-dimensional object.

Figure 9: Visit Decision, Age 35-45



a) Uninsured, Bad Health

b) Insured, Bad Health



4. Estimation

First, I present the functional forms I assume in the model which help in reducing the number of parameters to be estimated while still allowing for flexible parameterizations. Second, based on identification, I separate the parameters into three sets: i) a set of parameters to be calibrated outside of the model; ii) a set of parameters estimated outside of the model; iii) a set of parameters estimated within the model. Finally, I use Simulated Method of Moments to target choices (doctor visits, healthcare spending, and insurance take-up) and transitions (change in health with and without visit, death rate, health over the life-cycle), average spending ratio between rich and poor of the same health, and disability rates to identify health transition, mortality and disability shocks, utility gains from health, health production function and fixed costs associated with doctor visits and Medicaid take-up. In particular, I leave the health and spending by wealth untargeted and show an untargeted fit with respect to wealth moments in the next section.

4.1 Specification

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

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

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

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

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

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

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

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

4.2 Parameters Outside the Model

Two set of parameters that are set outside of the model. First, I present the parameters parameters that are calibrated outside of the model in table A.8.7. Two key parameters are: i) productivity by health ($\theta(h)$), which is taken from Ozkan (2014); ii) value of life or terminal value (V^T) is assumed to be 11.5M.

Second, I present the parameters which I estimate from the data. I feed in the initial distribution of health ($h_0(e = L, H)$), education $e = L, H$ and wealth ($\mu_L, \sigma_L, \mu_H, \sigma_H$) at the age 25 by education as initial conditions to the model. Income by age and education $y(e, a)$ as well as disability income y^D is estimated from the data. The exit intensity λ_h^a at health h and age a comprises of two components: λ_h^6 and the survival factors F_{25-35} - F_{65-75}. For λ_h^6, while I estimate the exit intensity for average health and age 75-85 within the model (λ_3^6), all other exit intensities are normalized based on this estimate outside the model. Therefore, I set λ_h^6 for $h = 1, 2, 4, 5$ and λ_h^a for $h = 1, 2, 3, 4, 5$ and $a = 1, 2, 3, 4, 5$ by using the exit probabilities for from the data by taking 15-day exit rates. For example, my 15-day exit rates show that those in poor health at age 75-85 λ_1^6 are 11.07 times more likely to die compared to those in average health at ages 75-85 λ_3^6. For the survival factors F_{25-35} - F_{65-75}, these are estimated from the data using aggregate age-specific instantaneous mortality.

Individuals aged 25-65 years who are on Medicare are used to estimate the cost being paid by Medicare in long-term-disability m^D. Exit rates of disabled individuals at each age a, λ^{Da}, is estimated relative exit rates of those in same age but average health λ_3^a, using 15-day exit rates. Similarly, while aggregate disability rate is estimated within the model κ_D, the gradient of disability by health is estimated outside using disability rates by health from the data.

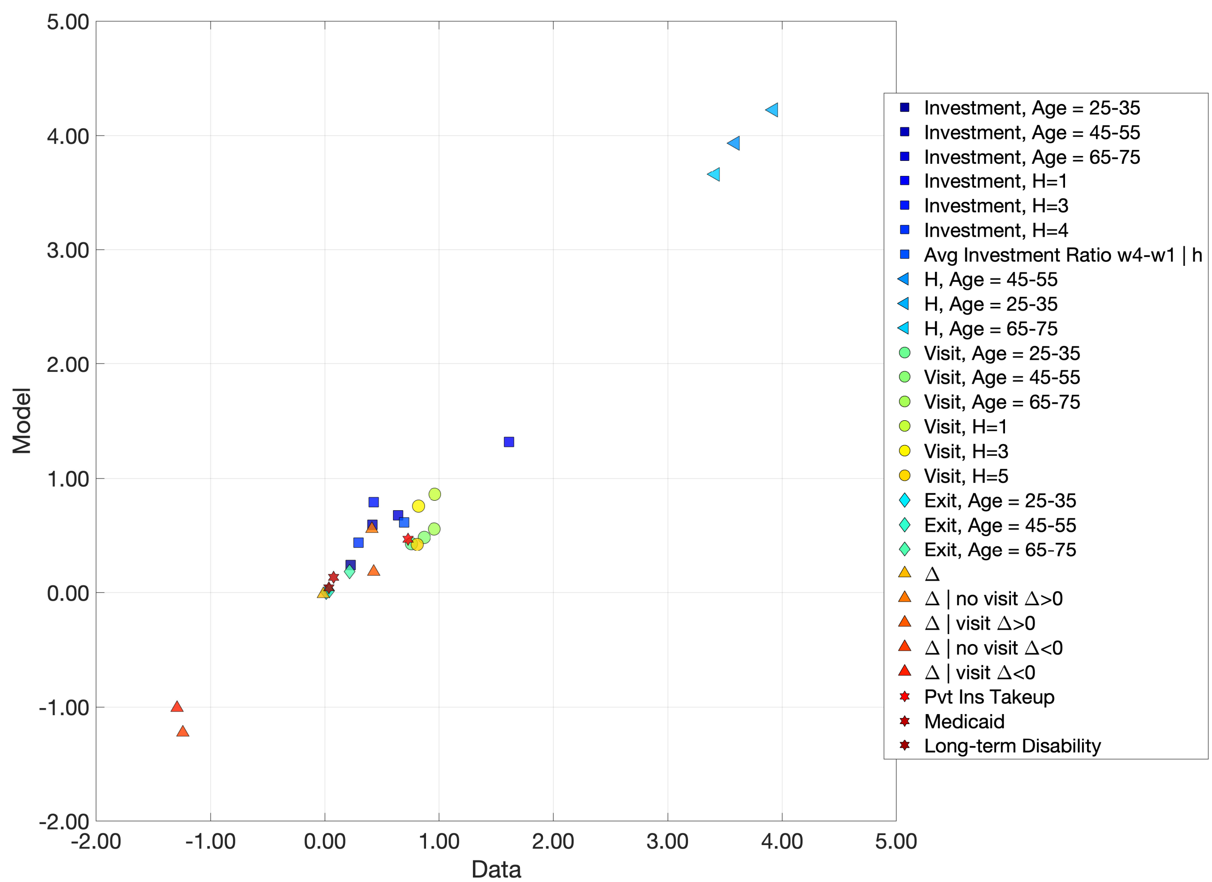
Average annual out-of-pocket insurance premium by age is used to estimate insurance premium by age $p(a)$. Effective price/out of pocket healthcare spending by insurance is used for out-of-pocket co-insurance $q(I)$. For uninsured, I estimate this by looking at charge-to-expenditure ratio of insured individuals. Put differently, I assume that for same service, if an uninsured visits the doctor, they would pay 1.45 times the total – not just out-of-pocket – amount paid for by a person who is insured.

4.3 Identification

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, the utility parameters ϕ_0, ϕ_1 and ϕ_2, fixed cost of Medicaid take-up f, disability rate κ^D and mortality rate λ^T.

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. More specifically, rate at which an individual transitions to worse and better health with and without doctoral visit is informative about age based depreciation and improvement of health. Health spending by age and health status pins down the utility gains from health. Fixing other parameters, health spending ratio by rich and poor for same health are informative about the curvature in the health production function, α_m. For example, for every low α_m, we would expect to see very little difference across rich and poor for same health compared to higher values of α_m. The fraction of individuals who take-up Medicaid is informative about the fixed cost in acquiring Medicaid. Lastly, fraction of those individuals who visit doctor is informative about fixed cost associated with that decision.

Figure 10: Model Fit: Targeted Moments



4.4 Estimates

I estimate the partial equilibrium model on individuals aged 25 and above. A natural limitation is that in the policy simulations, the general equilibrium effect – via clearing the insurance prices – would be missing and I would point out scenarios in which it could play an important role. In the appendix, I write down the ways to incorporate these provisions with insurance firms' problem and the estimation with those is left for future work. I select our sample from NLMS-MDAC and NHIS-MEPS as the privately insured individuals aged 25-85 with 10-year intervals. I 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.

I report the set of targeted moments and the model fit in table A.8.9 in the appendix and in the figure 10. The model does a good job of capturing health spending over the life-cycle and by health. Two place where model doesn't do a good job are: private insurance take-up for 25-65 year age (73% in data vs 47% in the model). One reason for this could be that for a lot of individuals in the US, the insurance choices available is tied to their jobs and the data isn't able to capture the employer-subsidies provided in the insurance market. Another reason could be the highly negotiated price for services by private insurance, something I try to address as well as possible with the data, as described previously.

I describe the estimates now. The estimated fixed cost is $k = 0.0335$, equivalent to \$335 per visit. i.e. on average individuals face \$335 per visit as equivalent monetary cost to visit the doctor. The estimates of d_0, d_1 and d_2 are 0.36, 0.04 and 0.003 respectively. Converting the implied Poisson intensities to expected duration, the estimates imply that the expected duration before going to a worse health state is 2 years and 7 months for those aged 25-35 and this number goes down to 1 year and 6 months for individuals in age 65-75. Similarly, based on the estimates of ν_0, ν_1 and ν_2, the natural improvement duration is 7 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. Finally, the estimates imply the marginal utility of consumption at same level of consumption for average health is about 2.56 times that in poor health, showing that health and consumption are complements in the utility function. This last results is consistent with Finkelstein et al. (2013).

Table 2: Parameter Estimates

Parameter	Type	Estimate
A	TFP	0.98
α_m	Elasticity w.r.t. m	0.10
k	Fixed Cost	0.0335
d_0	Depreciation Poission (Constant)	0.36
d_1	Depreciation Poission (Age)	0.04
d_2	Depreciation Poission (Age^2)	0.003
n_0	Natural Improvement (Constant)	0.13
n_1	Natural Improvement (Age)	-0.13
n_2	Natural Improvement (Age^2)	0
ϕ_0	Utility Cost of Health (Constant)	1.30
ϕ_1	Utility Cost of Health (Health)	0.99
ϕ_2	Utility Cost of Health (Health^2)	0.01
λ^T	Exit Intensity	0. 01872
q	Insurance Cost	0.02
κ_D	Disability Intensity	0.06

5. Results

With the estimated model, I now present data patterns across health, wealth and age to illustrate the model fit for the un-targeted moments and to show the mechanisms in the model.

5.1 Visit decision by health status

I first explore the key mechanism of the timing of healthcare spending. To understand the responsiveness of doctoral visits on health status for rich and poor wealth, I run an individual fixed effect regression of visiting a doctor on their health status for rich and poor separately. This is done for both data (using family income) and model (using wealth).While the model is simulated monthly, I perform the regression using quarterly frequency – same as the data – for better comparison. In figure ??, I present the estimated probability of doctoral visit for those in poor health relative to those in average health for

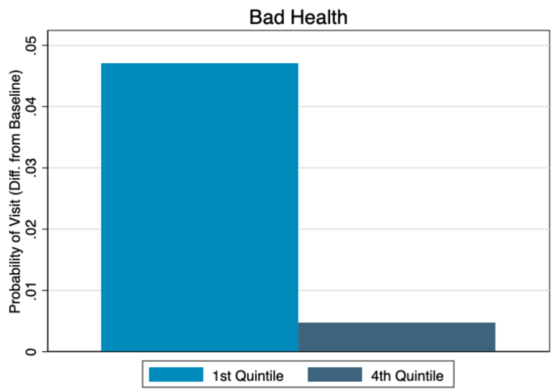


Figure 11: Visit Decision by Health Status: Model

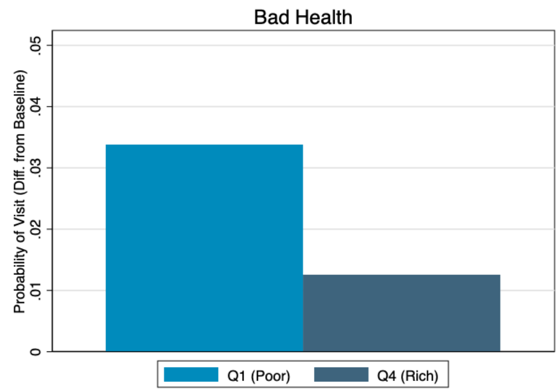


Figure 12: Visit Decision by Health Status: Data

income/ wealth rich and poor, for data and model respectively[22]. The results indicate that poor individuals' visit decision is highly responsive to their health state esp. for bad health shocks. An implication of this is that the poor individuals go to the doctor in a much more unhealthier state than the rich. Compared to a poor person in average health, a poor person in poor health is 4.7% points more likely to go to the doctor (vs 3.3% in data). This number is 0.5% in the model for the rich (vs 1.2% in data). 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 responsiveness for bad health is comparable to data, the responsiveness for excellent health in the model is higher compared to data. It is not surprising since in the model, the only way in which a person in excellent health goes to the doctor is if their health depreciates. In other words, it may be an artifact of a bounded health state. A way to address this would be to allow for people to invest in lowering depreciation intensity, d_h^a, which could be thought of as preventive spending.

5.2 Spending across health status

After looking at the visit decision, I present the quarterly spending by health and wealth from the model and data in Table 3 and 4, respectively. Fixing health, wealthy spend more on their health over the next year, thus transitioning to a better health with a higher

[22]The variation for this regression comes from the panel component where I observe an individual and its doctoral visit decision on their health status

Table 3: Model: Age 35-45

	Health				
	1	2	3	4	5
Q1 (Poor)	1.29	0.31	0.31	0.19	0.09
Q2	1.06	0.57	0.44	0.20	0.10
Q3	1.24	1.01	0.69	0.34	0.19
Q4 (Rich)	1.21	1.33	0.91	0.51	0.20

Table 4: Data: Age 35-45

	Health				
	1	2	3	4	5
Q1 (Poor)	1.61	0.81	0.43	0.29	0.21
Q2	1.88	0.92	0.47	0.31	0.20
Q3	2.02	0.98	0.55	0.33	0.23
Q4 (Rich)	2.40	1.19	0.61	0.39	0.26

probability. This pattern is true across all health states[23]. I also show that this compares well with the medical spending data by family income adjusted for family size and age quartile[24].

5.3 Health Transitions

Having looked at the choices of decisions and spending, I now show the outcomes, such as health transitions. I analyze the health transition of each wealth group, relative to the poor or bottom quartile. I 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. In figure 13, I find that after controlling for age and health in time t, those in top quartile have a health that is 20% higher than those in bottom quartile. This is a result of higher spending by the rich, due to which they transition to a better health with a higher probability in the next quarter. I conduct similar exercise albeit for family income group, which is an imperfect analogue to the model, and find similar differences across top and bottom family income quartile. One caution is that I am interpreting the categorical variable of health as an index from 1-5. For this, I perform similar analysis for a binary variable for health, as is common in the literature De Nardi et al. (2017), as well as a multinomial logit, and get similar results.

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

[24]Moments by wealth are pending from the data center and will be added as data release approval is received.

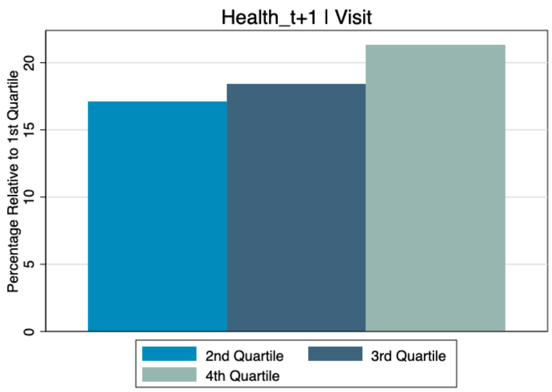


Figure 13: Model (by Wealth)

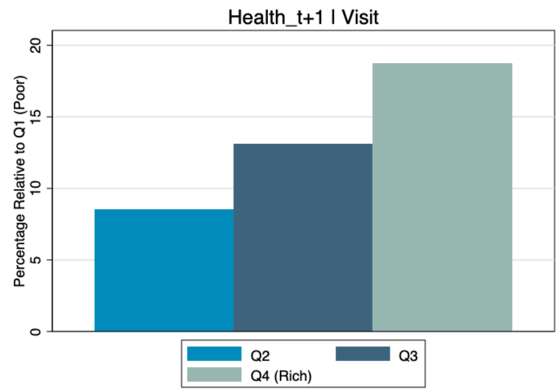


Figure 14: Data (by Family Income)

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

5.4 Spending and Outcomes

A key puzzle motivating this paper is the difference in life expectancy across rich and poor with comparable medical spending. Table 5 and 6 present the model and data moments on life expectancy, mean spending and mortality rates where the poor or bottom quartile are normalized to 1. First, the estimated model is able to predict about half of the gap in life expectancy between the top and the bottom quartiles. Second, the model also does a good job of capturing the flatness in medical spending across wealth groups – an untargeted 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.

The effect of difference in timing of health spending on spending and health outcomes primarily arises as a result of the complementarities in health production, where \$1 in average health is better than \$1 in worse health. Thus, the spending at a lower health state is less likely to result in a transition to good health. Poor individuals, due to lack of insurance or financial constraints delay their visit decision until they reach their stopping time (a lower health state), which causes them not to reap the benefit of their medical spending as opposed to rich, who do not delay their visit. This results in comparable healthcare spending but significant differences in health outcomes.

Table 5: Model

	Wealth Quartiles			
	Q1	Q2	Q3	Q4
Life-Expectancy	1.00	1.04	1.04	1.06
Mean Spending 25-35	1.00	1.06	1.47	1.15
Mean Spending 35-45	1.00	0.75	0.96	1.08
Mean Spending 45-55	1.00	0.74	0.82	1.65
Mean Spending 55-65	1.00	0.66	0.86	1.94
100 x Mortality 25-35	1.00	0.75	1.25	0.56
100 x Mortality 35-45	1.00	0.67	0.52	0.46
100 x Mortality 45-55	1.00	0.70	0.51	0.41
100 x Mortality 55-65	1.00	0.47	0.47	0.32

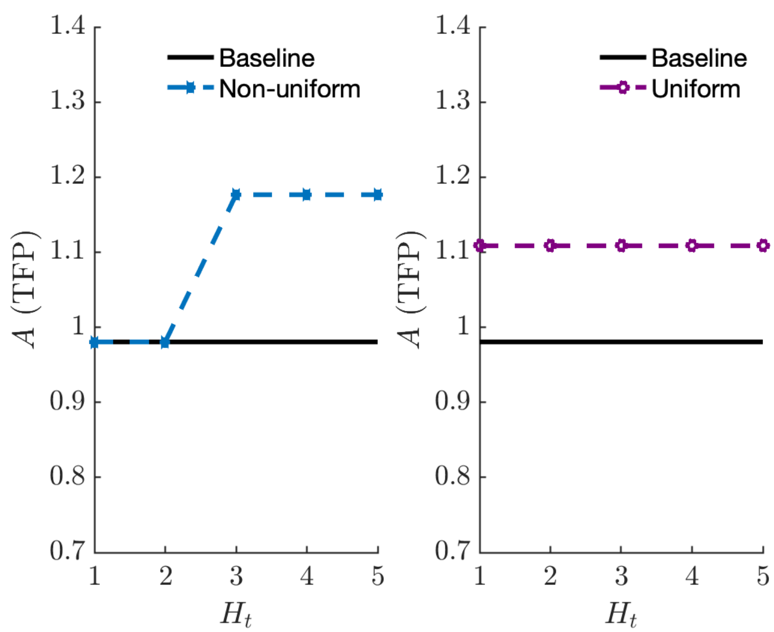
Table 6: Data

Wealth Quartiles			
Q1	Q2	Q3	Q4
1.00	1.05	1.10	1.12
1.00	0.90	0.99	1.07
1.00	0.89	0.86	0.93
1.00	0.74	0.72	0.73
1.00	0.89	0.90	0.93
1.00	0.87	0.87	0.86
1.00	0.51	0.48	0.35
1.00	0.55	0.41	0.37
1.00	0.59	0.47	0.32

6. Quantitative Experiments

6.1 Technology

Figure 15: Technological Progress Type



In order to understand the role of technological innovation on the rising health inequality in the US, I consider two types of innovations. First, a uniform broad-based 13% TFP improvements in the healthcare sector (which results in about 5 months of gains in life expectancy on average) where the medical innovation is happens across all the health spectrum and Second, a non-uniform 20% increase in technology (leading to same overall gains in life expectancy of 5 months) which leads to improvement for early diagnosis – such as cancer stage I – but not for later stages of cancer. The experiment is shown in the picture below.

I find that a uniform increase in the productivity of the healthcare sector reduces the inequality in life expectancy by about 2.5 months (50% of the average gain in life expectancy). Both poor and rich alike benefit from the progress and have higher life expectancy but the poor – starting from a lower initial life expectancy – gain more than the rich, leading to an overall reduction in the gap.

Figure 16: Role of Technological Progress

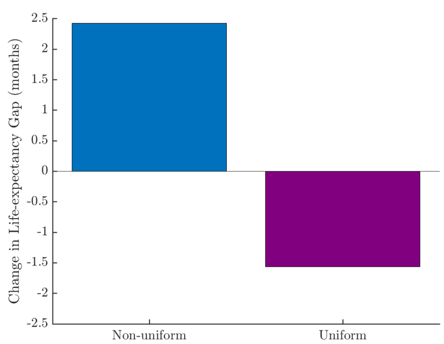
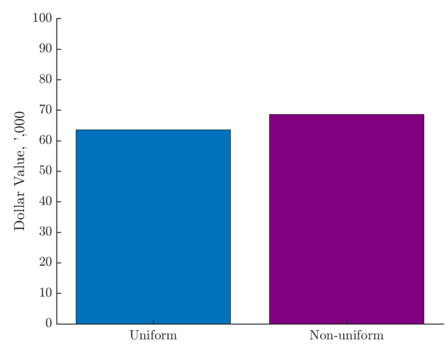


Figure 17: Value of Technological Progress



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, increasing the gap in life expectancy by 1.5 months (30% of the average gain in life expectancy). Thus, the timing of the health spending interacts with the technological progress to worsen the inequalities. An example to build intuition for this result: suppose that two decades ago, medical technology was such that only stage 1 cancer could be treated. Now suppose that due to technological progress in cancer treatments, the medical technology today is such that cancer until stage 2 can be treated. While the rich, frequently going to see the doctor, visit the doctor and invest in their health at stage 1, the poor, having deferred the treatment, only go for their visit and health spending when the cancer is in stage 3. [25] Thus, the poor not only end up spending the same amount as a rich person in any given year, they are also not able to reap the benefits of the medical technological progress that we have witnessed[26].

I use my model to quantify the dollar value of the two types of innovations in the healthcare sector discussed above. My findings can be summarized as follows. First, I find that society puts a large dollar value on medical innovations, ranging from $64,000 to $69,000 per individual (about 1.5 times income per capita in the model). Second, the value of innovation depends on whether it is uniform broad-based or limited to certain types. The value of a uniform broad 13% improvement in the healthcare sector that results in 5 months of gains in average life expectancy is $64,000 per individual (1.45 times income per capita in the model) compared to $69,000 per individual (1.58 times income per capita in the model) from non-uniform 20% improvements that results in about 5 months of gains in average life expectancy.

6.2 Insurance

In order to understand the role of insurance on health inequality, I perform three experiments. First, I shut down Medicaid. Second, I shut down Medicaid and private insurance together. Third, give everyone a comprehensive public health insurance (not unlike proposals for Medicare-for-all), financed by a flat 16% income tax along with 30% cost sharing. Figure 18 presents the results.

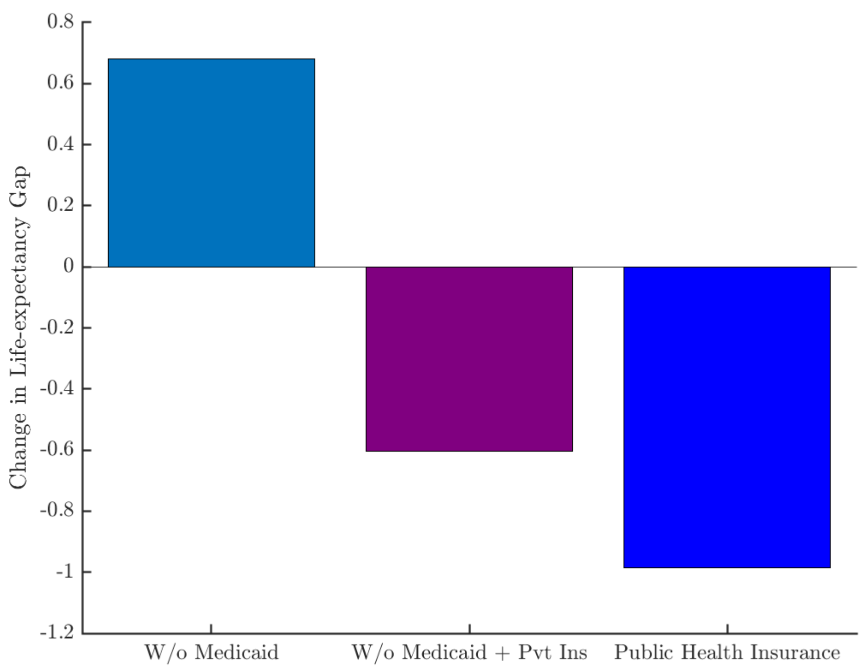
I find that Medicaid would lead to the inequality in health outcomes going up by 10% (6.2 years vs 5.5 years baseline). On the other hand, shutting down private Insurance exacerbates in inequality by almost twice as much. This is due to the fact that private insurance overwhelmingly is taken up by relatively wealthy – who face a lower "effective price" of goods and consume more. The role of private insurance on the inequality is ambiguous, ex ante. On one hand, an option to buy private insurance may increase disparities since only the rich would be willing to pay the premium and buy insurance

[25] 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 the basis for our example here.

[26] It is consistent with the fact that the type of cancer for which the survival rates have converged the most for the affluent and less affluent over the past 2 decades is Hodgkin Lymphoma Cancer Research UK, Accessed April 2021 for which the survival rate is relatively flat across cancer stages while the cancer for which the survival rates have diverged the most is oesophageal cancer, which has a steep one-year mortality rate across cancer stages Source: UK Cancer Cancer Research UK Accessed: April 2021

to diversify their health risks and smoothen out their consumption. On the other hand, unhealthy individuals would be the ones selecting into health insurance due to the well documented adverse selection in the insurance markets. This can be clearly seen in the insurance take-up problem in Figure 19 and 20. While for those in excellent health, only the wealthy take up private insurance, for those in good health, there is a selection of people whose expected duration of going to a better health is low or in other words, those who anticipate going for a doctoral visit, take up private insurance. The threshold below which people take-up private insurance is increasing in wealth. The same selection applied to Medicaid below the eligibility threshold. On net, I find that the wealth effect dominates and the effect of removing private insurance and Medicaid would lead to a modest increase in life expectancy inequality.

Figure 18: Role of Insurance



Comprehensive public health insurance, with fixed cost and co-pays, can reduce the inequality by about 20%. Comprehensive public health insurance illustrates a key trade-off in the policy making: while the inequality in health outcomes would go down, it has to be financed by income taxes, esp. if the public health insurance offers a lower out-

Figure 19: Good Health

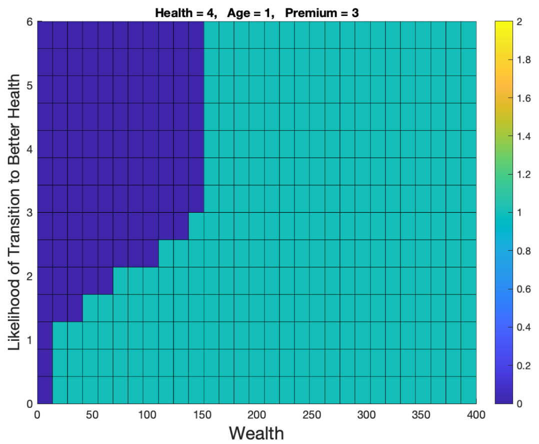
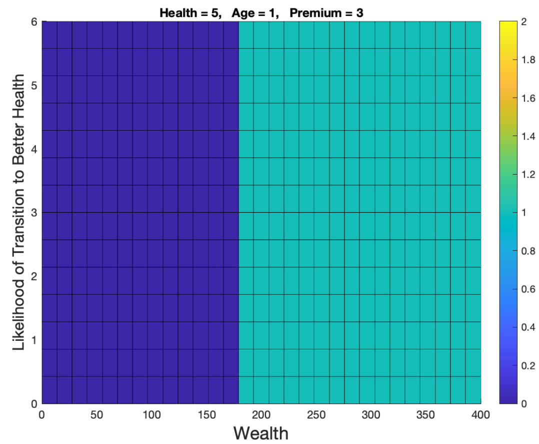


Figure 20: Excellent Health



of-pocket costs. Therefore, public health insurance with out-of-pocket same as private insurance can be financed at a lower tax but an blunt the effects of the policy.

I should emphasize here that the policy experiments involving private insurance and public health insurance maybe missing general equilibrium effects through the insurance firms' problem.

6.3 Role of Health in Income Inequality

I use my model to quantify the role played by health in exacerbating the existing income inequality. To end this, I look at three experiments: i) No feedback of health into productivity ii) Shutting down private insurance and Medicaid iii) Implementing comprehensive public health insurance policy.

I find that if there was no feedback of health into productivity, income inequality, as measured by 90-10 ratio, would go down by about 15% (3.44 v 3.65 in baseline). This is lower than the recent findings by Hosseini et al. (2021b), likely due to the fact that they do not incorporate the endogenous responses to reduced incentives to invest in health. Individuals lower their medical spending over the life-cycle by 20% as a result of a reduced incentive to invest in their health via productivity channel as shown in figure 22.

Figure 21: Income Inequality

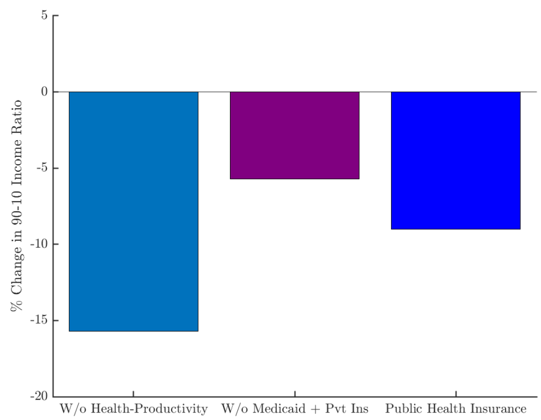
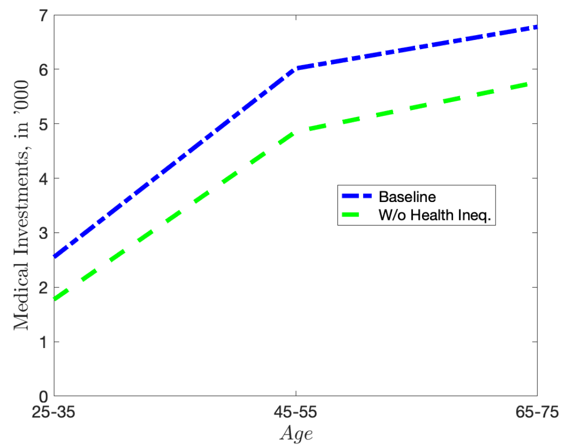


Figure 22: Healthcare Spending: Shutting down Health-Income Channel



Interestingly, I find that private insurance exacerbates the existing income inequality by about 5% whereas the comprehensive public health insurance reduces income inequality by 9%, as shown in figure 21. This is largely driven by the productivity channel of health wherein improvements in health for the low income individuals leads to higher labor income through higher productivity and subsequently, lower income inequality.

7. Conclusion

The large inequality in health outcomes and its worsening over time is puzzling, especially given that the rich and poor have comparable total health spending in any given year. This paper explores the role of insurance and technological progress on rising health inequality across income groups. I focus on a key mechanism: the timing of healthcare spending.

First, using a merged panel dataset of heath, health spending and health outcomes along with large-scale federal survey datasets on mortality, I document new facts on health spending and outcomes. i) While heart-related technological improvements are the biggest contributors to increased life expectancy equally across income groups, cancer-related technological improvements are the largest drivers of increased disparity in health outcomes. ii) Poor individuals' timing of spending is very responsive to their health status, i.e. poor delay their spending till they are in worse health relative to rich and thus are less likely to transition to a better health state even when they visit the doctor.

I then develop a dynamic stochastic life-cycle model with incomplete markets, where I explicitly model that individuals choose the timing of health spending and insurance take-up. A key feature of the model is that health production features complementarities between health and health spending; i.e. the return on each $ spent depends on an individual's health status when they visit the doctor. I estimate the model using the merged dataset using Simulated Methods of Moments. The key findings are: i) low-income/wealth individuals' visit decisions are more responsive to their health state – particularly when they are in poor health; ii) flatness in spending is a result of the complementarities in health and health spending, in the presence of borrowing constraints and fixed costs associated with the visit decision.

I show that different types of technological innovation interact with the timing of healthcare spending and have a first-order effect on health disparities. On one hand, a non-uniform increase in the productivity of the medical sector — where there are improvements in treating early stages of cancer, for example, but none for stage 4 — can lead to an increase in life expectancy inequality. In contrast, a uniform increase in the productivity of the healthcare sector, can lead to a reduction in health disparities. Focusing on the role of insurance, I find that while Medicaid alleviates health inequality, private insurance exacerbates inequality by almost twice as much. Finally, I find that a comprehensive public health insurance could not only reduce health inequality, it could also lower existing income inequality.

In future work, extending the model to incorporate the general equilibrium effects of health insurance markets would allow us to think about an optimal health insurance policy. Technological access and diffusion across geographies (counties and countries) is another aspect to be explored in future work. Incorporating other types of healthcare investments (such as smoking cessation and exercise), which can be complementary to healthcare spending in health production function, is something I leave for future work.

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A.8. Tables Appendix

Table A.8.7: 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	11.5M
$\theta(h)$	Productivity by Health	11% per h (Ozkan (2014))
$\bar{w}$	Medicaid Cutoff	20 % ptile wealth
h^D	Disability health (utility function)	1
η	Aging Poisson, all ages	$\frac{1}{10}$
ϕ	Insurance Intensity	1/12

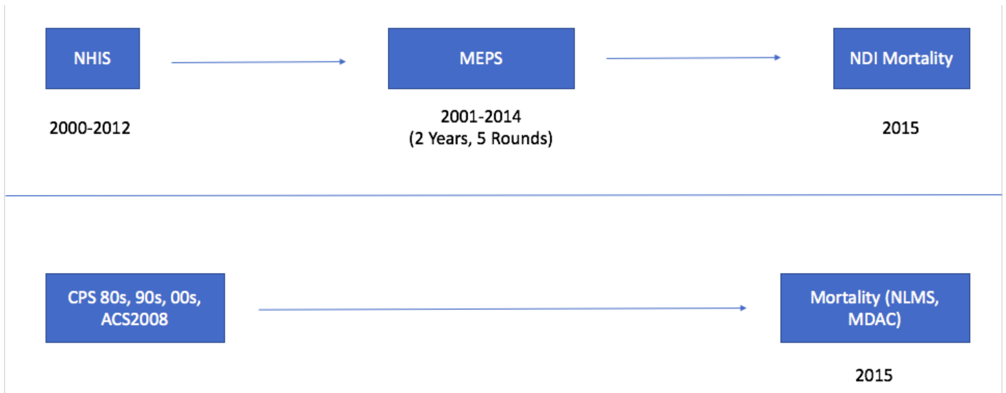
Table A.8.8: Estimated Outside of the Model

Meaning	Parameter	Value
Mortality Rate, Age 75-85	$\lambda_1^6, \lambda_2^6, \lambda_3^6, \lambda_4^6, \lambda_5^6$	$(11.07, 1.82, 1, 0.45, 0.07)\lambda^T$
Survival Factor by age	$F_{75-85}, F_{65-75}, F_{55-65}, F_{45-55}, F_{35-45}, F_{25-35}$	1, 2.05, 4.53, 12.43, 26.56,41.78
Disability Exit relative to Avg Health, by age	$\frac{\lambda^{Da}}{\lambda_3^a}$	3.10, 6.75, 6.48, 5.96, 5.96, 5.96
Income by Education and Age ($10,000)	$y(e = L, a)$	2.49, 3.23 ,3.55, 3.34, 2.66, 2.23 ACS (2013)
Income by Education and Age ($10,000)	$y(e = H, a)$	4.73, 7.41, 8.35, 7.68, 6.27, 5.15 ACS (2013)
Initial wealth distribution by education	$\mu_L, \sigma_L, \mu_H, \sigma_H$	0.94, 3.52, 1.73, 2.88
Disability Income ($10,000)	y^D	1.53 ACS (2013)
Insurance Premium by Age	$p(a)$	0.25, 0.31, 0.33, 0.35, 0.25, 0.25 OOP Premium (NHI
OOP Rate Pvt Ins, Medicaid, Uninsured	$q(I)$	0.33, 0.15, 1.45 (MEPS)
Annual Spending, Long-term Disability ($10,000)	m^D	1.48 (MEPS)
Initial health distribution (%),e = L	$h_0(e = L)$	1.10, 5.03, 24.12, 34.86, 34.89 (MEPS)
Initial health distribution (%), e = H	$h_0(e = H)$	0.27, 1.54, 11.66, 34.82, 51.71 (MEPS)
Initial education distribution (%)	e = L,H	69.49 30.51 (ACS2013)
Disability factor by h	$\kappa^D(h)$	$(0.34, 0.16, 0.06, 0.03, 0.0)\ \kappa^D$

Table A.8.9: Model Fit

Moment	Data	Model
Investment, Age = 25-35	0.22	0.24
Investment, Age = 45-55	0.41	0.60
Investment, Age = 65-75	0.64	0.68
Investment, H=1	1.61	1.32
Investment, H=3	0.43	0.79
Investment, H=4	0.29	0.44
Avg Investment Ratio w4-w1 | h	0.69	0.62
H, Age = 45-55	3.59	3.93
H, Age = 25-35	1.09	1.07
H, Age = 65-75	0.95	0.93
Visit, Age = 25-35	0.76	0.43
Visit, Age = 45-55	0.87	0.49
Visit, Age = 65-75	0.96	0.56
Visit, H=1	0.96	0.86
Visit, H=3	0.82	0.76
Visit, H=5	0.81	0.42
Exit, Age = 25-35	0.01	0.00
Exit, Age = 45-55	0.04	0.02
Exit, Age = 65-75	0.21	0.18
Δ	-0.01	-0.01
$\Delta \mid$ no visit $\Delta > 0$	0.41	0.56
$\Delta \mid$ visit $\Delta > 0$	0.43	0.18
$\Delta \mid$ no visit $\Delta < 0$	-1.24	-1.22
$\Delta \mid$ visit $\Delta < 0$	-1.29	-1.01
Private Insurance Takeup	0.73	0.47
Medicaid	0.08	0.13
Long-term Disability	0.03	0.04

Figure A.9.23: Data Chart



A.9. Data Appendix

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

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

   - Demographic and Socio-Economic Variables: Education, Income, Age, Sex, Occupation, Family Income, Hours worked, Health Insurance: type and coverage
   - Health Care Utilization: Number of shots , Number of visits to doctor in the past 12 months, time since physical breast exam, blood stool test, genetic test, mammogram, skin cancer exam, CT scan

- Health Outcomes: Body Mass Index, Bed Disability Days, lost days of work, history of diseases requiring diagnosis including asthma, cancer, coronary heart disease, diabetes, emphysema, heart attack, etc., date and detailed cause of death

Variables from MEPS include (not an exhaustive list):

- Demographic and Socio-Economic Variables: Education, Income, Age, Sex, Occupation, Family Income, County and State of Residence
- Medical Conditions: life-threatening including cancer, diabetes, high cholesterol, hypertension, heart disease, and stroke; chronic conditions including arthritis, asthma
- Event-level Medical Visit, ICD-9 Diagnosis and Procedure Code, Expenditure and Charge: Detailed event-level visit and expenditure variables; Expenditure by visit type such as outpatient, hospitalization, emergency; Expenditure by payment source such as private insurance, Medicaid and out of pocket
- Health Insurance: type and nature of coverage under each plan; duration of coverage; payment source of policy premium; employer and non-employer related coverage
- Preventive Care: Mammogram, Pap test, breast exam, PSA test, physical exam, blood pressure reading, and flu shot

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

A.10. Facts Appendix

Expenditure and Charge

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[27], which would likely increase poor's spending. Note that the expenditure/ spending is the amount that finally gets paid, i.e. the negotiated amount after the discounts and is lower than the charge. There are certain limitations to this spending data. First, prices are not known. Therefore, if the insurance providers negotiate a better price for the same quantity, the poor get a lower quantity of medical goods even after spending the same amount. It is also worth noting that public provisions such as Medicaid, which is available for the poor subject to income 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 3 for those in 45-55 ages, are one of the most efficient negotiators and negotiate some of the lowest prices for the medical services (see for example, Clemens and Gottlieb (2017)).

Second, another potential concern is that the same service is being provided to the poor, at a higher price, simply because they visit the ER while rich visit outpatient. To address these concerns to the extent I can based on the available data, I 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 I expect similar service – such as ambulatory optometrist or ambulatory dentist – the charge-to-expenditure ratio is comparable all across the income spectrum with rich (1.2) only slightly lower than poor (1.4). This can be further done at the service level, such as Magnetic Resonance Imaging, MRI or an X-Ray, something that will be added in the later versions due to data limitations.

Decomposition of changes in life-expectancy across income groups

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,

[27] 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

survival function directly maps into life-expectancy[28].

With time, the survival rate changes and is now given by S'. Now, if I 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, I 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, $S_{c,i,a} = \prod_{k \neq i} S_{k,a} S_{i',a}$. I implement the above decomposition by considering 8 major cause of death groupings defined by NCHS and age groups 20-50, 50-80 and 80+. I 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. I 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 I are interested in.

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

[28] I 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

Table A.10.10: (Robustness) Gains in Life-expectancy, Age3: 1983 to 2003

	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.

Table A.10.11: Gains in Life-expectancy, by Race: 1983 to 2003

	Whites	Blacks
Total Change (1980s - 2000s)	3.2	4.9
By cause of death:		
Heart	3.3	3.2
Cancer	0.5	1.0
Diabetes	-0.1	-0.2
Respiratory	0.0	-0.1
Cerebrovascular	0.4	0.5
Accidents	0.0	0.6
Alzheimer's	-0.3	-0.2
Suicide	0.0	0.0
Kidney Disease	-0.1	0.1
All Other	-0.6	-0.2

Life-expectancy conditional on surviving until age 20.

Table A.10.12: Gains in Life-expectancy, by Income (Some College and Above): 1983 to 2003

	Q1 (Poor)	Q2	Q3	Q4 (Rich)
Total Change (1980s - 2000s)	-2.63	-2.99	1.23	2.99
By cause of death:				
Heart	1.69	0.90	1.48	2.09
Cancer	-1.14	-0.68	0.04	0.75
Diabetes	-0.39	-0.57	-0.09	-0.18
Respiratory	-0.62	-0.65	0.13	0.24
Cerebrovascular	0.58	0.45	0.01	0.44
Accidents	-0.48	-0.34	0.01	-0.09
Alzheimer's	-0.31	-0.35	-0.34	-0.14
Suicide	0.05	-0.11	0.02	0.06
Kidney Disease	-0.16	-0.10	-0.08	0.29
All Other	-1.59	-1.42	-0.16	-0.42

Life-expectancy conditional on surviving until age 20.
Note that education attainment have changed dramatically over this time, college graduates ending up in the lower bin features selection that has changed over these decades.

Table A.10.13: (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.

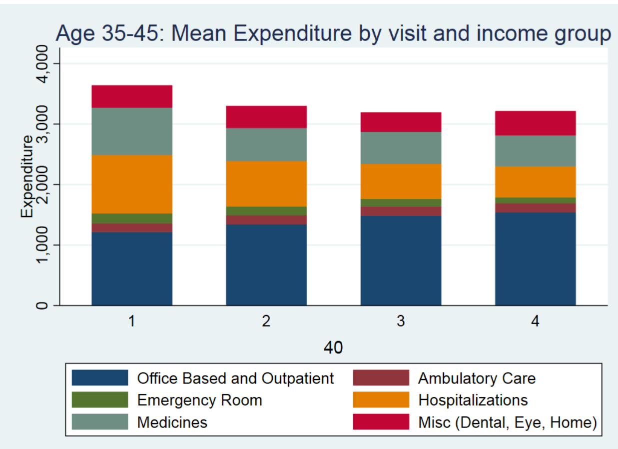
Table A.10.14: (Robustness) Gains in Life-expectancy, Age8: 1983 to 2003

	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.

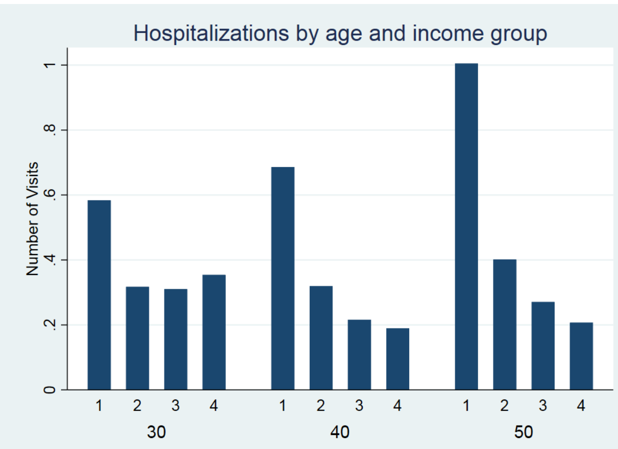
Poor spend more on Hospitalizations and Emergency Rooms while rich spend more on Outpatient visits

Figure A.10.24: Mean Expenditure by Visit, Age 35-45



Source: NHIS-MEPS

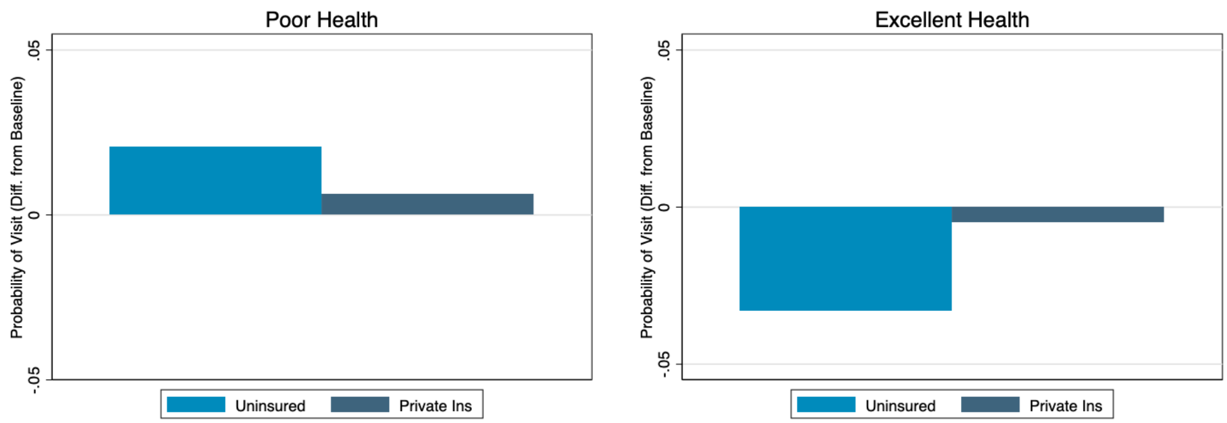
Figure A.10.25: Number of Hospitalizations by Age and Income



Source: NHIS-MEPS

While the rich and poor, defined based on family income quartiles, spend comparable amounts in total medical expenditures, those in bottom quartile of the distribution spend significantly more on hospitalizations ($1000 for first quartile vs $500 for the top quartile for ages 35-45) and emergency room while those in top quartile of the distribution spend more on office based and outpatient visits ($1100 for the first quartile vs $1500 for the top quartile for ages 35-45, Figure A.10.24). This is also evident from the number of hospitalizations in Figure A.10.25. Individuals in top income quartile had less than a third of hospitalizations than bottom income quartile for age 35-45.

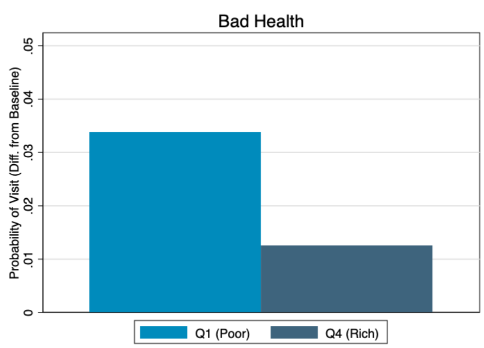
Figure A.10.28: Timing of Visit by Insurance



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

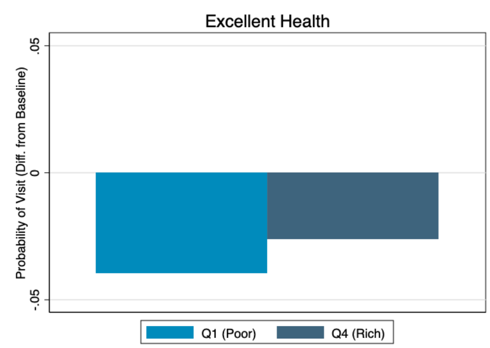
Rich individuals go to the doctor in a much healthier state

Figure A.10.26: Responsiveness to Health State: Poor vs Rich



Source: NHIS-MEPS

Figure A.10.27: Responsiveness to Health State: Poor vs Rich



Source: NHIS-MEPS

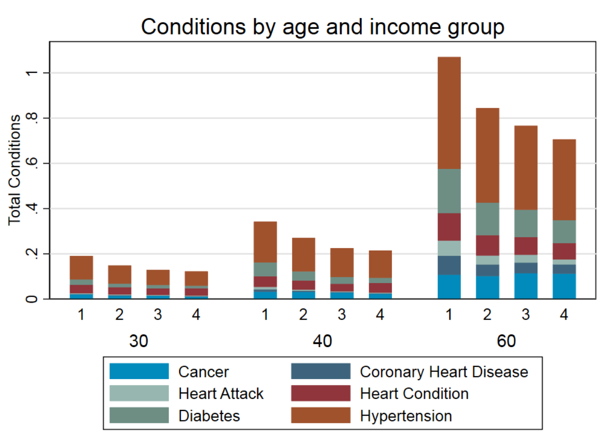
Notes: Includes individual fixed effect regression of doctoral visit from t to $t+1$ on health in time t, run separately by income groups. Base set to average health in each income group regression.

Figures A.10.26 and A.10.27 document the responsiveness of doctoral visit w.r.to self-reported health status for rich and poor. To this end, I 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 I observe an individual and its doctoral visit decision on his/ her health status. I 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 responsiveness to their health state. Compared to a poor person in average health, a poor person in poor health is 4% points more likely to go to the doctor. This number is only 1% points for the rich. Similarly, compared to a poor person in average health, a poor person in excellent health is 4% points less likely to go to the doctor. This indicates that while rich go to the doctor all the time, poor only go to the doctor in poor health. These results suggest that compared to the rich, poor individuals wait until their health deteriorates to a much worse health state before they go to the doctor and get the treatment. Note that for this analysis, I 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.

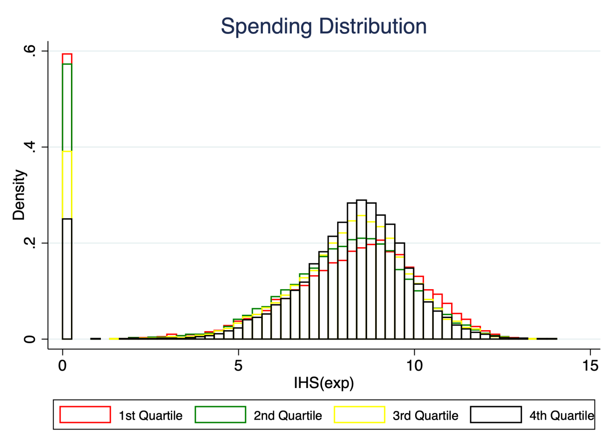
Health Conditions by Age and Income

Figure A.10.29: Mean Medical Investment: Age 25-35



Source: NLMS-MDAC

Figure A.10.30: Mean Medical Investment: Age 45-55



Source: NHIS-MEPS

This inequality in health outcomes isn't limited to mortality as documented in Figure **??**. Across the age-distribution, individuals in bottom quartile of family income distribution report having more medical conditions such as hypertension and diabetes, compared to

Table A.10.15: 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 A.10.16: w/o 0 by Income: Age 35-45

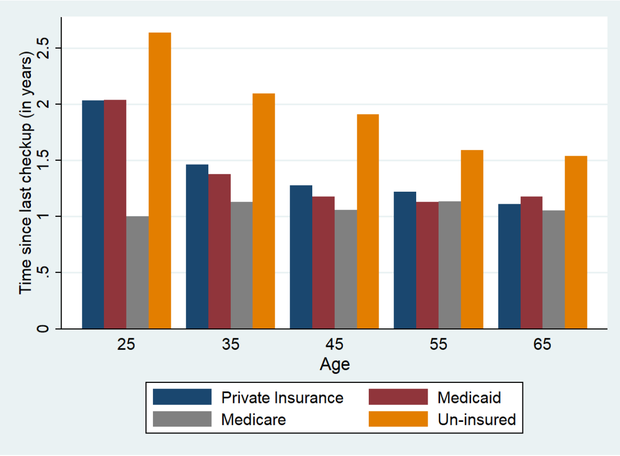
	p1	p25	p50	p75	p99
1st Quintile	10	239	838	3158	51506
2nd Quintile	13	284	855	2520	36688
3rd Quintile	24	328	958	2714	29267
4th Quintile	26	373	1035	2741	28800

Source: NHIS-MEPS

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.

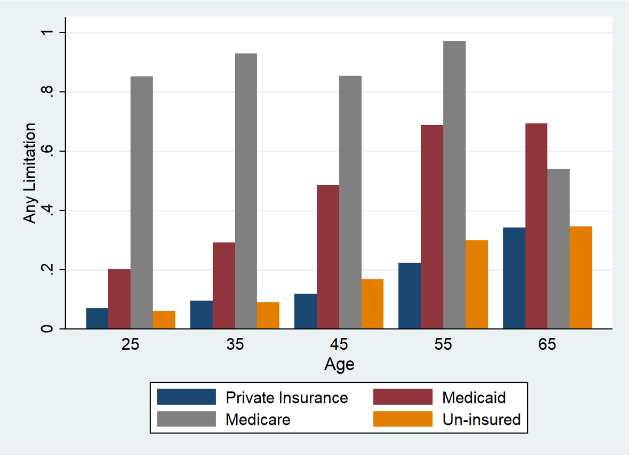
While the rich and poor, defined based on family income quartiles, spend comparable amounts in total medical expenditures, those in bottom quartile of the distribution spend significantly more on hospitalizations ($1000 for first quartile vs $500 for the top quartile for ages 35-45) and emergency room while those in top quartile of the distribution spend more on office based and outpatient visits ($1100 for the first quartile vs $1500 for the top quartile for ages 35-45, Figure A.10.24). This is also evident from the number of hospitalizations in Figure A.10.25. Individuals in top income quartile had less than a third of hospitalizations than bottom income quartile for age 35-45.

Figure A.10.31: Time Since Cholesterol Checkup (with pre-existing condition)



Source: NHIS-MEPS

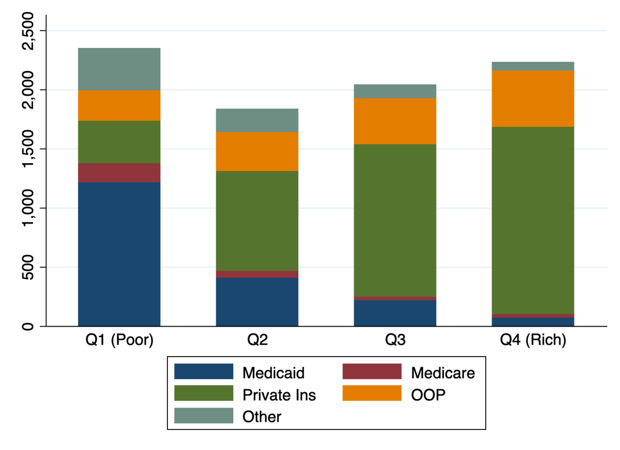
Figure A.10.32: Any Limitation by Age and Insurance Status



Source: NHIS-MEPS

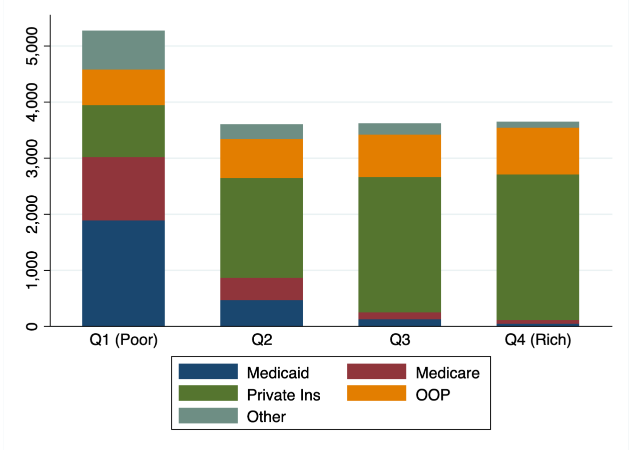
Health investments by Age and Income

Figure A.10.33: Mean Medical Investment: Age 25-35



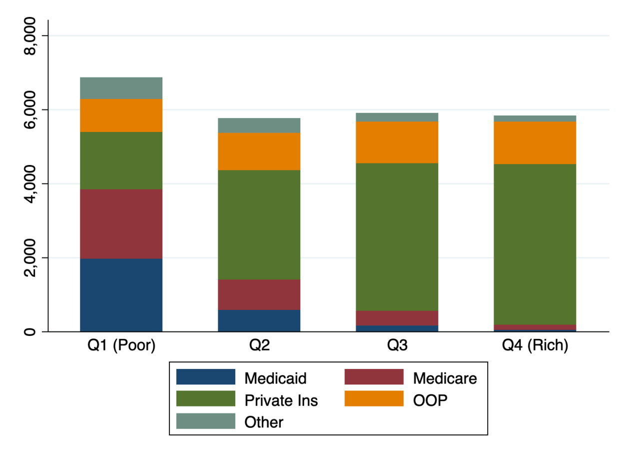
Source: NHIS-MEPS

Figure A.10.34: Mean Medical Investment: Age 45-55



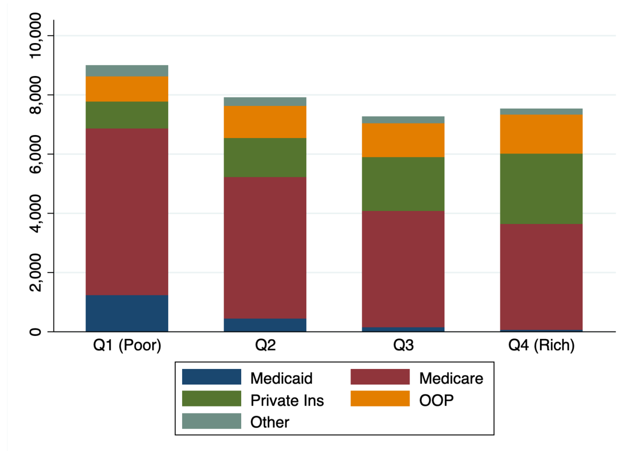
Source: NHIS-MEPS

Figure A.10.35: Mean Medical Investment: Age 55-65



Source: NHIS-MEPS

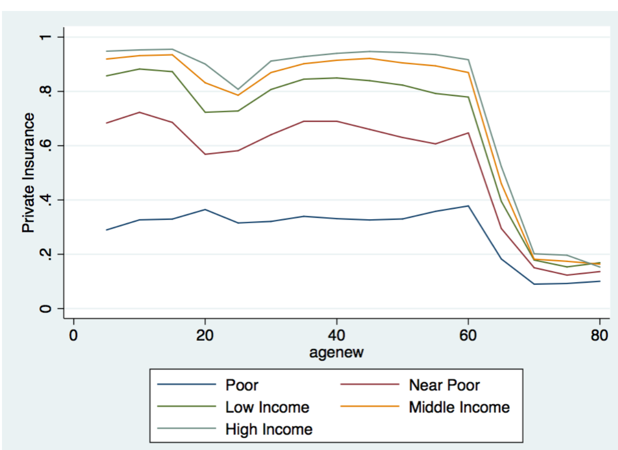
Figure A.10.36: Mean Medical Investment: Age 65-75



Source: NHIS-MEPS

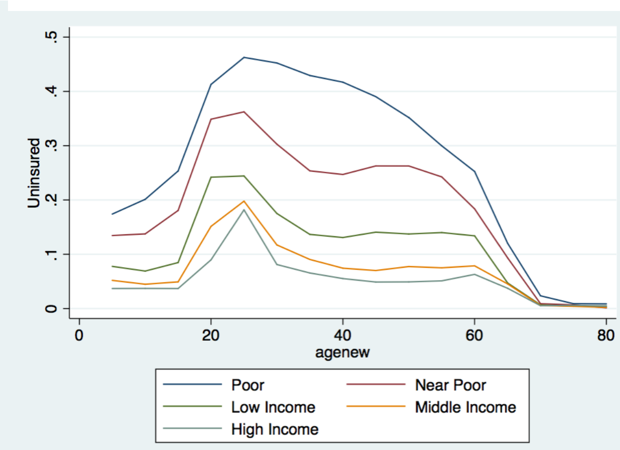
Health Insurance by Age and Income

Figure A.10.37: Fraction with Private Insurance by Income and Age



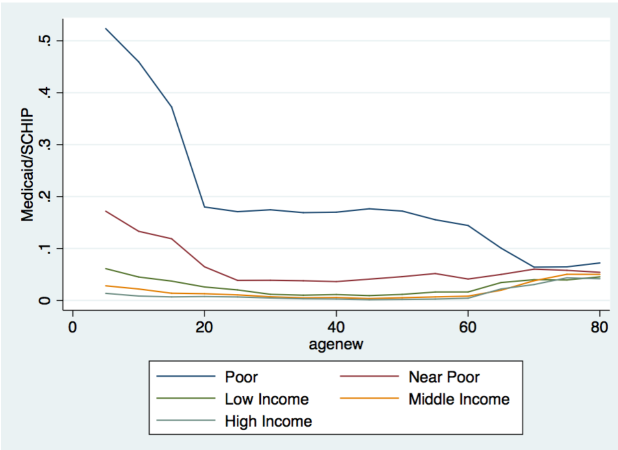
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure A.10.38: Fraction Uninsured by Income and Age



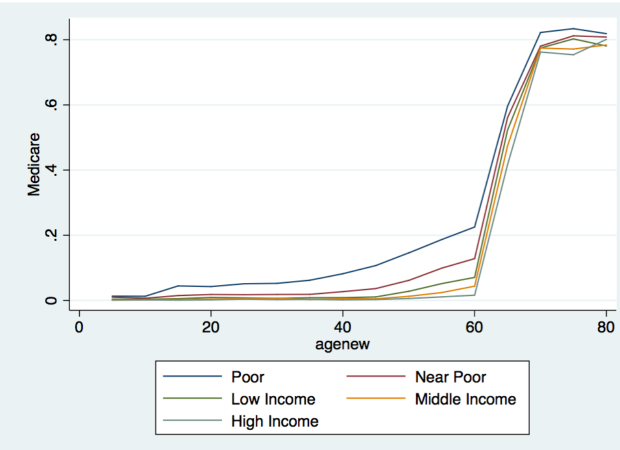
Source: NLMS-MDAC

Figure A.10.39: Fraction with Medicaid and SCHIP by Income and Age



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

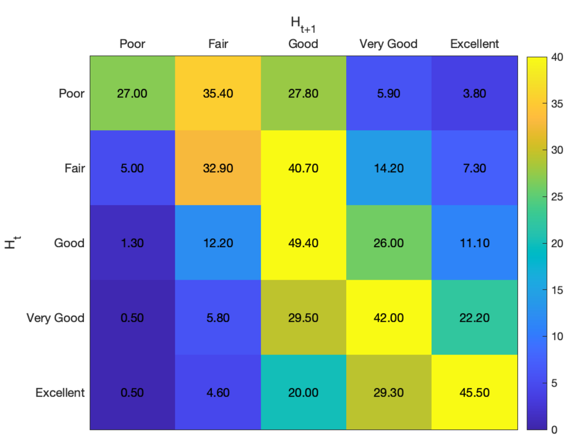
Figure A.10.40: Fraction with Medicare by Income



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

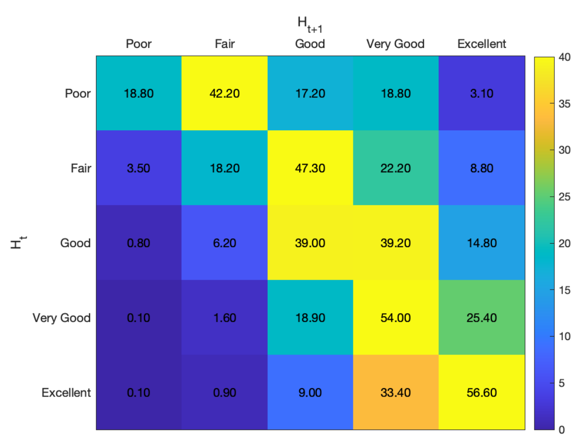
Transition Matrix by Age and Income

Figure A.10.41: Transition matrix | visit: Poor age 25-35



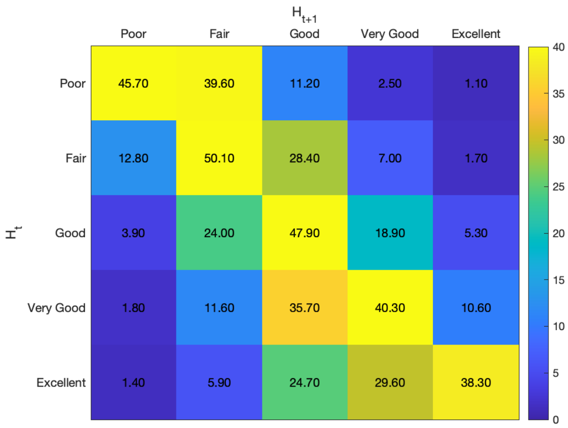
Source: NHIS-MEPS

Figure A.10.42: Transition matrix | visit: Rich aged 25-35



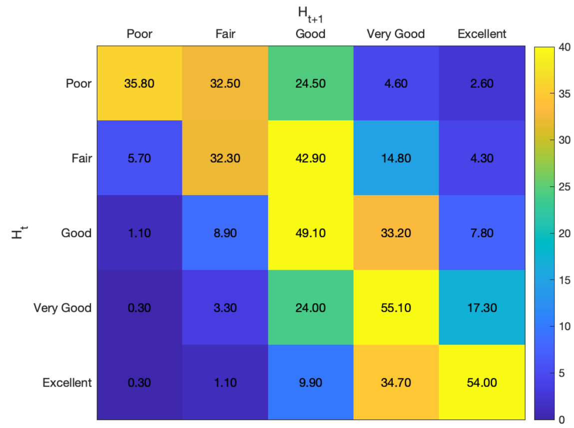
Source: NHIS-MEPS

Figure A.10.43: Transition matrix | visit: Poor age 45-55



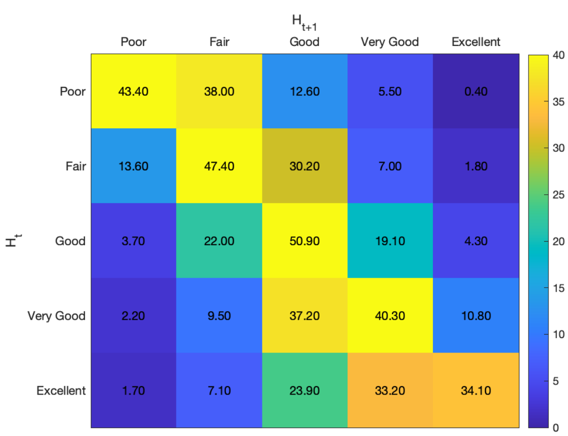
Source: NHIS-MEPS

Figure A.10.44: Transition matrix | visit: Rich aged 45-55



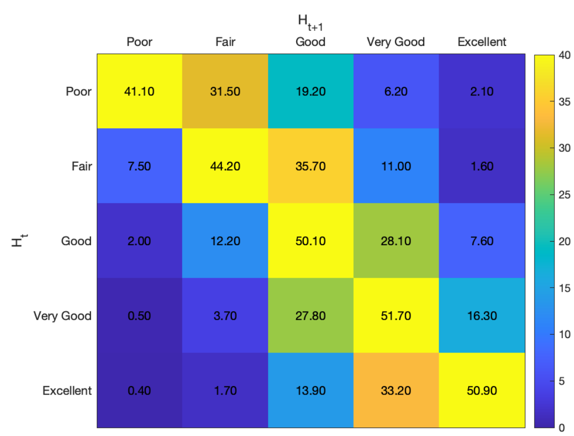
Source: NHIS-MEPS

Figure A.10.45: Transition matrix | visit: Poor age 55-65



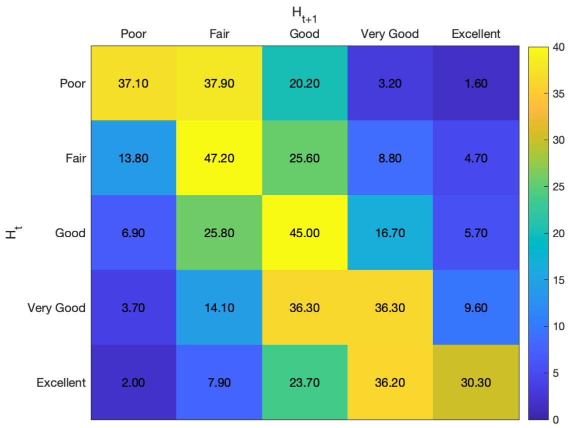
Source: NHIS-MEPS

Figure A.10.46: Transition matrix | visit: Rich aged 55-65



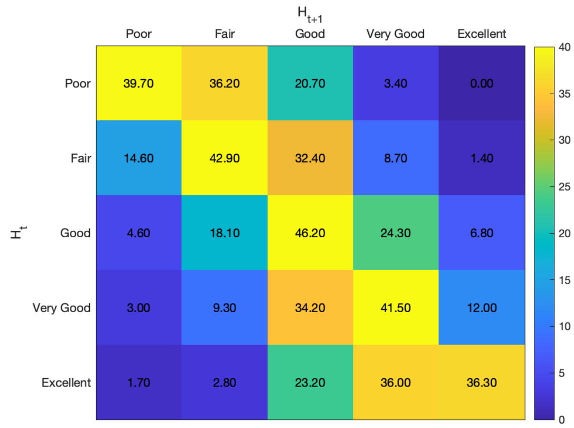
Source: NHIS-MEPS

Figure A.10.47: Transition matrix | visit: Poor age 65-75



Source: NHIS-MEPS

Figure A.10.48: Transition matrix | visit: Rich aged 65-75



Source: NHIS-MEPS

A.10.1 External validation: Insurance and Mortality

Effect of Medicaid on Mortality

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

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

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

Where z is a categorical variable when $z = 1$ for states for which 50-75% FPL were ineligible for Medicaid and $z = 2$ for states in which they were. After controlling for income, education, age, sex, average education and income in the state the (local average treatment) effect of Medicaid is 9.5% points less likely to die compared to the ones who don't have Medicaid (Table A.10.17).

Table A.10.17: 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 A.10.17 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)[29]. 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[30]. We make the following identifying assumptions:

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

The estimator can be written as:

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

We use nearest-neighbor matching and check for common support assumption in figure A.10.49, A.10.50 and A.10.51 and leave out the bins without overlap to ensure that common support assumption is not violated. Our propensity score specification is the following:

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

Standard errors were calculating following Abadie and Imbens (2016) work on propensity score matching. Note that our matching estimate could still have some selection problem. In particular, we can only match based on observables. However, the selection could also be happening because of unobservables. As described in table A.10.17, 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.

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

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

Figure A.10.49: Support for Propensity Score Matching, Wave 6a

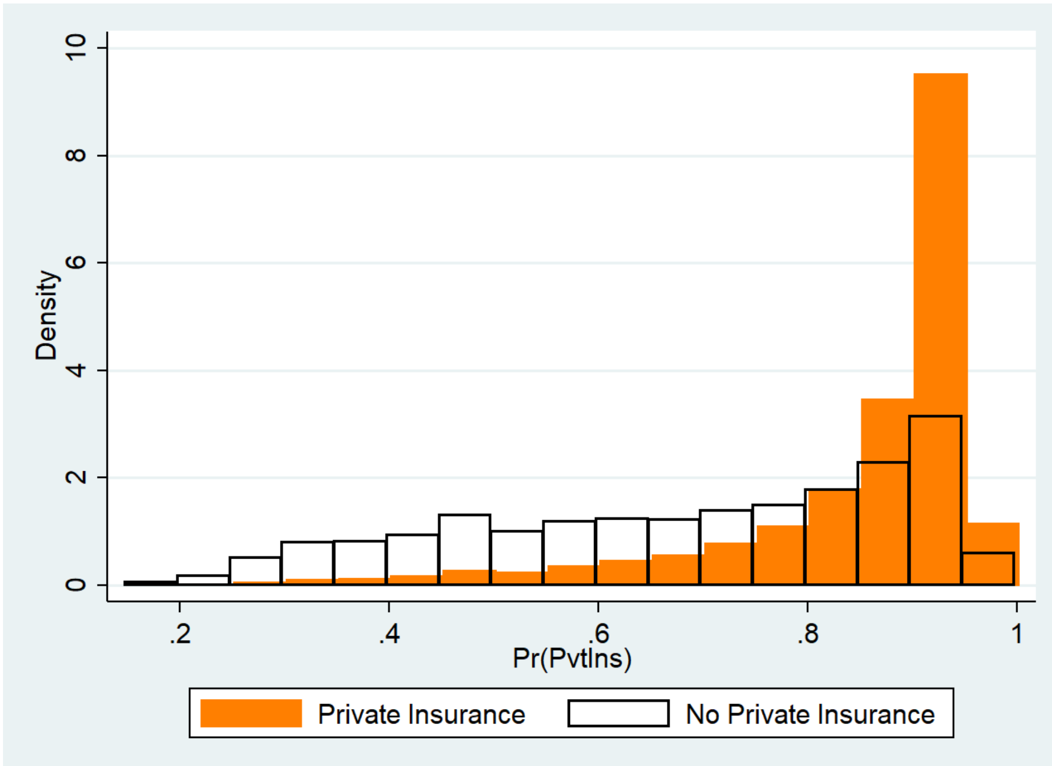
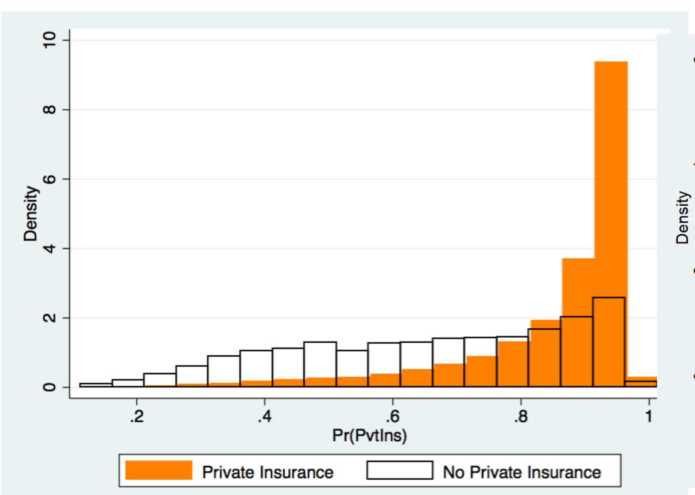
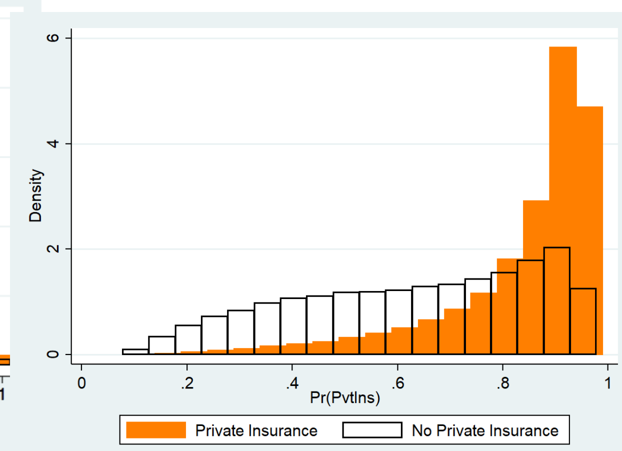


Figure A.10.50: Support for Propensity Score Matching, Wave 6b



Source: NLMS-MDAC

Figure A.10.51: Support for Propensity Score Matching, Wave 6c



Source: NHIS-MEPS

A.11. Extensions

A.11.1 COVID-19 Shock

I use my model to quantify the role of COVID-19 on life-expectancy, health inequality and dollar equivalent of value lost. I calibrate a COVID-like shock by increasing annual mortality by 15%, based on the empirical estimates from the first year of COVID-19. I compute the life-cycle trajectories under normal times and under COVID-19. I find that life-expectancy goes down by 1.6 years. COVID-19 exacerbates existing health inequalities due to higher mortality rate for those in poor health than rich, leading to the inequality in life-expectancy going up by 19%, as shown in figure A.11.52. This is due to the fact that poor individuals are relatively unhealthy and have more pre-existing conditions than the rich, consistent with the findings by Eichenbaum et al. (2021). Due to higher death rates in those with poorer health during the COVID-19 pandemic, the inequality in life-expectancy rises substantially. Third, the dollar value lost due to COVID-19 per person is about $22,000 on average. Lastly, I find that faced with higher mortality rates, individuals increase their medical spending over the life-cycle by about 4%, largely concentrated towards the elderly., as documented in figure A.11.53.

Figure A.11.52: COVID-19 and Health Inequality

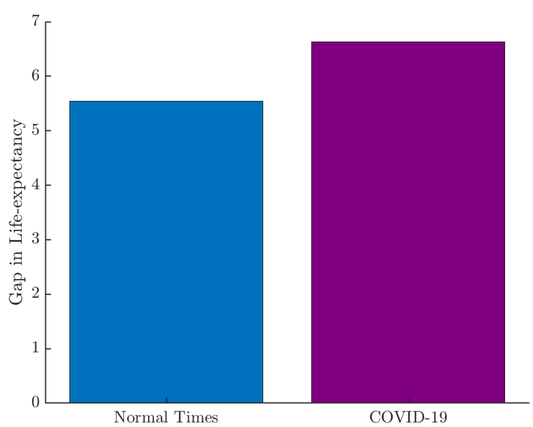
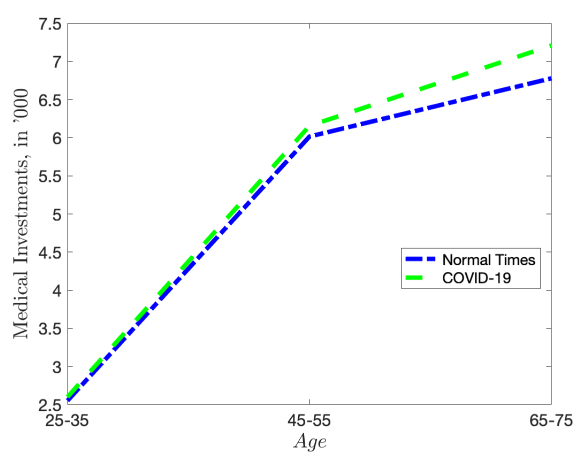


Figure A.11.53: COVID-19 and Investments



The model can be easily extended to incorporate various interesting mechanisms we discussed in the results section, something we leave for future work.

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.

$$\rho F(w,h,\nu,a,I,p_0) = p_0 + \underbrace{\eta[F(w,h,\nu,a+1,I,p) - F(.)]}_{\text{aging to } a+1} +$$

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

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

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

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

$$\lim_{\tau \to 1} F(.) = -mq(I) + F(w',h,\nu',a,I,p) \tag{17}$$

$$w' = w - k(I_0) - m(1 - q(I_0)) \tag{18}$$

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

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