Health Inequality: The Role of Insurance and Technological Progress

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Abstract

The paper investigates the role of insurance and technological progress on rising health inequality across income/wealth groups in the US. 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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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

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[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). See, e.g. Horenstein and Santos (2019) for healthcare expenditures over time.

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 visits. 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, poten-

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

[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.

tial 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 cannot 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.

[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

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 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

[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)

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 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

[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.

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 (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 differential impact of technological innovation on health inequalities that 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, its comparability across rich and poor or the differential role of technological innovation on health inequality over time. Unlike the previous literature, this paper looks at the flatness in spending, cross-sectional differences in outcomes, *and* increased health disparities over time.

[11] See Appendix A.10.

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), 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 A.9, is a rotating panel of nationally representative data on 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 the mortality status of over 9 million individuals, to decompose the long-term changes in life expectancy.

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

2.1 Health outcomes and health spending: A puzzle

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

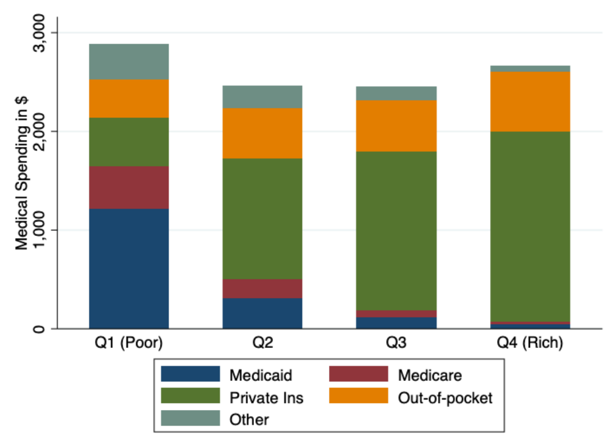
The leading causes of death across the income distribution are cancer and heart conditions based on the 1-year crude mortality rates from MDAC. As shown in Figure 2, across all age groups and causes of death, individuals in the fourth quartile of the family income distribution[13] have a lower aggregate and cause-specific mortality-rate compared to individuals in the first quartile. This pattern has been well documented in the literature, including Chetty et al. (2016). For those in the 52-65 age group, the mortality rate of the top quartile is less than half of the mortality rate of the bottom quartile.

As documented by Ales et al. (2012), mean total medical spending, including the

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

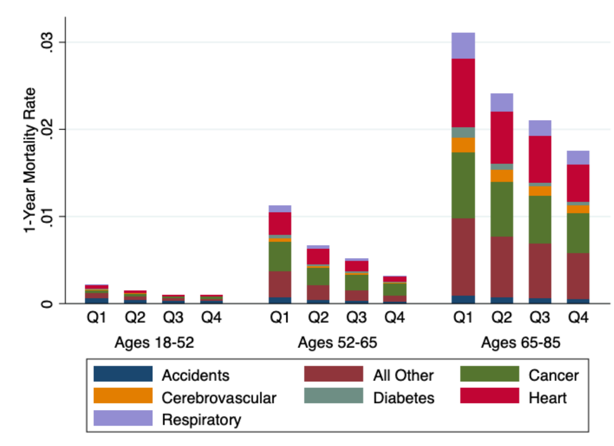
[13]The patterns are very similar when I define the quartiles based on wealth.

Figure 1: Medical spending ages 35-45



Source: NHIS-MEPS (2000-15).

Figure 2: 1-Year mortality rate by age & income



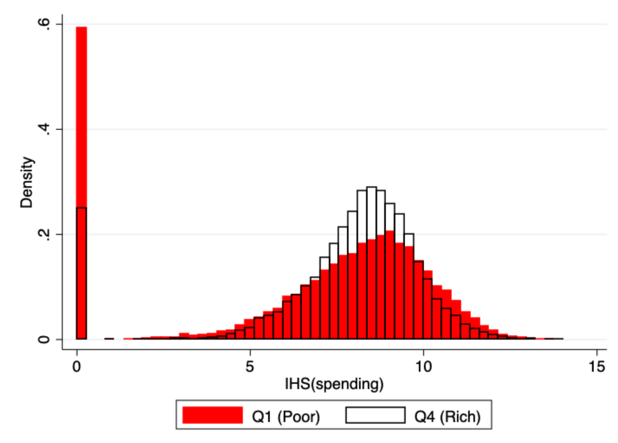
Source: MDAC (2008).

portions covered by private insurance, Medicaid, Medicare, and out-of-pocket spending, looks comparable across the family income distribution. For instance, for ages 35-45, individuals in the bottom quartile spent a little more than \$3,500 annually, while those in the top quartile of the distribution spend about \$ 3,100 annually, as shown in Figure 1. Similar patterns holds for other age groups, as shown in the appendix. A detailed discussion on charges and expenditures is provided in Appendix A.9. Breaking down spending by source of payment reveals that a very low fraction of poor individuals' total medical spending comes from private insurance.

A natural question that arises from looking at the two facts documented in the literature is: why is it that, although the rich and poor end up spending roughly the same amount in absolute dollars on medicare care annually, the outcomes are drastically different? Moreover, why is the disparity getting worse over time?

In order to understand the sources of disparity, 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.

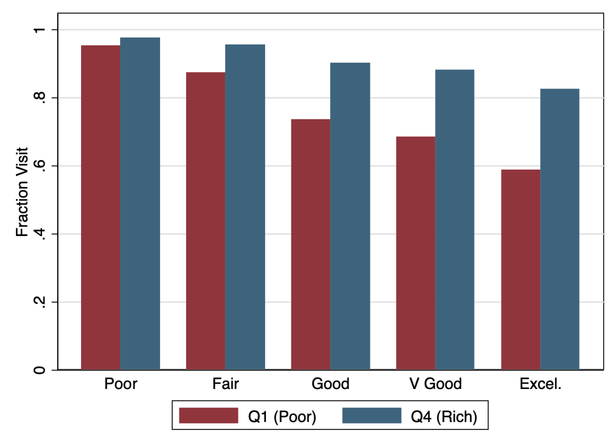
Figure 3: Medical spending distri. ages 45-55



Source: NHIS-MEPS (2000-15).

Notes: Inverse Hyperbolic Sine (IHS) transformation of annual medical spending for ages 45-55

Figure 4: Timing of spending by health state



Source: NHIS-MEPS (2000-15).

Notes: Aggregate fraction that have positive spending from t to $t+1$ by H_t.

2.2 Facts

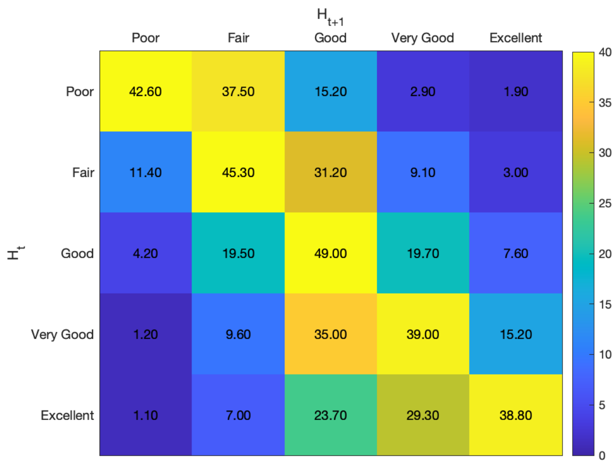
Fact 1. The poor spend more on hospitalizations and emergency room visits, while rich spend more on outpatient visits

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

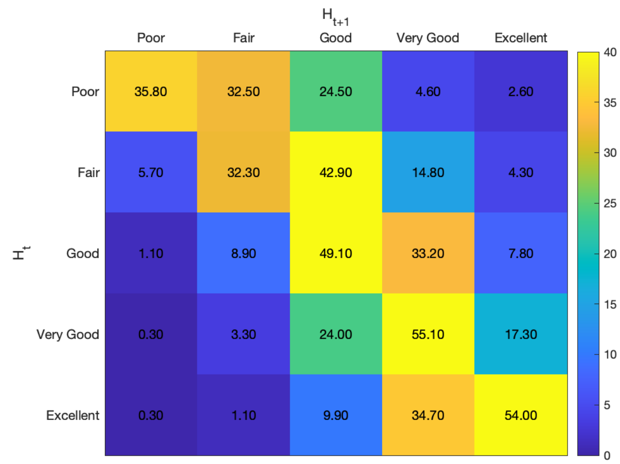
Figure 5: Transition matrix | visit: Poor ages 35-45



Source: NHIS-MEPS (2000-15).

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

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



Source: NHIS-MEPS (2000-15).

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

who visit the doctor ranges from close to 1 for those in poor health to 0.83 for those in excellent health. On the other hand, the visit decisions of poor individuals is very responsive to their health status: it goes from 0.95 for those in poor health to less than 0.6 for those in 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.

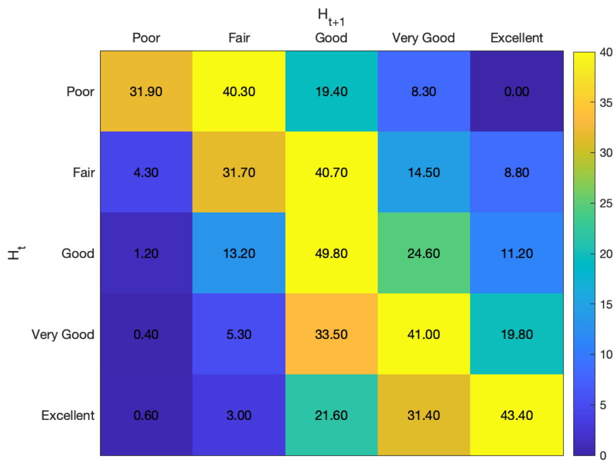
In addition, I also run a fixed-effect regression[14] where the variation comes from the panel component where I observe the health status and the visit decision. The findings are similar, and I present them in Appendix A.10.

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

In Figures 5 and 6, I compare the annual transitions in health for individuals in the first and fourth quartiles of family income distribution conditional on medical visit for ages 35-45 years. For those in poor health in time t, 42.6% of the poor remained in poor health compared to 35.8% of the rich. Similarly, more than 56% of the poor in fair health remain in poor or fair health compared to 37% of the rich. The pattern is similar across

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

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



Source: NHIS-MEPS (2000-15).

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

age groups, as shown in the appendix.

This is also a good place to emphasize the need to model the visit decision. I compare the transition matrix of the poor who did not visit the doctor (Figure 7) with that of those who did (Figure 5). I find that those who did not go to the doctor transitioned to 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 the visit decision is crucial in understanding health outcomes.

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

I find that, conditional on surviving until age 20, there is a gap of about 8.5 years in life expectancy between the top and bottom quartiles. From 1983 to 2015, those in bottom quartile gained about 2 years and 11 months, while those in top quartile gained 5 years and 5 months. This aggregate increase in the life expectancy gap is also consistent with others who have looked at aggregate life expectancy, such as Chetty et al. (2016).

In order to understand the underlying components of the changes in life expectancy, I decompose by age and cause specific mortality across the four family income groups adjusted for family size,[15], à la Becker et al. (2005). In appendixA.10, I describe the

[15]I define the groups using age-adjusted poverty percentage variable, which adjusts for family size.

exercise as well as provide robustness checks across different thresholds, samples, and races, where I find convergence in life expectancy across races.

While fewer deaths from heart-related causes have contributed the highest gains in life expectancy, the distributional impact has been limited. As shown in Table 1, while the poor have gained 4.1 years in life expectancy due to heart-related deaths, the rich have gained 4.3 years. Malignant neoplasms (cancer) have contributed significantly to the rising health inequality across the rich and poor over the two decades from 1983 to 2015. The age-based decomposition of life expectancy gains tells us that while most gains have been for ages 50-80, gains above age 80 have also 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

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

[16] Note that drug-overuse (for e.g., Case and Deaton (2015)) is attributed to accidents. For aggregate trends in the causes of deaths, see this CDC Report. The "other" category includes Alzheimer's and other forms of dementia, for which occurrences have gone up in the recent decades.

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

3. Model

I develop a dynamic stochastic life-cycle model of an economy where individuals choose insurance, the timing of spending in their health capital, consumption, and savings. The model brings continuous-time methods, a popular tool used in macroeconomics and finance, into a problem involving individuals' 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 a continuous state variable, health is a discrete state from 1-5 with 1 being poor health and 5 being excellent health, as observed in the data.[17]. Individuals' transition from one health state to another as governed by 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 five parts: i) deterioration governed by intensities d_h^a as a function of health, h, and age, a; ii) improvement governed by intensities ν_h^a; iii) sudden illnesses which could lead to long-term disability, κ_h^a; iv) mortality governed by intensities λ_h^a; and v) stochastic aging governed by intensity η[18]. Other than the standard consumption-saving decisions, individuals face two crucial decisions: whether 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 a medical

[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 the literature uses include questions about disease diagnosis (such as cancer and diabetes), which suffer from selection in the context of my model as diagnoses require doctor 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 reduces the computation burden, a standard practice.

visit, in other words, health is common knowledge at all times. I leave for future research a version in which health capital cannot be observed perfectly.

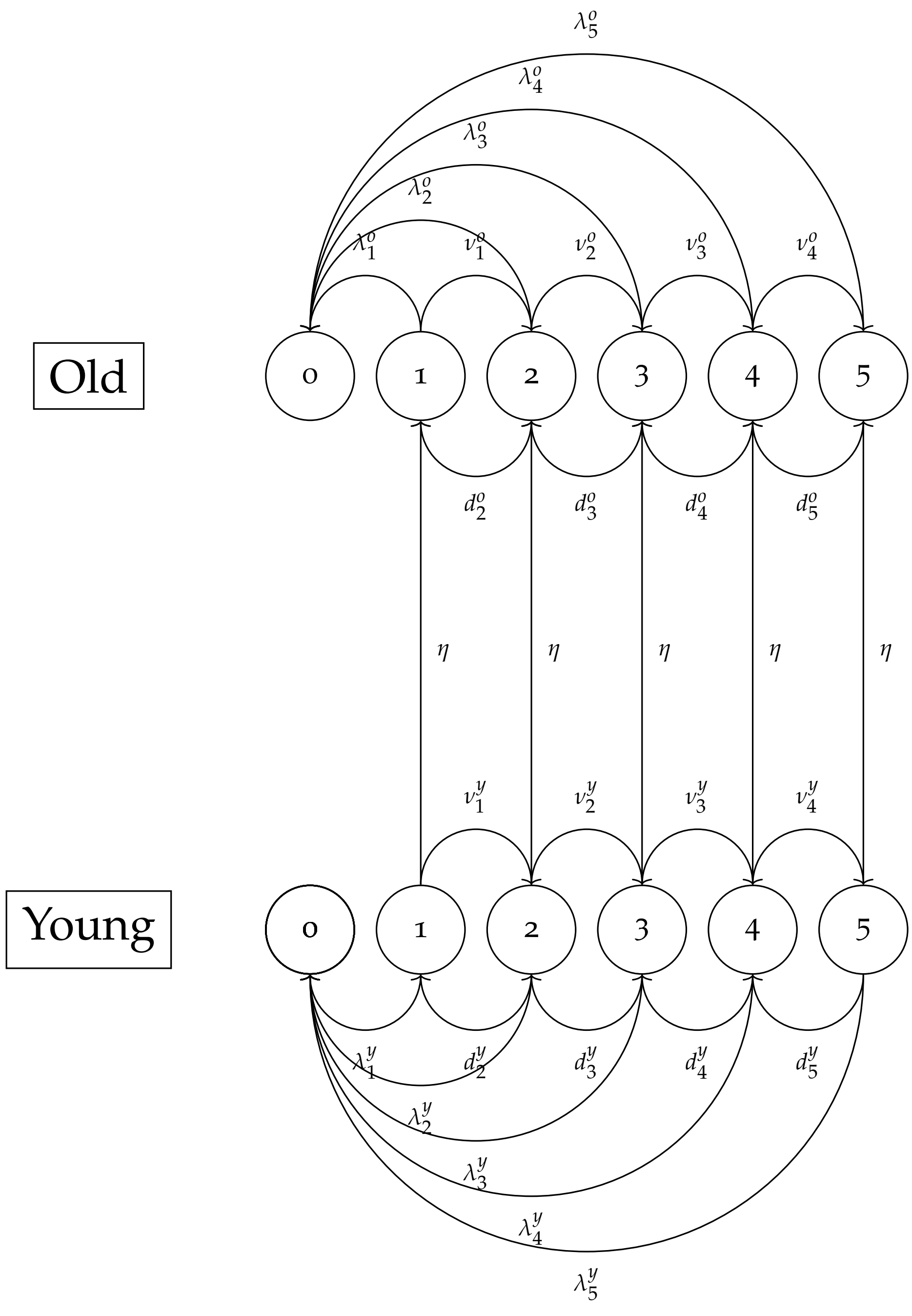
Evolution of health capital

An alternative way to think about the health evolution process is to consider it 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 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 at which a person of age a goes from state h to $h+1$. Individuals age at 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, health depreciates at a higher intensity. Individuals in health state h and at 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 become disabled or die at a much lower rate compared to individuals in poor or bad health of 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 by 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 the two age groups. Consider a young individual born in the very good health state, i.e. in node 4 in the figure. They can transition to good health state, i.e. node 3, with intensity d_4^y; transition to the better (excellent) health state, i.e. node 5, with 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 mortality shock λ_4^y and exit the model.

The formulation is general enough to capture a potential increase in health depreciation as individuals age and a reduction in health improvement. Due to data limitations, I only allow for health transitions to move one step up or down. Given that I only observe five snapshots for the two years an individual is observed in data, I do not know the exact amount of time individual stayed in a particular health state or the transition path of health that followed. For example, I observe that an individual is in health state 4 in

Figure 8: Illustrative health evolution with two ages



quarter 1 and health state 2 in quarter 2, but I won't be able to see if they transitioned directly from 4 to 2 or they went from 4 to 2 via 3 or even 1 for that matter. Therefore, I must impose an identifying restriction 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 these assumptions about transitions in health states may sound restrictive, given that the model is in continuous-time, the 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 in discrete-time, where I would 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, and their (endogenous) insurance status I_0. Individuals can invest in the likelihood of transitioning to a better health state, i.e. invest in 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, that captures the feature of the data that shows individuals may transition to a better health state without doctor visits; and 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 TFP A and a returns-to-scale parameter of α_m governing the concavity of the production function. The evolution equation is as follows:

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

I assume that individuals choose medical spending but that it is analogous to an altruistic physician who makes a care plan for the individual. 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 doctor visit. Since individuals are investing in the probability 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. Individuals 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 fixed cost k, individuals don't invest in their health continually and it becomes a stopping time problem where individuals choose the timing of healthcare spending. Thus, 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 benefit from a better health: direct utility from being able to enjoy consumption more, higher labor productivity resulting in higher labor income, the lower likelihood of becoming disabled and the lower likelihood of dying.

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. An individual consumes c and pays a health insurance premium p if insured (otherwise, it is set to 0 for Medicaid and the 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 in a better health state. Note, however, that I am not imposing that health and consumption are complements vs substitutes, as the functional form of $\phi(h)$ can handle either possibility.

Insurance take-up problem

Insurance take-up is governed by a Poisson process of intensity ϕ. This intensity implies that individuals are given the option to take up insurance at random intervals throughout their life cycle. When this option occurs (or at the time of a Poisson realization), they are offered a premium $p(a)$ based on their age a. Individuals then decide whether to take up insurance. If they do, then the premium stays the same until another (random) realization of the Poisson. The insurance premium and risk sharing are obtained from the data.

At the time of Poisson realization, 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 Medicare after age 65 is the same as private insurance, 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 the 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 as these individuals needing $\bar{m}$ spending continually—such as dialysis treatment for end-stage renal failure, which is paid for by Medicare.

Thus, the Hamilton-Jacobi-Bellman (HJB) equation becomes:

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

3.2 Individual's problem

The individual's problem is composed of two branches: i) a continuation region, where the individual does not go to the doctor and the only decisions are consumption-savings and whether to take up insurance in case of Poisson realization, and ii) 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 by 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 state, the likelihood and value from dying and the change in the 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,

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

On the other hand, in the stopping region, given the individual's decision to invest in health, they choose medical expenditure m_t, which increases ν, i.e. lowers the expected duration of going to a 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 fixed-cost k, individuals don't invest in their health continually and it becomes a stopping-time problem where individuals make the discrete choice to invest in their health by visiting the doctor.

Thus, under the assumptions of at most linear growth and Lipschitz continuity,[19] the

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

individual's problem can be written compactly as,

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

or

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

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]

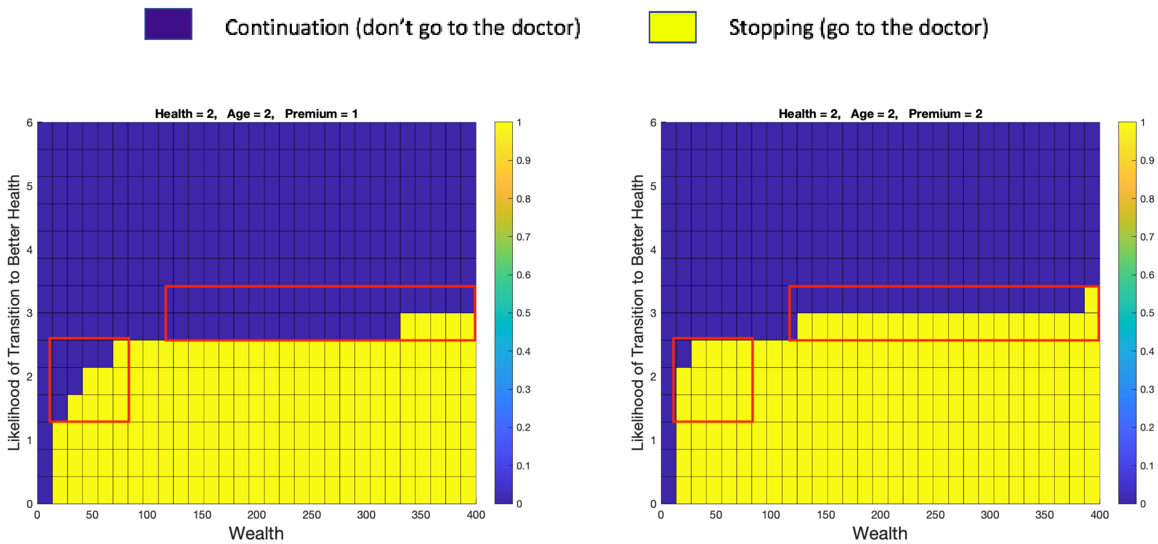
3.3 Policy function: Doctor visits

To provide a description of one of the key choices of the model, I look at the visit decision for individual ages 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 find 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 a cutoff in improvement intensity below which the individual goes to the doctor and spends on healthcare. It is also clear that rich individuals go to the doctor much earlier (at a higher improvement intensity) than poor individuals. On the other hand, comparing the 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, and I look at some cross sections of it.

Figure 9: Visit decision, ages 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 calibrated outside of the model; ii) a set of parameters estimated outside of the model; and 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 status with or without a doctor visit, the death rate, and health status over the life-cycle), the average spending ratio between rich and poor of the same health, and disability rates, to identify health transitions, mortality and disability shocks, utility gains from health, the health production function, and fixed costs associated with doctor visits and Medicaid take-up. In particular, I leave 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 a 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 a proportional increase in mortality rates across age groups, keeping the gradient of health from λ_h^6. In other words, I allow for 5 factors, F_{25-34} - F_{65-74} such that:

$$\lambda_h^a = \begin{cases} \lambda_h^6/F_{25-34} \text{ if age } \in \{25-34\} \\ \lambda_h^6/F_{35-44} \text{ if age } \in \{35-44\} \\ \lambda_h^6/F_{45-54} \text{ if age } \in \{45-54\} \\ \lambda_h^6/F_{55-64} \text{ if age } \in \{55-64\} \\ \lambda_h^6/F_{65-74} \text{ if age } \in \{65-74\} \end{cases} \tag{12}$$

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

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

Second, I present the parameters that 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 age 25 by education as the initial conditions to the model. Income by age and education $y(e, a)$ as well as disability income y^D are estimated from the data. The exit intensity λ_h^a at health h and age a comprises two components: λ_h^6 and the survival factors F_{25-34} - F_{65-74}. For λ_h^6, while I estimate the exit intensity for average health at ages 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 from the data by taking 15-day exit rates. For example, my 15-day exit rates show that those in poor health at ages 75-85 λ_1^6 are 11.07 times more likely to die than those in average health at ages 75-85 λ_3^6. The survival factors F_{25-34} - F_{65-74} are estimated from the data using aggregate age-specific instantaneous mortality.

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

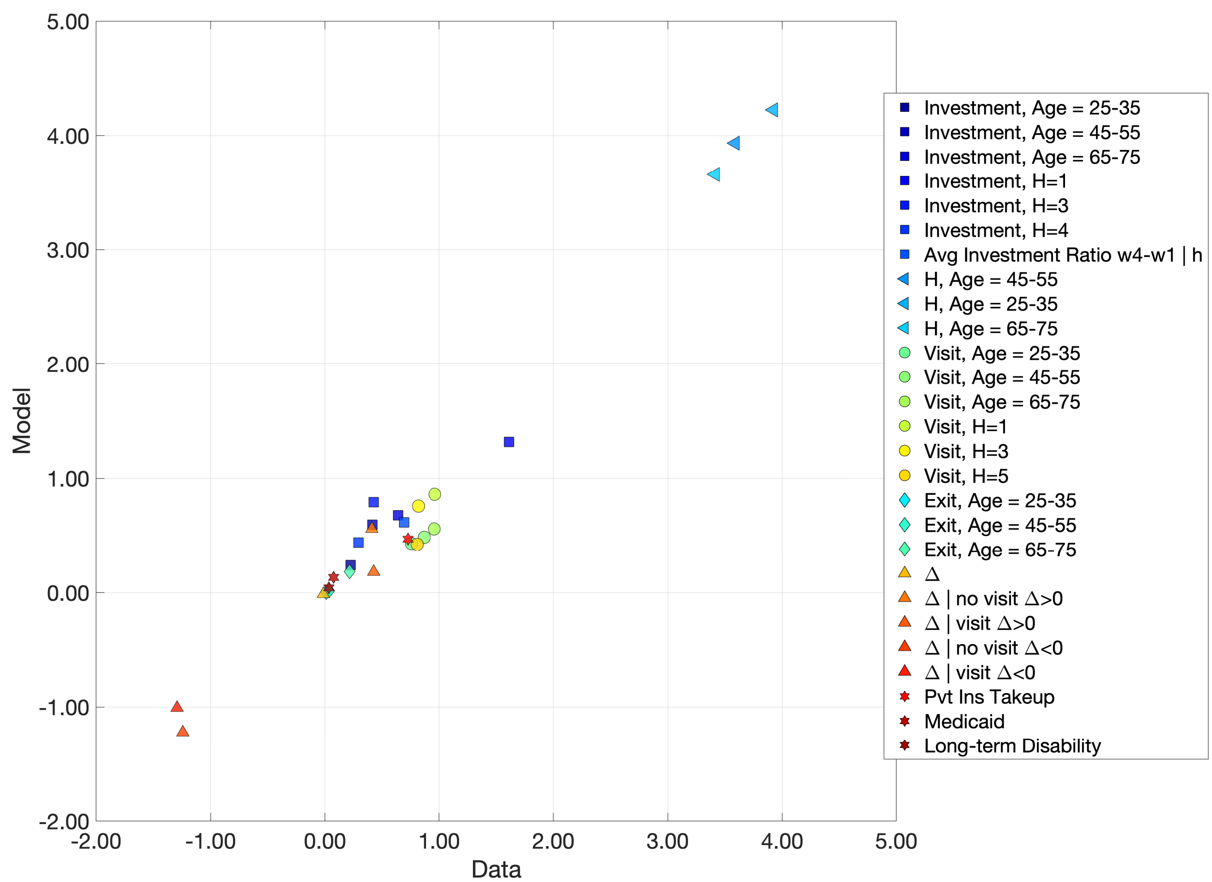
The average annual out-of-pocket insurance premium by age is used to estimate the insurance premium by age $p(a)$. Effective price or out-of-pocket healthcare spending by insurance is used to estimate out-of-pocket co-insurance $q(I)$. For the uninsured, I estimate this spending by looking at the charge-to-expenditure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

4.3 Identification

The remaining parameters to be estimated include health production parameters A and α_m; the fixed cost of a doctor 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, the fixed cost of Medicaid take-up f, disability rate κ^D and mortality rate λ^T.

While a lot of the moments co-move with the parameters, identification uses observable heterogeneity in decisions, such as the fraction of individuals that visit a doctor 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 status to pin down the technology parameters. More specifically, the rate at which an individual transitions to a worse or better health state with or without a doctor visit is informative about age-based depreciation and health improvement. Health spending by age and health status pins down the utility gains from health. Fixing other parameters, the health spending ratio between the rich and the poor of the same health is informative about the curvature in the health production function, α_m. For example, for lower values of α_m, we would expect to see very little difference across the rich and the poor of the same health compared to the difference between them for higher values of α_m. The fraction of individuals who take-up Medicaid is informative about the fixed cost in acquiring Medicaid. Lastly, the fraction of those individuals who visit the doctor is informative about the fixed cost associated with that decision.

Figure 10: Model fit: Targeted moments



4.4 Estimates

I estimate the partial equilibrium model for individuals ages 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 note ways to incorporate these provisions with insurance firms' problem and the estimation with the insurance firm problem is left for future work. The sample is from NLMS-MDAC and NHIS-MEPS and includes individuals ages 25-85 in 10-year age 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 figure 10. The model does a good job of capturing health spending over the life-cycle and by health status. Two place where the model doesn't do a good job are: i) private insurance take-up for ages 25-65 (73% in the data vs 47% in the model) ii) visit decision for higher health status. One reason for private insurance could be that for a lot of individuals in the US, insurance choices available are tied to their jobs and the data isn't able to capture the employer-provided subsidies in the insurance market. Another reason could be the highly negotiated prices that private insurance pays for services, something I try to address as well as possible with the data, as described previously. For the lower fraction of doctoral visit for excellent health in the model compared to data, I don't allow individuals to invest in reducing the depreciation or lower health shocks, therefore, the only reason an individual in best health goes to the doctor is due to transitioning to worse health state.

I describe the estimates now. The estimated fixed cost is $k = 0.0335$, equivalent to \$335 per doctor visit. 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 durations the estimates imply that the expected duration before going to a worse health state is 2 years and 7 months for those ages 25-35 and goes down to 1 year and 6 months for those ages 65-75. Similarly, based on the estimates of ν_0, ν_1 and ν_2, the natural improvement duration is 7 years for those ages 25-35 to move to a better health status, while those ages 65-75 never go to a better health state naturally. Finally, the estimates imply that the marginal utility of consumption for those with average health is about 2.56 times that of those with poor health, showing that health and consumption are complements in the utility function. This last finding 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 Poisson (Constant)	0.36
d_1	Depreciation Poisson (Age)	0.04
d_2	Depreciation Poisson (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

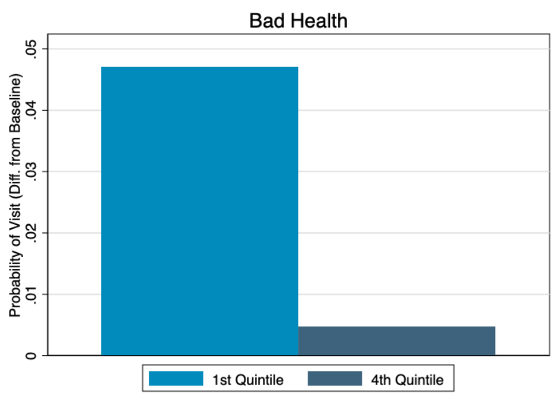
5. Results

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

5.1 Visit decision by health status

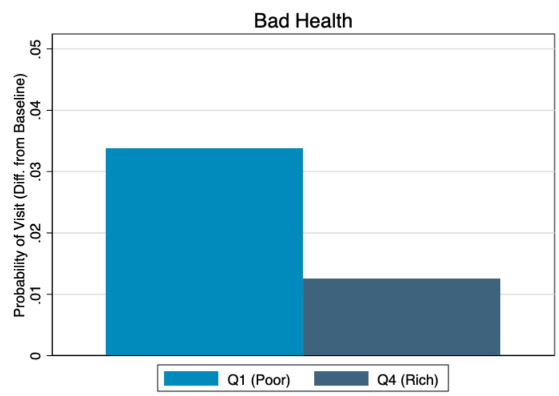
I first explore the key mechanism of the timing of healthcare spending. To understand the responsiveness of doctoral visits to health status for rich and poor individuals, I run an individual fixed effect regression of a doctor visit on the health status of the rich and poor separately. This is done for both the data (using family income) and the model (using wealth). While the model is simulated monthly, I perform the regression using a quarterly frequency – same as the data—for better comparison. In figures 12 and **??**, I present the estimated probability of visiting a doctor for those in poor health relative to those in average health for the rich and the poor (based on wealth) in the model and

Figure 11: Visit decision by health status: Model



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

Figure 12: Visit decision by health status: Data (NHIS-MEPS 2000-2015)



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

in the data, respectively.[22] The results indicate that poor individuals' visit decision is highly responsive to their health state, especially for bad health shocks. An implication of this is that poor individuals go to the doctor in a much unhealthier state than rich individuals. Compared to a poor individual in average health, a poor person in poor health is 4.7 percentage points more likely to go to the doctor (vs 3.3 in data). This number is 0.5 percentage points in the model for the rich (vs 1.2 in data).

While the responsiveness to poor health in the model is comparative to that in the data, the responsiveness to excellent health in the model is higher than that in the data. It is not surprising since in the model, a person in excellent health only goes to the doctor if their health depreciates. In other words, the higher responsiveness to excellent health 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.

Table 3: Healthcare spending ($'000), ages 35-45: Model

	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: Healthcare spending ($'000), ages 35-45: Data (MEPS 2000-15)

	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

5.2 Spending across health status

After looking at the visit decision, I present quarterly spending by health status and wealth for the model and data in Tables 3 and 4, respectively. Fixing a given health status, the rich spend more on their health over the next year, thus transitioning to a better health status with a higher probability. This pattern is true across all health states.[23] I also show that this finding is comparable to that based on medical spending data by family income adjusted for family size and age quartile.[24]

5.3 Health transitions

Having looked at the choices, doctor visit and spending decisions, I now show the outcomes, such as, health transitions. I analyze the health transition of each wealth group relative to the poor (bottom quartile). I plot the coefficient of the wealth group dummy for quartiles 2 to 4 as a percent of the base (quartile 1, the poor) of a regression of H_{t+1} controlling for H_t and age for individuals who have visited the doctor in the past year. In figure 13, I find that after controlling for age and health status in time t, those in the top quartile have average health that is 20% higher than that of those in the bottom quartile. This is a result of higher spending by the rich, which gives them a higher probability of transitioning to a higher health status 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 the top and bottom family income quartiles. One caution is

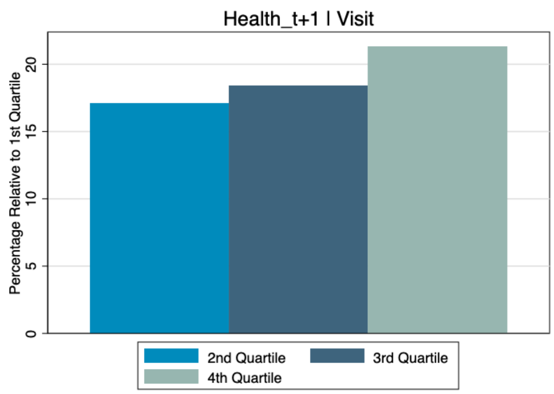
[22]The variation for this regression comes from the panel component, where I observe an individual's decision to visit a doctor and their health status.

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

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

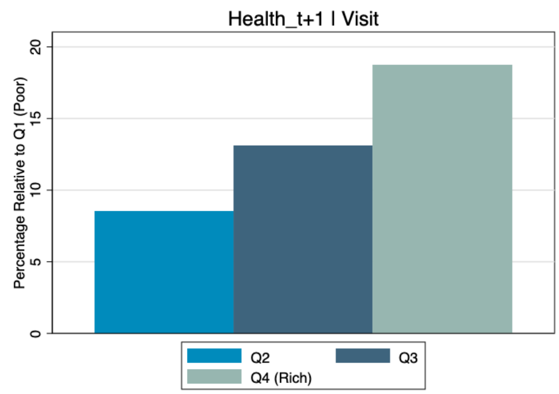
that I am interpreting the categorical variable of health-status as an index from 1-5. For robustness, I perform a similar analysis for a binary variable for health, as is common in the literature De Nardi et al. (2017), as well as a multinomial logit and get similar results.

Figure 13: Health transitions by wealth: Model (MEPS 2000-15)



Notes: Regress Health$_{t+1}$ on Health$_t$, Age, Age^2; base set to wealth poor

Figure 14: Health transitions by family income: Data (MEPS 2000-15)



Notes: Regress Health$_{t+1}$ on Health$_t$, Age, Age^2; base set to family income poor

5.4 Spending and outcomes

A key puzzle motivating this paper is the difference in life expectancy across the rich and poor with comparable medical spending. Tables 5 and 6 present the model and data moments on life expectancy, mean spending and mortality rates, where the poor (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 those for the rich are not driven by higher spending by the rich.

The effect of differences in the timing of health spending on health outcomes primarily arises as a result of the complementarities in health production, where \$1 spent on average health has better outcomes than \$1 spent on poor health. Thus, spending at a lower health state is less likely to result in a transition to good health state. Poor indi-

Table 5: Medical spending and outcomes: 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

Notes: Q1 normalized to 1 for comparison.

Table 6: Medical spending and outcomes: 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

Notes: Q1 normalized to 1 for comparison.

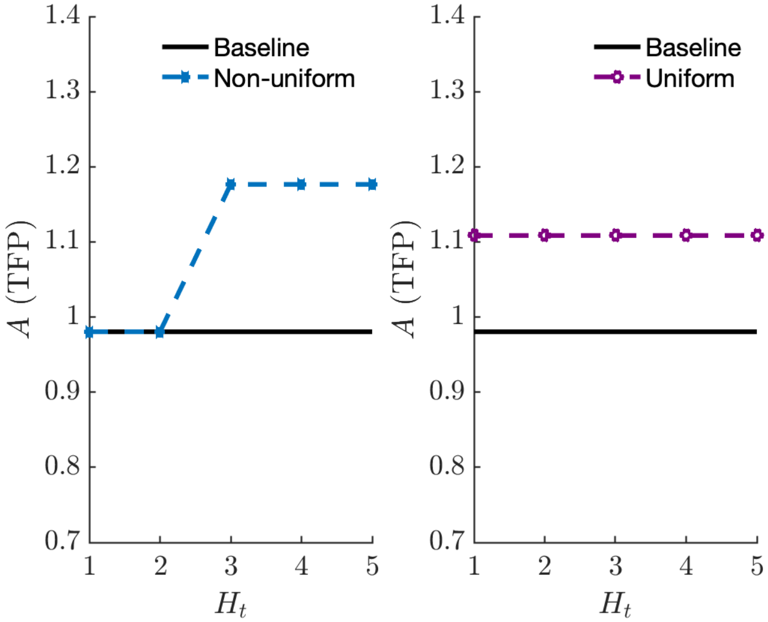
viduals, due to lack of insurance or financial constraints, delay their visit decision until they reach their stopping time (a lower health state), which causes them not to reap the benefit of their medical spending like the rich do, who do not delay their visit decision. These choices result in comparable healthcare spending but significantly different health outcomes.

6. Quantitative experiments

6.1 Role of technological progress

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 improvement in the healthcare sector (which results in about 5 months of gains in life expectancy on average) where the medical innovation takes place across the health spectrum, and, second, a non-uniform 20% increase in technology (leading to same overall gains in life expectancy of 5 months), where the innovation improves the outcomes for an early diagnosis—such as cancer stage I—but not for later stages of cancer. The experiment is shown in Figure 15.

Figure 15: Technological progress type



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). 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

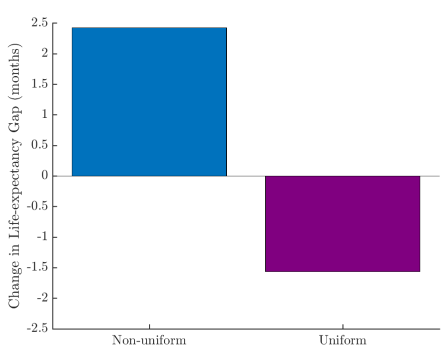
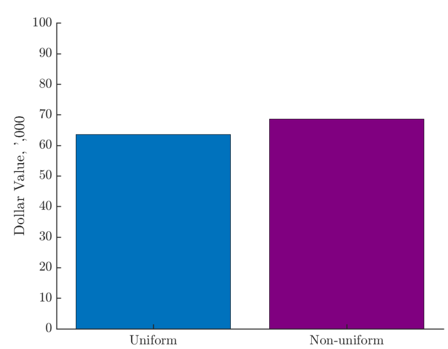


Figure 17: Value of technological progress



On the other hand, a non-uniform increase in TFP—where the medical system gets better at treating the early but not the later state of illnesses, disproportionately improves life expectancy for the rich but 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 health spending interacts with technological progress to worsen inequality. 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, who frequently go to the doctor, visit the doctor and invest in their health at stage 1, the poor, who defer going to the doctor, only visit the doctor and invest in their health at stage 3 of cancer. [25] Thus, the poor not only end up spending the same amount as the rich in any given year, they also do not reap the benefits of the medical technological progress.[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 and broad based or non-uniform limited to certain health states. The value of a uniform, broad-based 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 a non-uniform 20% improvement that results in about 5 months of gains in average life expectancy.

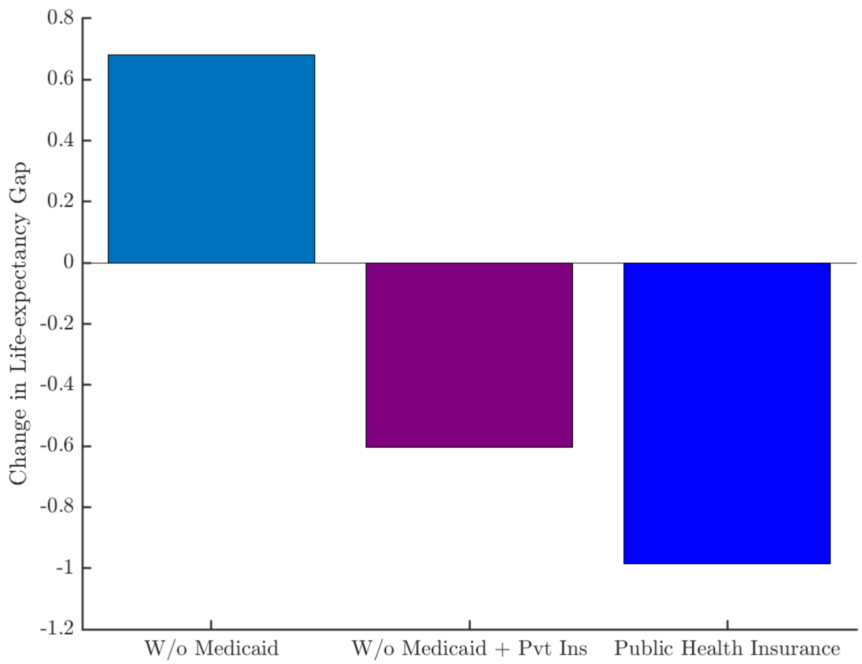
6.2 Role of insurance

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, I 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.

[25]See, for example, Walker et al. (2014) and Niu et al. (2013), who use Surveillance, Epidemiology, and End Results (SEER) registry data to document the differences in the stages 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

Figure 18: Role of Insurance



I find that shutting down Medicaid would lead to inequality in health outcomes going up by 10% (6.2 years vs 5.5 years baseline). On the other hand, shutting down private insurance would exacerbate inequality by almost twice as much. This 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. The role of private insurance on 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 to diversify their health risks and smooth 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 Figures 19 and 20. Of those in excellent health, only the wealthy take up private insurance; of those in good health, those who do not expect to move to a better health status without going to the doctor, take up private insurance. The threshold below which people take-up private insurance is increasing in wealth. The same selection applied to Medicaid is 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 19: Private Insurance take-up: Good health

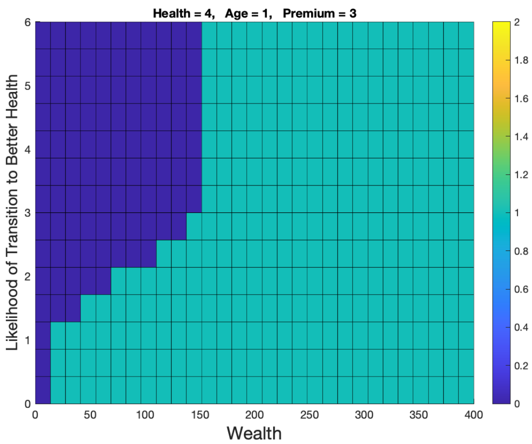
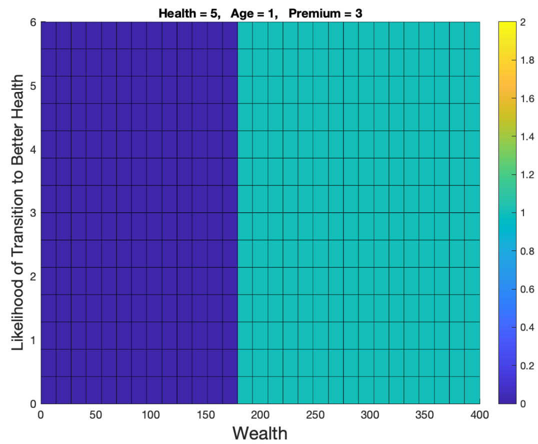


Figure 20: Private Insurance take-up: Excellent health



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

I should emphasize here that policy experiments involving private insurance and public health insurance may be 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.

I find that if there were no feedback of health into productivity, income inequality, as measured by the 90-10 ratio, would go down by about 15% (3.44 vs. 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 reduce incentives to invest in health. Individuals lower their medical spending over the life-cycle by 20% as a result of the reduced incentive to invest in their health via the productivity channel shown in Figure 22.

Figure 21: Income inequality

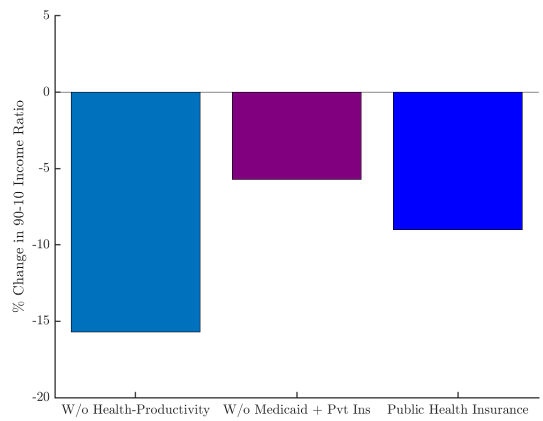
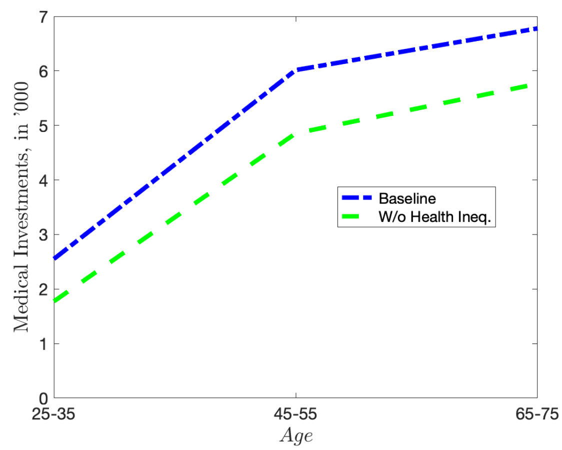


Figure 22: Healthcare spending: Shutting down health-income channel



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 reduction is largely driven by the health productivity channel wherein improvements in health for 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 percentile wealth
h^D	Disability health (utility function)	1
η	Aging Poisson, all ages	$\frac{1}{10}$
ϕ	Insurance Intensity	1/12

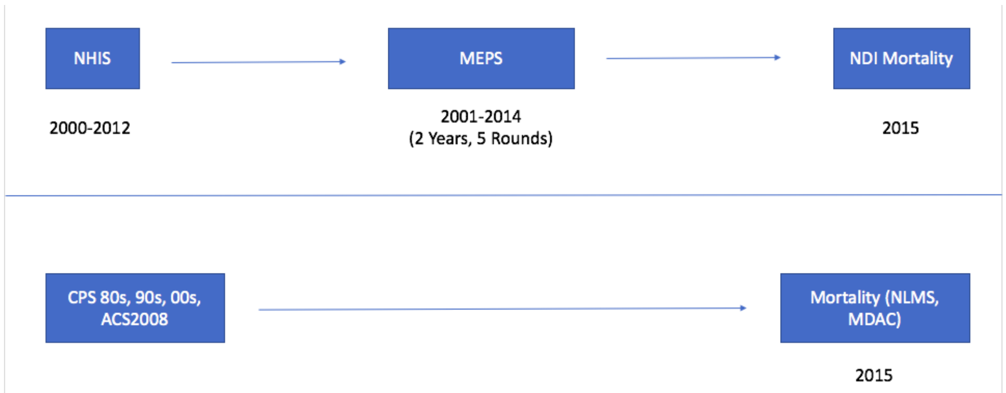
Table A.8.8: Estimated outside of the model

Meaning	Parameter	Value
Mortality Rate, Age 75-85	$\lambda^6_1, \lambda^6_2, \lambda^6_3, \lambda^6_4, \lambda^6_5$	$(11.07, 1.82, 1, 0.45, 0.07)\lambda^T$
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	$\frac{\lambda^{Da}}{\lambda^a_3}$	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, the merged National Health Interview Survey (NHIS) and Medical Expenditure Panel Survey (MEPS), the National Longitudinal Mortality Survey (NLMS), and the Mortality Differentials Across Communities (MDAC). MEPS is a rolling panel and provides us with 5 snapshots over 2 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 2000 to 2015 along with ex-post mortality status until 2015 irrespective of the sample year. We provide a brief description of the datasets here.

1. The merged National Health Interview Survey (NHIS) and Medical Expenditure Panel Survey (MEPS): We use harmonized Integrated Public Use Microdata Series (IPUMS)-NHIS data from 2000 to 2015 and augment it with variables from the 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 conditions including cancer, diabetes, high cholesterol, hypertension, heart disease, 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, 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, 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 data across multiple CPS waves from 1980- 2008. In particular, we get three normalized waves for 1983, 1993, 2003 what track the cause of death for 6 years starting the date of interview 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 provide about 9 million records in various waves from 1980 to 2015 and merged mortality information from death certificates until 2015 (up to 35 years of mortality tracking). Detailed zip codes and longitudes and latitudes of residences are also available in this dataset.

A.10. Facts appendix

Expenditure and charges

It is also important to understand how spending, or expenditure, is reported. Spending is anything for which the provider was compensated for and thus does not include uncompensated care[27], which would likely increase the poor's spending. Note that the expenditure/ spending is the amount that finally gets paid, i.e. the negotiated amount after discounts, and is lower than the charge. There are certain limitations to this spending data. First, prices are not known. Therefore, if insurance providers negotiate a better price for the same quantity, the poor get a lower quantity of medical services 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 the 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 facilities. 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, the charge-to-expenditure ratio goes from 1.4 early in the life-cycle to 1.5 after age 65, while for the poor it goes from 4.7 early in the life-cycle to 1.5 for later ages. This suggests that, if anything, medical services are more intensely negotiated for the poor than for the rich. For the visits for which I expect similar service—such as an ambulatory optometrist or ambulatory dentist—the charge-to-expenditure ratio is comparable across the income spectrum, with that for the rich (1.2) only slightly lower than that of the poor (1.4). This comparison could also be done at the service level, such as for Magnetic Resonance Imaging or an X-ray, something that will be added in later versions due to data limitations.

[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

Decomposition of changes in life expectancy across income groups

Let S_i be the survival rate implied by cause-of-death i. If there are K competing causes-of-death, assumed independent, the survival rate is given by $S = \prod_{k=1}^{K} S(k)$. As is standard, the 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 as if only the cause-of-death $i \in \{1, 2, ..K\}$ had changed from S_i to S'_i, the counterfactual survival rate would be 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. The change in life expectancy implied by the survival rate S_{ci} and S would, thus, be the change in life expectancy if there were changes in cause-of-death i.

Similarly, I can extend this analysis to age and cause-specific survival where $S_{i,a}$ is the survival rate implied by cause-of-death i at age, a. The counterfactual survival rate if only the cause-of-death $i \in \{1, 2, ..K\}$ at 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 the 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 and use wave c for the average mortality rate in the 2000s. This is done to increase the sample size by exploiting whole person-year observations, given the age and mortality specific decompositions I am 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-sectional information and mortality follow-up in NLMS-MDAC and, thus, am unable to do such decomposition with other classifications. Another limitation of this decomposition is that since it uses population mortality/ survival rates, it treats large reductions in mortality rates for a small fraction of the population similar to small reductions in mortality rates for a large fraction of the population. I perform robustness checks for this pattern across finer age bins and the results are similar.

[28] I use period life expectancy, which is commonly used by the US Social Security Administration, computing the expected duration a person of a given age at time t is going to live if they were subject to the same mortality rate as experienced by the whole population in period t. More details can be found here.

Table A.10.10: (Robustness) Gains in life expectancy (3 age groups), 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: 1980s to 2000s

	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

Notes: Life expectancy conditional on surviving until age 20.
1980s is computed by NLMS 6a wave 6-year average mortality rates; 2000s is computed by NLMS 6c wave 6-year average mortality rates.

Table A.10.12: Gains in life expectancy (some college and above): 1980s to 2000s

	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

Notes: Life expectancy conditional on surviving until age 20.
1980s is computed by NLMS 6a wave 6-year average mortality rates; 2000s is computed by NLMS 6c wave 6-year average mortality rates.
Note that educational attainment has changed dramatically over this time: the college graduates who show up in lower family income bin has changed over these decades.

Table A.10.13: (Robustness) Gains in life expectancy (4 age groups): 1980s to 2000s

	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

Notes: Life expectancy conditional on surviving until age 20.
1980s is computed by NLMS 6a wave 6-year average mortality rates; 2000s is computed by NLMS 6c wave 6-year average mortality rates.

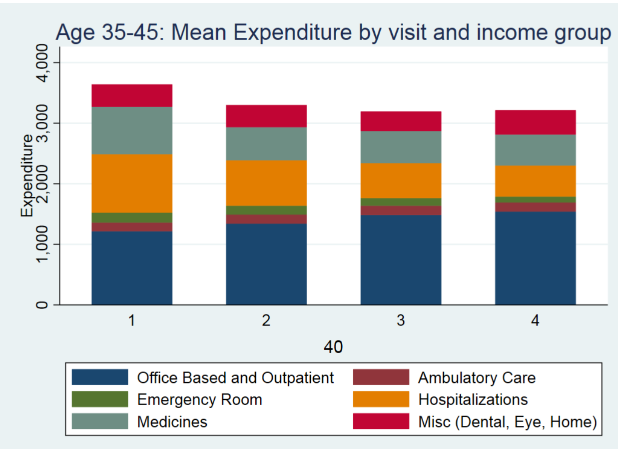
Table A.10.14: (Robustness) Gains in life expectancy (8 age groups): 1980s to 2000s

	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

Notes: Life expectancy conditional on surviving until age 20.
1980s is computed by NLMS 6a wave 6-year average mortality rates; 2000s is computed by NLMS 6c wave 6-year average mortality rates.

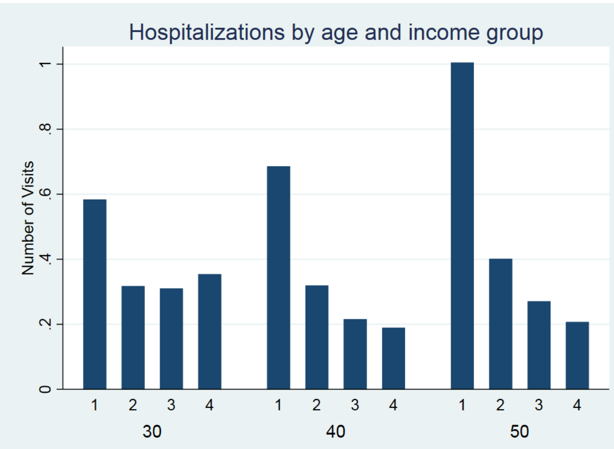
The poor spend more on hospitalizations and emergency rooms while rich spend more on Outpatient visits

Figure A.10.24: Mean expenditure by visit, Ages 35-45



Source: NHIS-MEPS (2000-15).

Figure A.10.25: Number of hospitalizations by age and income

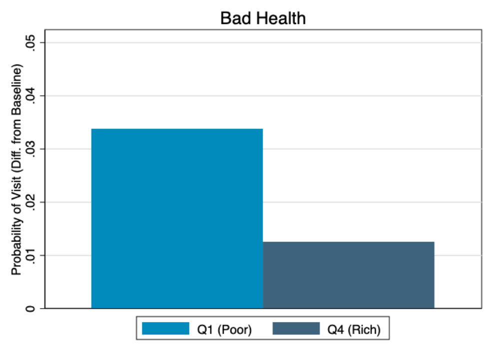


Source: NHIS-MEPS (2000-15).

While the rich and poor, defined based on the family income quartiles, have comparable total medical expenditures, those in the bottom quartile of the distribution spend significantly more on hospitalizations ($1000 for the first quartile vs $500 for the top quartile for ages 35-45) and emergency room visits 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 the top income quartile had less than a third of the hospitalizations that those in the bottom income quartile had for ages 35-45.

Rich individuals go to the doctor in a much healthier state

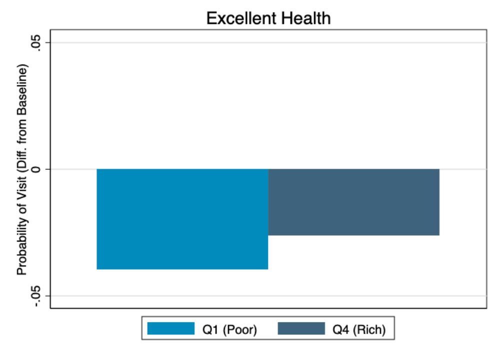
Figure A.10.26: Responsiveness to poor health state: Poor vs rich



Source: NHIS-MEPS (2000-15).

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

Figure A.10.27: Responsiveness to excellent health state: Poor vs rich



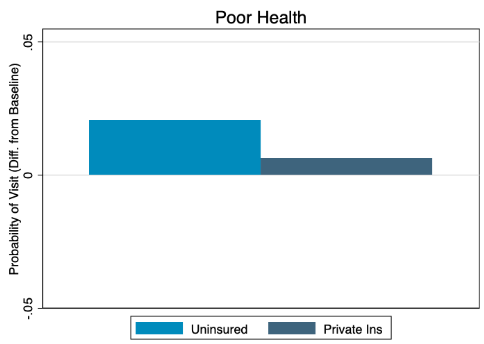
Source: NHIS-MEPS (2000-15).

Notes: Includes individual fixed effect regressions of doctor visit from t to $t+1$ on health in time t, run separately by family income group. 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 of the rich and poor. To this end, I run two fixed-effect regressions for each income group, with the base set as the average health state. The variation for this regression comes from the panel component where I observe an individual's doctor-visit decision and health status. I plot the regression coefficient associated with the health status dummy, with values for poor health and excellent health for each income group regression.

The results indicate that poor individuals' visit decisions are 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 the rich go to the doctor at any time, the poor only go to the doctor when 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 treatment.

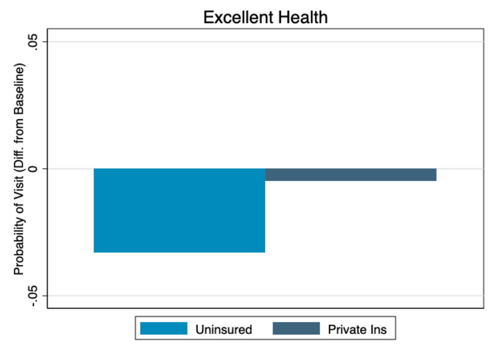
Figure A.10.28: Responsiveness to poor health state: Insured vs uninsured



Source: NHIS-MEPS (2000-15).

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

Figure A.10.29: Responsiveness to excellent health state: Insured vs uninsured



Source: NHIS-MEPS (2000-15).

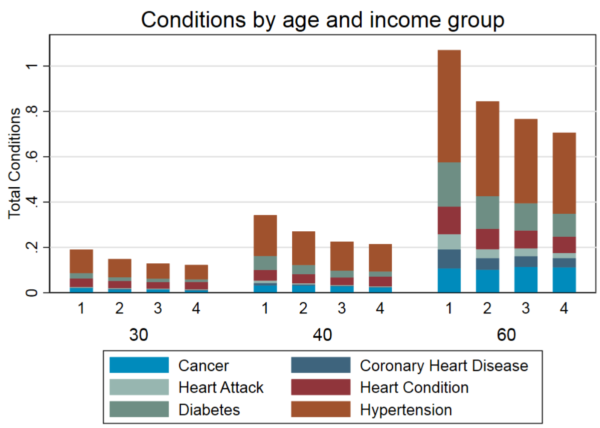
Notes: Includes individual fixed effect regressions of doctor visit from t to $t+1$ on health in time t, run separately by family income group. Base set to average health in each income-group regression.

Note that for this analysis, I do not need the self-reported 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

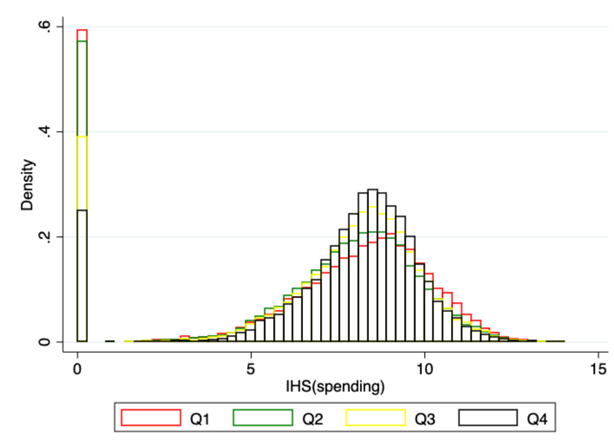
Inequality in health outcomes isn't limited to mortality, as documented in Figure A.10.30. Across the age distribution, individuals in the bottom quartile of the family income distribution report having more medical conditions, such as hypertension and diabetes, compared to their rich counterparts. For individuals ages 55-65, the average number of conditions for a person in bottom quartile is more than 1, which is about 50% higher than the average number of medical conditions for a person in the top quartile.

Figure A.10.30: Health conditions by age and income



Source: NHIS-MEPS (2000-15).

Figure A.10.31: Healthcare spending distribution: Ages 45-55



Source: NHIS-MEPS (2000-15).

Table A.10.15: Expenditure by income: Ages 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

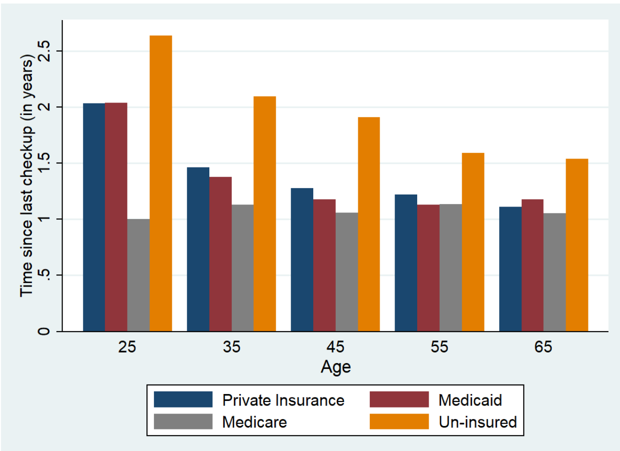
Source: NHIS-MEPS (2000-15).

Table A.10.16: w/o 0 by income: Ages 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

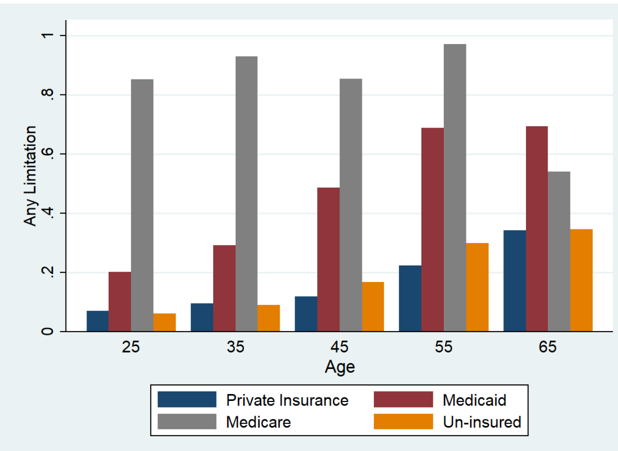
Source: NHIS-MEPS (2000-15).

Figure A.10.32: Time since cholesterol checkup (with pre-existing condition)



Source: NHIS-MEPS (2000-15).

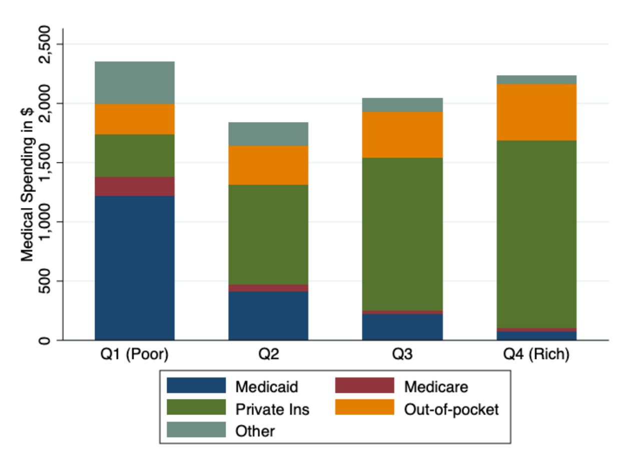
Figure A.10.33: Any limitation by age and insurance status



Source: NHIS-MEPS (2000-15).

Medical spending by age and income

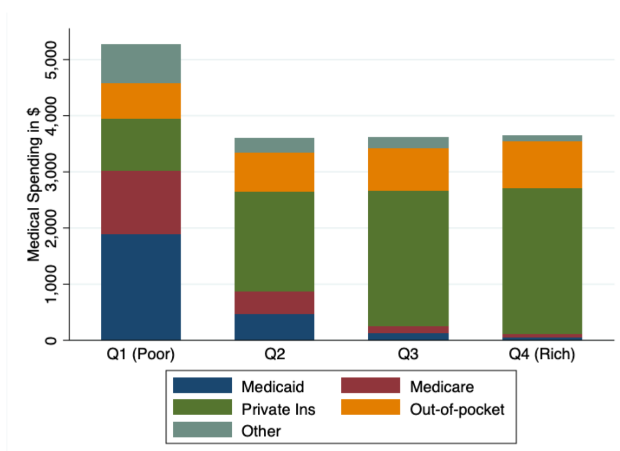
Figure A.10.34: Medical spending ages 25-35



Source: NHIS-MEPS (2000-15).

Notes: Other includes all other sources of payments.

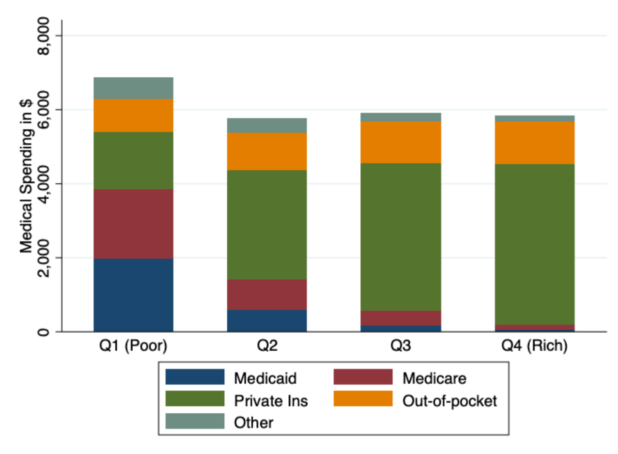
Figure A.10.35: Medical spending ages 45-55



Source: NHIS-MEPS (2000-15).

Notes: Other includes all other sources of payments.

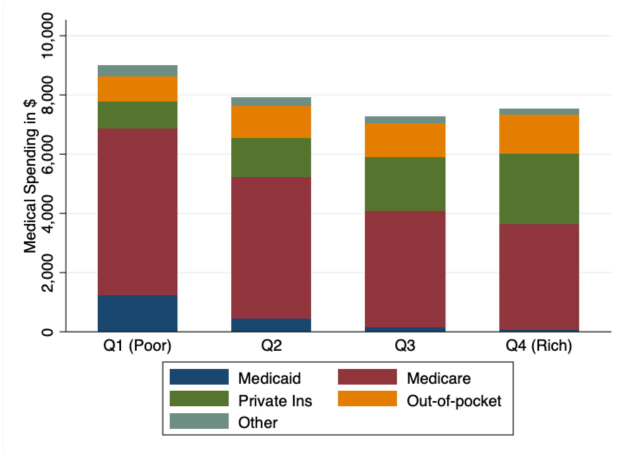
Figure A.10.36: Medical spending ages 55-65



Source: NHIS-MEPS (2000-15).

Notes: Other includes all other sources of payments.

Figure A.10.37: Medical spending ages 65-75

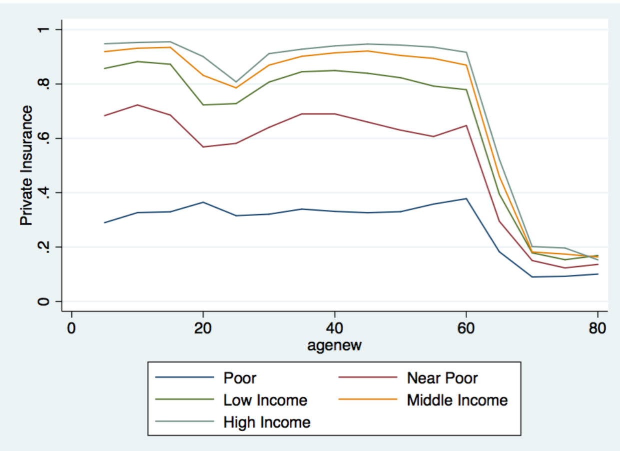


Source: NHIS-MEPS (2000-15).

Notes: Other includes all other sources of payments.

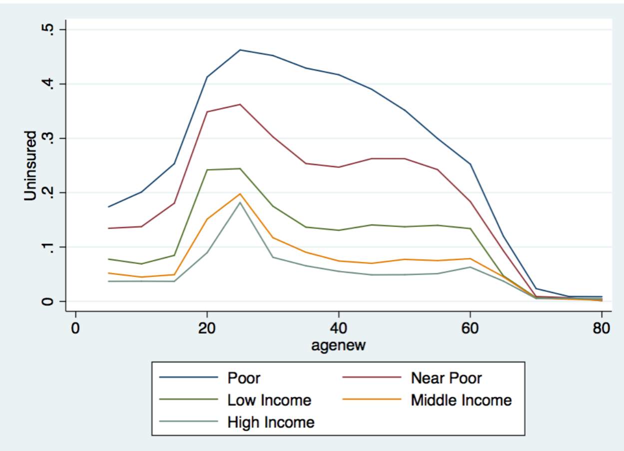
Health insurance by age and income

Figure A.10.38: Fraction with private insurance by income and age



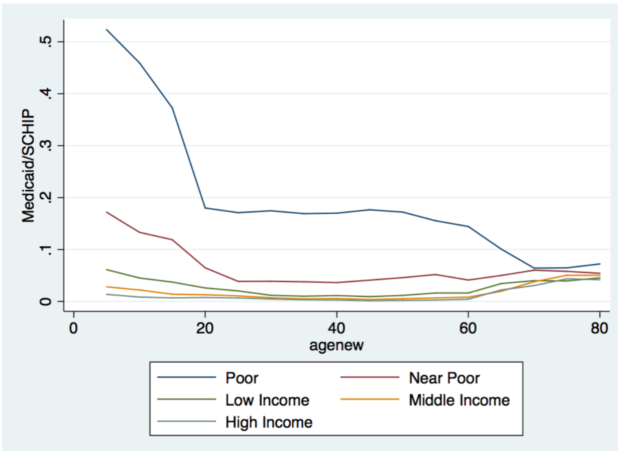
Source: NLMS (early-2000s Wave)

Figure A.10.39: Fraction uninsured by income and age



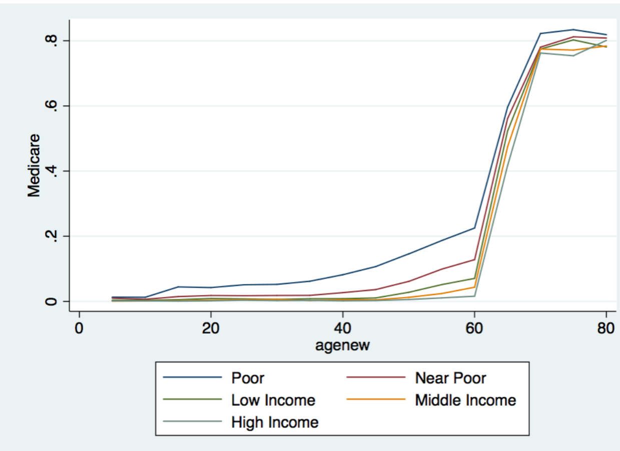
Source: NLMS (early-2000s Wave)

Figure A.10.40: Fraction with Medicaid and SCHIP by income and age



Source: NLMS (early-2000s Wave)

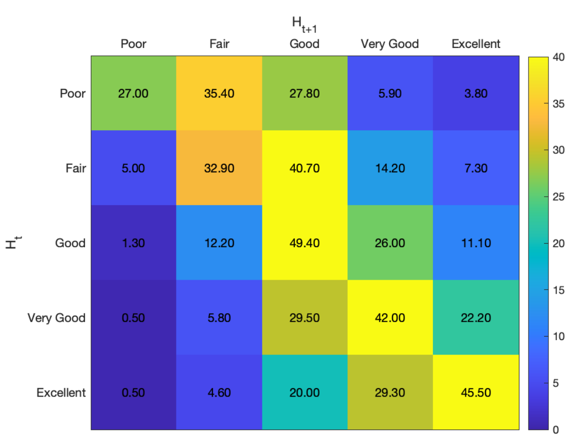
Figure A.10.41: Fraction with Medicare by income



Source: NLMS (early-2000s Wave)

Transition matrix by age and income

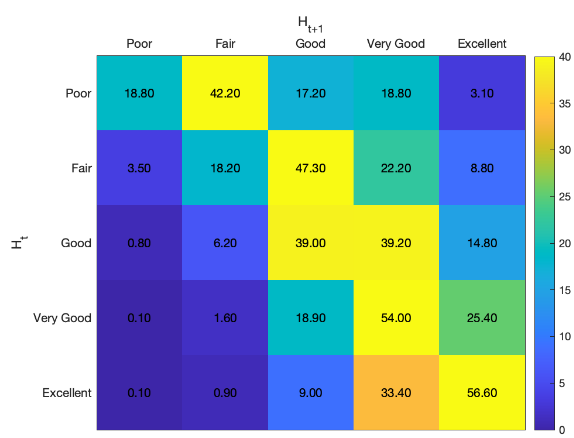
Figure A.10.42: Transition matrix | visit: Poor ages 25-35



Source: NHIS-MEPS (2000-15).

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

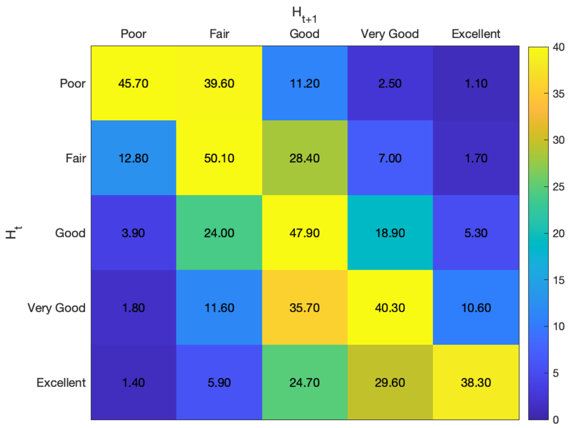
Figure A.10.43: Transition matrix | visit: Rich ages 25-35



Source: NHIS-MEPS (2000-15).

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

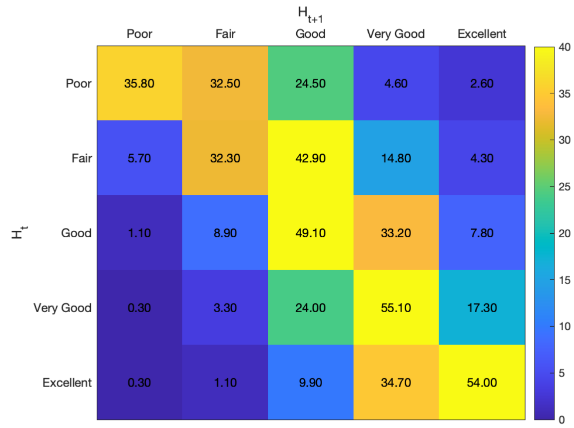
Figure A.10.44: Transition matrix | visit: Poor ages 45-55



Source: NHIS-MEPS (2000-15).

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

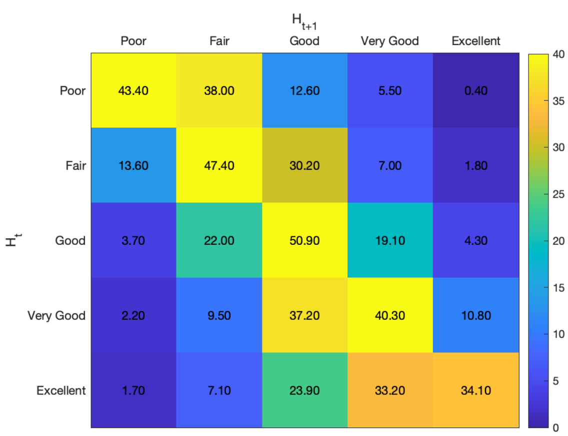
Figure A.10.45: Transition matrix | visit: Rich ages 45-55



Source: NHIS-MEPS (2000-15).

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

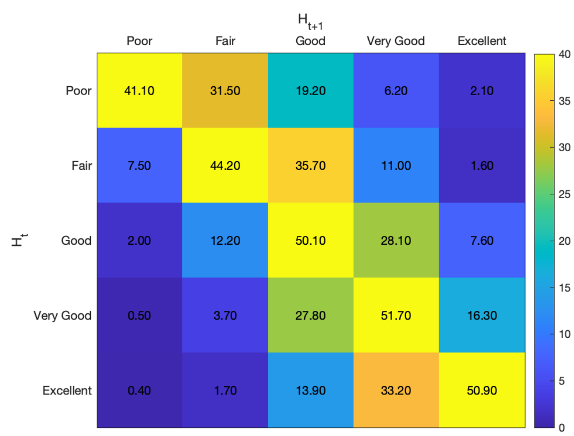
Figure A.10.46: Transition matrix | visit: Poor ages 55-65



Source: NHIS-MEPS (2000-15).

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

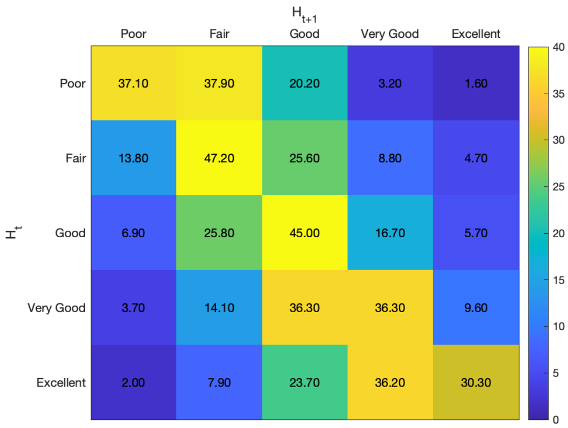
Figure A.10.47: Transition matrix | visit: Rich ages 55-65



Source: NHIS-MEPS (2000-15).

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

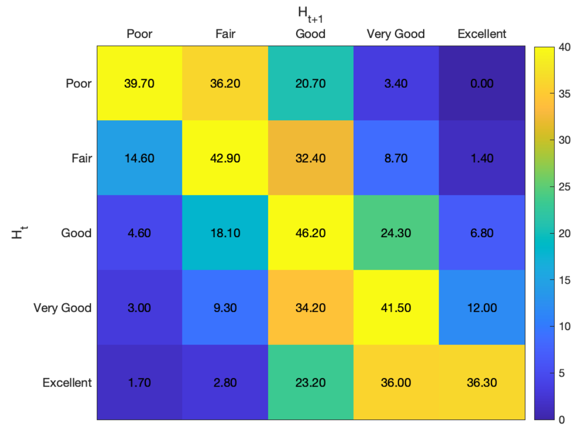
Figure A.10.48: Transition matrix | visit: Poor ages 65-75



Source: NHIS-MEPS (2000-15).

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

Figure A.10.49: Transition matrix | visit: Rich ages 65-75



Source: NHIS-MEPS (2000-15).

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

A.10.1 External validation: Insurance and mortality

Effect of Medicaid on mortality

NLMS data provides us with three cross sectional waves of the initial survey, which includes demographic and socio-economic status, and one "panel" component is whether an individual died at the end of 6 years and what the cause of death was. An ideal survey is one with panel data along with cause of death data mapped from death certificate. Due to the unavailability of such data, I make the assumption that socio-economic status, insurance status and type of insurance remain the same for all 6 years. This could be problematic because of Medicaid access for poor children; thus I exclude children ages 0-18. Since Medicare is available, in principle, to almost everyone above age 65, I also exclude elderly people with age > 65 from our sample. Note that while the federal government mandated a minimum poverty level cutoff, states have flexibility in deciding their own eligibility criteria.

I exploit the variation in state-wide eligibility cutoff in the year 2000 to estimate the effect of Medicaid on mortality. Let's describe the ideal discontinuity design setting. Suppose a state has Medicaid cutoff at 75% of federal poverty line (FPL). I 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, I compare individuals at 50-75% of FPL in states where they were eligible for Medicaid and with individuals at that level in states where they weren't eligible. I 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 an individual dies at the end of 6 years based on insurance status, education, age, age sq, income, income squared and sex (some of which have been excluded from the table). xx denotes the corresponding wave number of NLMS, where 6a represents the early (for all 1980s), 6b represents early 1990s and 6c represents early 2000s.

Effect of private insurance on mortality

I first estimate a logit regression of mortality on insurance, age, education and income. The exact specification is described in table A.10.17 columns 1, 3 and 5 for three waves of NLMS. The reduced form regression specification in the table suffers from a potential selection problem. In particular, the decision to take up health insurance may not be random and there could be idiosyncratic gains from treatment. In order to get around the selection problem, I use the propensity score matching estimator a la Heckman et al. (1998)[29]. Following Caliendo and Kopeinig (2008), the 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] I 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:

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

I use nearest-neighbor matching and check for the common support assumption in Figures A.10.50, A.10.51 and A.10.52 and leave out the bins without overlap to ensure that the common support assumption is not violated. The propensity score specification is the following:

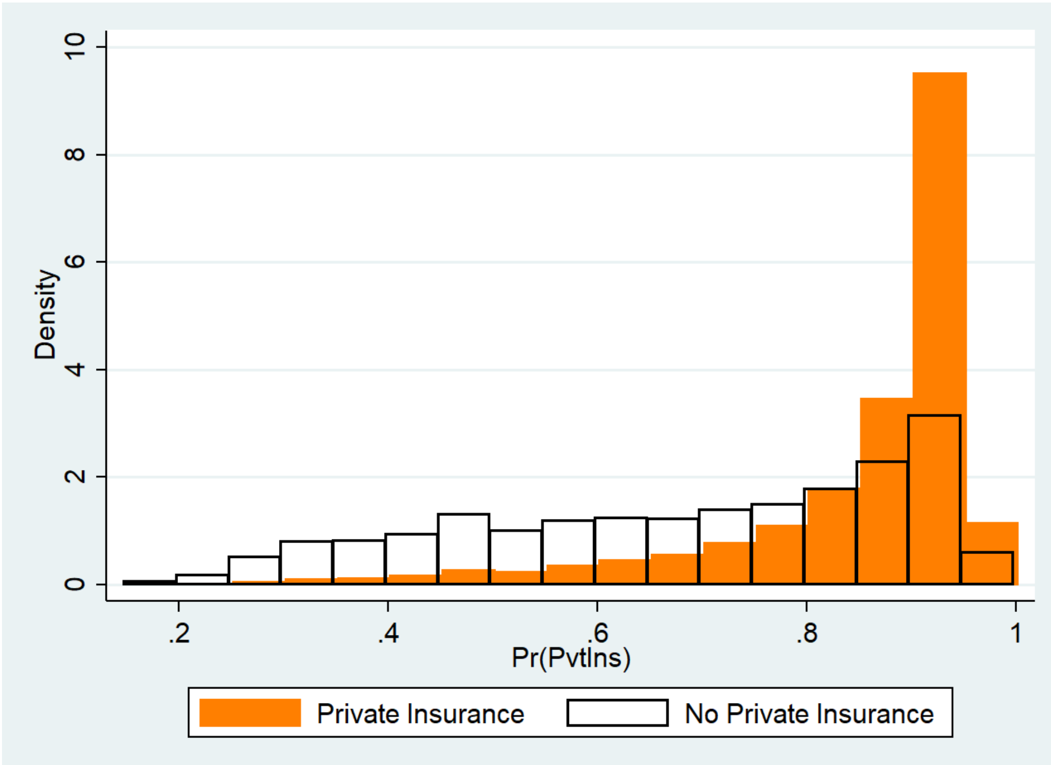
$$P(D = 1|age, sex, income) = \beta_0 + \beta_1 \text{ x } age + \beta_2 \text{ x } sex + \beta_3 \text{ x } income + \beta_4 \text{ x } education \tag{16}$$

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, matching can only be based on observables. However, 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.

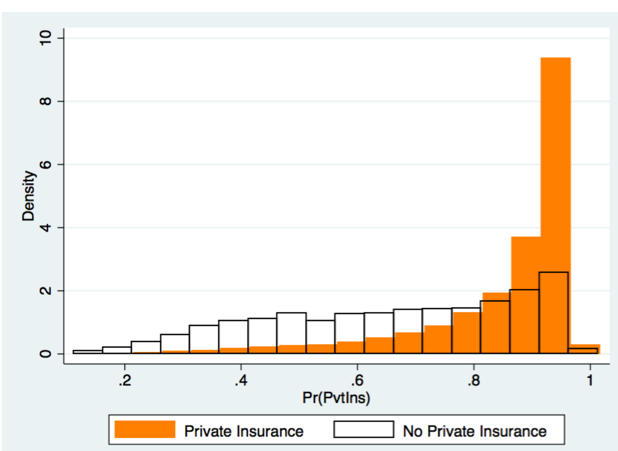
[30]NLMS matches the mortality status only for 6 years after the interview

Figure A.10.50: Support for propensity score matching, wave 6a



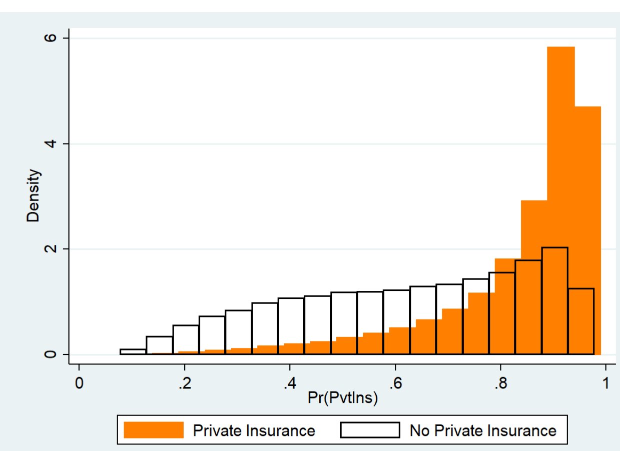
Source: NLMS 6a

Figure A.10.51: Support for propensity score matching, wave 6b



Source: NLMS 6b

Figure A.10.52: Support for propensity score matching, wave 6c



Source: NLMS 6c

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 the dollar equivalent of value lost. I calibrate a COVID-19-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 a higher mortality rate for those in poor health, leading to the inequality in life-expectancy going up by 19%, as shown in figure A.11.53. This is due to the fact that poor individuals are relatively unhealthy and have more pre-existing conditions than rich-individuals, 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.11.54.

Figure A.11.53: COVID-19 and Health Inequality

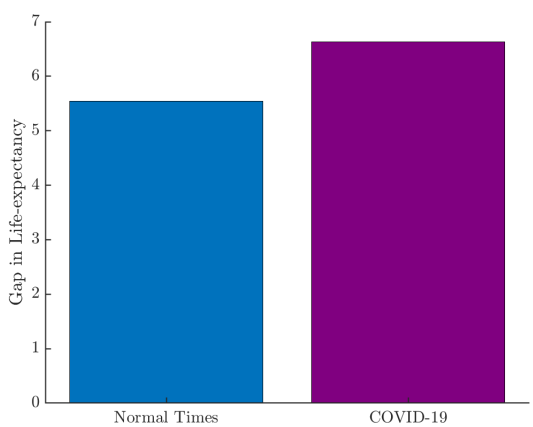
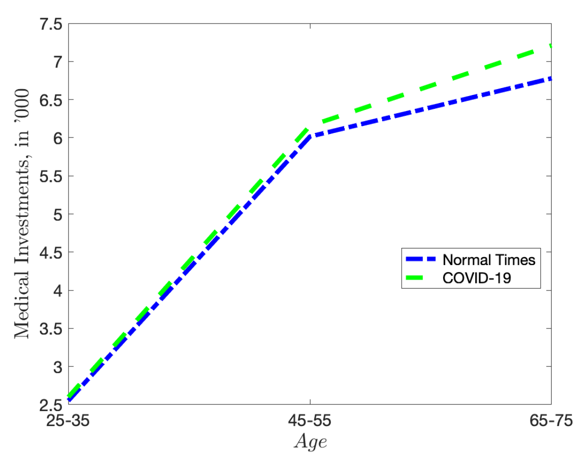


Figure A.11.54: COVID-19 and Investments



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

Insurance firm's problem

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

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

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

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

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