Health Inequality: Role of Insurance and Technological Progress

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Abstract

The paper investigates the role of insurance and technological progress on the rising health inequality across income groups and its aggregate output costs for the US. We develop a continuous-time life-cycle model of an economy where individuals decide consumption-hours worked, whether to take up health insurance, when to visit a doctor, how much to invest in their health capital and whether to engage in bad behavior. A simple version of the model is able to explain about 50% of the gap in life-expectancy across income groups observed in data. In our model, consistent with the pattern in data, uninsured individuals, having deferred the treatment aren't able to reap the benefits of the technological progress, thus resulting in poorer outcomes. The policy simulation with a plausible public health insurance scheme reduces the disparity in health outcomes to half. We use National Longitudinal Mortality Survey (NLMS), Mortality Differentials Across Communities (MDAC) and linked National Health Interview Survey (NHIS)- Medical Expenditures Panel Survey (MEPS) data to estimate the parameters of the model. As a cross-validation exercise using National Longitudinal Mortality Survey (NLMS) data, we exploit the state variation in Medicaid eligibility and find that among the working age individuals with low family income, Medicaid reduces the probability of dying by 9%. Using propensity score matching estimator, we find that private insurance reduces the probability of dying by upto 25% when compared to the uninsured.

Keywords: Health Inequality, Technological Progress, Health Insurance, Continous-time, Health Capital

JEL Classification: I12, I13, I14, O11

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1. Introduction

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

It is quite puzzling that while the total healthcare spending looks very similar across income groups, the health outcomes are very different and have worsened over time. The literature in the past has focused on behavioral factors such as smoking and role of education; however, it seems unlikely that smoking and education alone can explain not only the inequality in cross section but also the increasing and diverging trend, as documented in Chetty et al. (2016). In this backdrop, this paper explores the role of health insurance and its interaction with medical technological progress to explain part of the rising health inequality[2] in the US over the past decade.

There are significant differences in individuals across income and insurance status. Using National Longitudinal Mortality Survey (NLMS), Mortality Differentials Across Communities (MDAC) and linked National Health Interview Survey (NHIS)- Medical Expenditures Panel Survey (MEPS) from 2000s, we present the following empirical facts. For those in the bottom 40 percentile of income distribution, 35 percent of the individuals have no insurance as opposed

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

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

[2]Defined as life expectancy at the age of 25 or 40

to only 5 percent in the top 20 percentile of the income group. Moreover, possibly due to the lack of insurance, time since last checkup is significantly higher for the uninsured than those with private insurance. For individuals with preexisting heart conditions, the time since last cholesterol checkup for uninsured individuals was at least 25 percent more than the private insurance individuals across age. Unconditional mortality rates and mortality rates conditional on having a medical condition are substantially higher for poor than the rich (source: MDAC). We also see that while larger fraction of poor have zero medical spending, they also have very high expenditures- they spend more on Hospitalizations and Emergency Rooms while rich spend more on Outpatient visits. Interestingly, for individuals in lower income group, visiting doctor seems to have little or no effect on transition from poor health to good health while visits to the doctor significantly improves the transition from poor to good health for rich.

When it comes to time-allocation, using time use data from ATUS, we see that lower fraction of low income group individuals report that they exercise[3] (Figure 18). Moreover, the (mean) weekly exercise time for low income individuals of age 50 was 1.6 hours compared to 3.4 hours for high income group (Figure 19). The pattern was robust across all age groups and sex. It is also seen that the poorest of the counties[4] were also the ones with highest number of uninsured individuals as well as the ones with lower fraction of diabetic patients going for a hemo-test (Table 13).

Motivated by these empirical facts and following the strand of literature modeling health as health capital starting from the seminal paper by Grossman (1972) and Gilleskie (1998), we build a general equilibrium model with endogenous health insurance premium explicitly incorporating the decisions to purchase health insurance, timing to visit the doctor, how much to invest in their health capital and whether to engage in addictive bad behavior. Insurance firms offer health insurance in alternative premium contracts: a) where insurance premium can depend on the health status and b) under ACA where insurance premium cannot depend on health status. There is stochastic aging in the model and as the model economy age, the insurance premium would go up. Given that the health shocks can arrive continually, our model brings continuous time methods[5], a popular tool used in macroeconomics and finance, into a problem involving individual's health related decisions. We summarize our findings from the model, which is consistent from the data, below:

- While the total health spending across income groups is similar, *who pays* for that spending matters in the timing and how much individuals decide to invest in their health capital.

[3]It could be the case that poor people work in occupations requiring higher physical work or that they walk to work which may not be picked up as exercise; however, it appears that the poor also have less working hours, less leisure and more sleeping time.

[4]Those with highest number of people below Federal Poverty Line (FPL) in 2010.

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

- Low wealth individuals optimally choose to remain uninsured and defer getting the treatment and are thus, not able to reap the benefits of the medical technological progress. The rich insured individuals, on the other hand, frequently go to the doctor and invests in his/her health capital and remains at the frontier of the health technology.

- As a poor uninsured individual defers getting the treatment until his health deteriorates significantly, poorer individuals aren't able to improve their health even by spending the same amount of money, i.e. they don't get the bang for the buck.

We can provide an example to narrate our hypothesis. Suppose that the medical technology today is such that cancer until stage 2 can be treated. While the rich, frequently going to see the doctor, is able to diagnose cancer at stage 1, the poor, having deferred the treatment, is able to diagnose only when his cancer is in stage 3[6]. Thus, he not only ends up spending the same amount as a rich person in any given year, he is also not able to reap the benefits of the medical technological progress that we have witnessed.

Our rich quantitative model – estimated from the newly available data – would be well suited to: understand and quantify the channel through which health insurance affects individual's decisions on health spending, frequency of visits to the doctor, health outcomes such as mortality and through affecting health, the impact on productivity and output; understand the channels through which income groups benefit differently from the medical technological progress and guiding policy to ensure health equity; quantify the impact of making health insurance premium not dependent on pre-existing health conditions (Affordable Care Act) on health outcomes, worker productivity, hours worked and output; evaluate lower age for Medicare and "Medicare-for-all" on worker productivity, working hours and their health outcomes; and effect of population aging on the optimal design of health policies.

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

- We borrow the evaluation methods used in microeconometrics literature and use the propensity score matching estimator to find the effect of private health insurance on the probability of dying. We find that private insurance reduces the probability of dying in the next 6 years by 15-25% across various NLMS waves as compared to the uninsured (baseline) (Table 12)

- Using state variation in Medicaid eligibility in 2000, we find that among the working age individuals with low family income, Medicaid reduces the probability of dying by 9% (Table 12).

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

The remaining of the paper is divided as follows: section 2 includes literature review and placing the paper into the literature, section 3 provides the motivating empirical facts, section 3.1 documents some additional aggregate patterns, section 4 describes the model, and section 7 concludes.

2. Literature Review

The paper builds upon and contributes to many strands of literature both theoretical and empirical. Closest to us is Scholz and Seshadri (2011) and Ozkan (2014). We describe the detailed literature review in this section. Readers interested in the model and data section may skip this section.

Models of Health Capital and/or Health-Wealth Dynamics: Grossman (1972) in his seminal paper proposed modeling health as a capital stock which deteriorates with age and can be increased by investment. Gilleskie (1998) modeled the medical care consumption and absenteeism decisions of employed individuals by explicitly incorporating a decision to visit a doctor in an environment of exogenous insurance decision. Murphy and Topel (2006) develop a framework to value health improvements by quantifying improved quality of life and longevity. Scholz and Seshadri (2011) model health capital investment and wealth in a life-cycle model and match OOP medical expenditure, health status and wealth. Prados et al. (2012) studies the joint dynamics of health and earnings inequality over the life cycle. De Nardi, Pashchenko, and Porapakkarm (2017) analyze the effects of health risks on income inequality to quantify the lifetime costs of bad health by structurally estimating a model with health risks. They find that lifetime costs of bad health, including morbidity costs, are very concentrated and unequally distributed across health types. They also document that the duration of unhealthy state affects the future health states. In a related work, Poterba, Venti, and Wise (2017) looked at the end-of-life wealth inequality and its determinants such at retirement wealth and health shocks early in the life. Cole, Kim, and Krueger (2016) evaluate a trade-off between social health insurance and incentives to make costly investments in health and argue that wage non-discrimination law and no prior conditions law implemented together deteriorates individual's incentive to invest in health. Ozkan (2014) considers two different types of health capital: physical health determines survival probabilities and preventive governs endogenous distribution of shocks to physical health capital. In the model, rich have higher investment in preventive health capital and thus expected life span is longer. Finkelstein et al. (2013) estimate the effect of health status on marginal utility of consumption and find that health shocks decrease the marginal utility of consumption. They essentially rule our separability of utility in consumption and health which motivates the choice of utility function in our paper.

Role of Health Insurance Coverage on Health Outcomes: In their survey article, Sommers et al.

(2017), documented the summary of literature on impact of health insurance coverage on health outcomes. He documents conflicting evidence of whether or not private insurance is an independent predictor of mortality. To be specific, Kronick (2009) does a cox proportional hazard survival analysis and concludes that there is no difference in the risk of subsequent mortality between uninsured and employer sponsored insurance group. On the other hand, Wilper et al. (2009) finds that after controlling for demographics and behavioral characteristics, uninsured were more likely to die than those with insurance. We believe that both of the above analysis suffered with multiple endogenity and selection issues leading to conflicting results. For the effect of Medicaid expansion on mortality, Sommers et al. (2012) did a difference-in-difference and found that state Medicaid expansions were associated with reduced mortality as well as improved coverage and self reported health. They also find a decrease in people opting to delay care because of costs. Finkelstein et al. (2012) use the first year data after Oregon experiment and found that after the first year, the treatment group had higher health care utilization, lower OOP medical expenditure and better self reported and mental health. In a followup after two years of data from the experiment, Baicker et al. (2013) found that Medicaid coverage significantly increased the probability of diagnosis of diabetes and subsequent medication. As the study tracked the individuals for only two years, there was no significant impact on the measured actual health outcomes in the first two years, as one may expect.Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013) explore the possibility of selection based on moral hazard by the individuals.

Effect of Medicaid on Child Mortality: Goodman-Bacon (2013) uses a difference and difference framework to document the effect of Medicaid on child and infant mortality rates in 1960s and 1970s. In an earlier paper, Currie and Gruber (1996) use fraction of children in the eligible for Medicaid in a state as an instrument for individual eligibility to study the effect of Medicaid expansion on medical care and child mortality and found a positive impact on the expansion on Medicare care and negative impact on infant mortality.

Causes of Dealth: McGinnis and Foege (1993) categorize the causes of death in the US based on the underlying behavioral factors. While they acknowledge the importance of socioeconomic status as an underlying cause of death, they don't incorporate that in their analysis. Becker, Philipson, and Soares (2005) incorporates the gains in longevity to find a reduction in world inequality. They study the sources of decreased inequality in the health outcomes across countries and find that infectious, respiratory, and digestive diseases contributed to the reduction in life expectancy inequality.

Value of Subsidizing Healthcare: Using the randomization provided by the Oregon Medicaid lottery, Taubman et al. (2014) found that Medicaid coverage increases the emergency use across a range of type of visits. Finkelstein et al. (2015) estimate that the value of Medicaid to recipients is between one-third to three-quarters of the monetary transfers to medical providers who implicitly insure low-income individuals against high medical expenditures without Medicaid.

Their welfare analysis doesn't include the cost of delaying treatment both in terms of mortality and morbidity. Finkelstein et al. (2017a) use Massachusetts' subsidized insurance exchange data to estimate the willingness to pay for health insurance by low-income individuals and find that the willingness to pay is less than half of own expected cost for those in the bottom 70% of the willingness to pay distribution. In a closely related work, Finkelstein et al. (2017b) claim that the uncompensated care explains the limited take-up of subsidized health care and why the recipients value health insurance at lower cost to insurers. Card et al. (2007) and Card et al. (2008) use the changes in insurance status at the age 65 when Medicare kicks in on health care utilization to find an increase in the treatment intensity at the age of 65.

Uninsured Deferring Treatment: American College of Physicians-American Society of Internal Medicine (1999) survey cites about 120 papers by physicians and practitioners and documents that uninsured Americans lack the proper access to health care[7], more likely to delay seeking care, report to have not received needed care and have worse health outcomes[8]. While the studies cited in the survey suffer selection and endogenity issues, it's interesting to get the perspective of the medical service providers and practitioners on the topic. Walker et al. (2014) use Surveillance, Epidemiology, and End Results (SEER) registry data to document the differences in diagnosis stage of cancer across insurance groups in the US. They found that uninsured individuals were more likely to be present with advanced stage cancer. Myerson et al. (2017) uses the discontinuity in medicare eligibility at the age of 65 and document an increase in cancer detection, fraction of cancer detected early and one year survival conditional on detection at the age 65.

Determinants of Health Inequality: Arcaya and Figueroa (2017) qualitatively argue that the trends in technology, socioeconomic inequality, health reforms and environmental factors could contribute to the health inequality trends in the US. Glied and Lleras-Muney (2008) estimate the role of interaction of education and technological progress on the rising health inequality using data on disease specific mortality rates for 1980 and 1990 and cancer registry data from 1973-1993. Ozkan (2014) explicitly models preventive and physical health capital where rich individuals have higher investment in preventive health capital and thus higher life expectancy. Hai and Heckman (2015) build and estimate a dynamic model of health, wealth and addiction to explain low health, education and wealth.

With this literature review in mind, we next the data and empirical estimates.

3. Data

Our dataset is constructed from four main sources, namely, Merged National Health Interview Survey (NHIS)-Medical Expenditure Panel Survey (MEPS) and National Longitudinal Mortality

[7] Less likely to have a regular source of care, have had a recent physician care, use preventive services

[8] Generally higher mortality, three times more likely than insured individuals to experience adverse health, four times more likely to require avoidable hospitalizations and emergency care

Survey (NLMS) and Mortality Differentials Across Communities (MDAC). We provide a brief description of the datasets here.

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

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

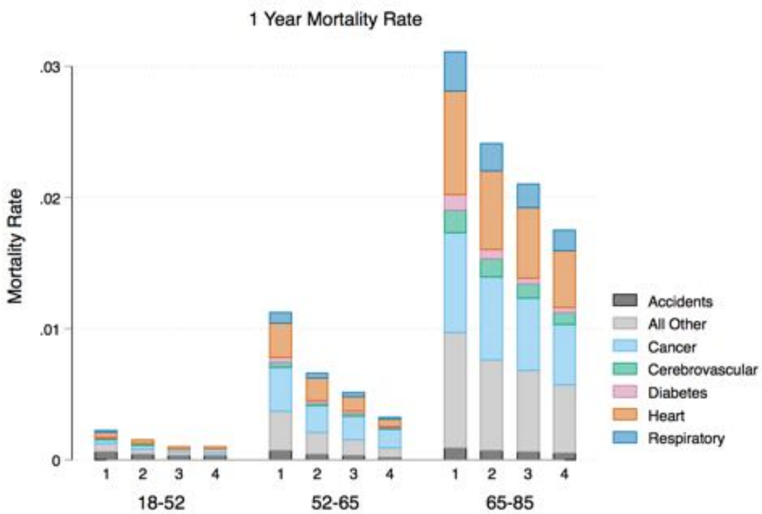
    Variables from MEPS include (not an exhaustive list):

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

    NHIS-MEPS will be augmented with Area Health Resources Files (AHRF) which includes the number of Health Care Professions and Health Facilities at the county level.

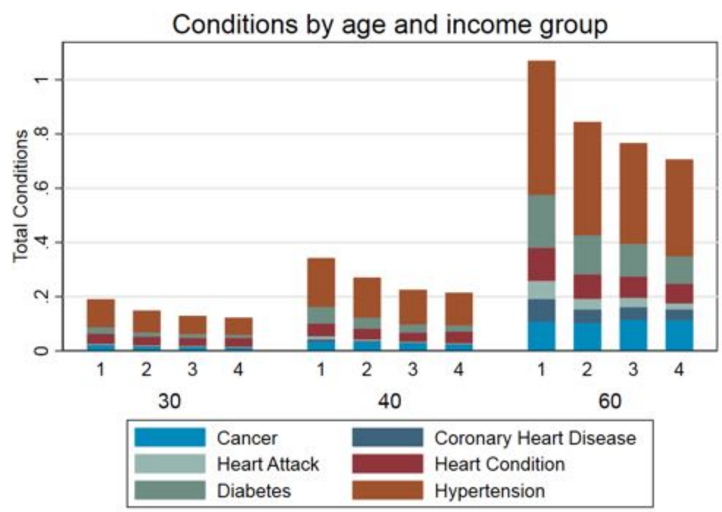
2. National Longitudinal Mortality Survey (NLMS) and Mortality Differentials Across Communities (MDAC): Besides the demographic and socio-economic variables described earlier, NLMS includes detailed date and cause of death across multiple CPS waves from 1980-

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



Source: NLMS-MDAC

Figure 2: Conditions by Age and Income



Source: NHIS-MEPS

2008. Some waves include additional information on tobacco use. Similar to NLMS, MDAC covers individuals interviewed in ACS 2008 and their matched mortality details until 2015. Together, NLMS and MDAC would provide us with about 9 million records in various waves from 1980 to 2015 and merged mortality information from death certificate until 2015 (upto 35 years of mortality tracking). Detailed zip codes and longitudes, latitudes of residence are also available in this dataset.

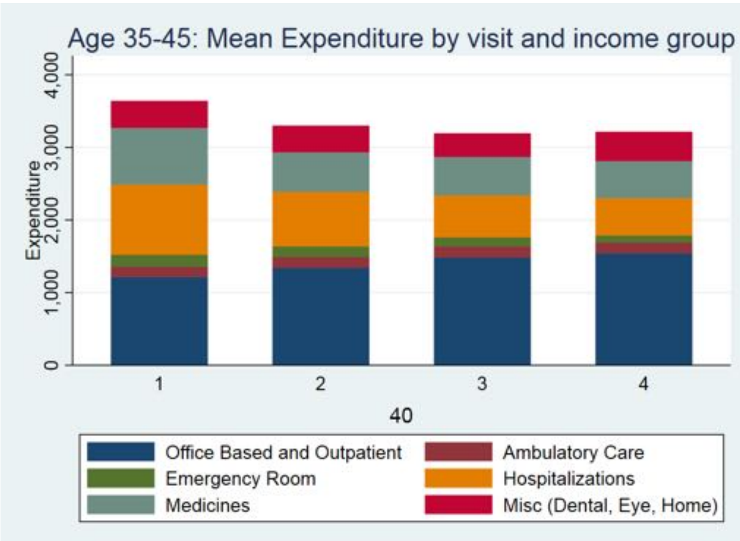
3.1 Empirical Facts

Fact 1. Poor have a higher mortality rates and more medical conditions compared to rich

The leading cause of death across the income distribution were cancer and heart conditions based on 2008 year data from MDAC. As shown in figure 1, we find that across all age groups and cause of death, individuals in fourth quartile of family income distribution have a lower aggregate and cause-specific mortality-rate compared to individuals in first quartile of family income distribution. For those in 52-65 age group, the mortality-rate of top quartile of income is less than half of the mortality-rate of the bottom quartile of income. This inequality in health outcomes isn't limited to mortality as documented in figure 2. Across the age-distribution, individuals in bottom quartile of family income distribution report having more medical conditoins such as hypertension and diabetes, compared to their rich counterparts. FOr individuals in age group 55-65, average number of conditions in a person in bottom quartile is more than one, which is about 50% higher than average number of medical consitions in a person in the top family income quartile.

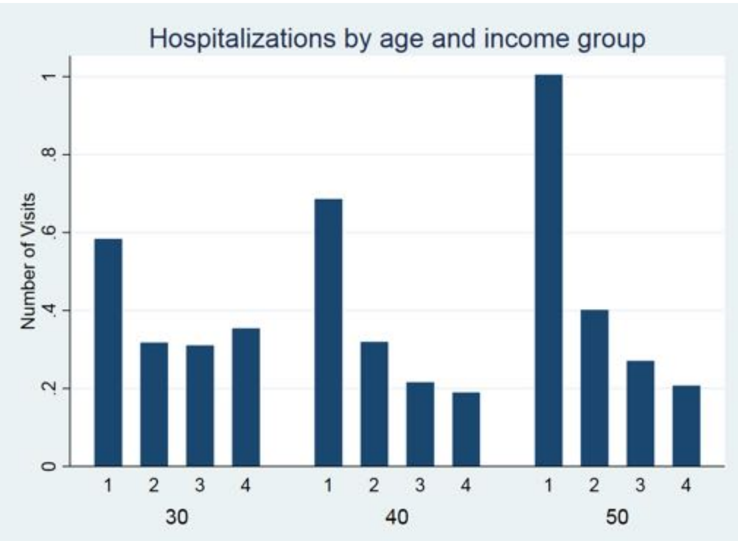
Fact 2. Mean medical spending (including private and public insurance, out-of-pocket) across income groups is comparable.

Figure 3: Mean Expenditure by Income, Age 35-45



Source: NHIS-MEPS

Figure 4: Number of Hospitalizations by Age and Income



Source: NHIS-MEPS

Similar to the findings by Ales, Hosseini, and Jones (2012), we see that the mean total medical spending including private insurance, Medicaid and Medicaid and out-of-pocket looks comparable across family income distribution. Individuals in bottom quartile of the family income distribution spent a little more than $ 3,500 annually while those in top quartile of the distribution spend about $ 3,100 annually as shown in figure 3.

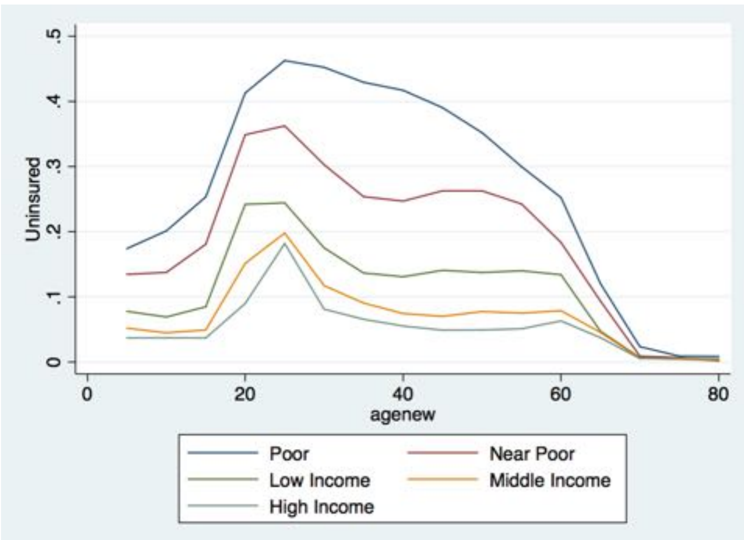
Fact 3. Poor spend more on Hospitalizations and Emergency Rooms while rich spend more on Outpatient visits

While the rich and poor spend comparable amounts in total medical expenditures, those in bottom quartile of the distribution spend significantly more on hospitalizations and emergency room while those in top quartile of the distribution spend more on office based and outpatient. This is also evident from the number of hospitalizations in figure 4. Individuals in top income quartile had less than a third of hospitalizations than bottom income quartile for age 35-45.

Fact 4. More fraction of poor are uninsured; very low fraction of their total medical spending comes from private insurance

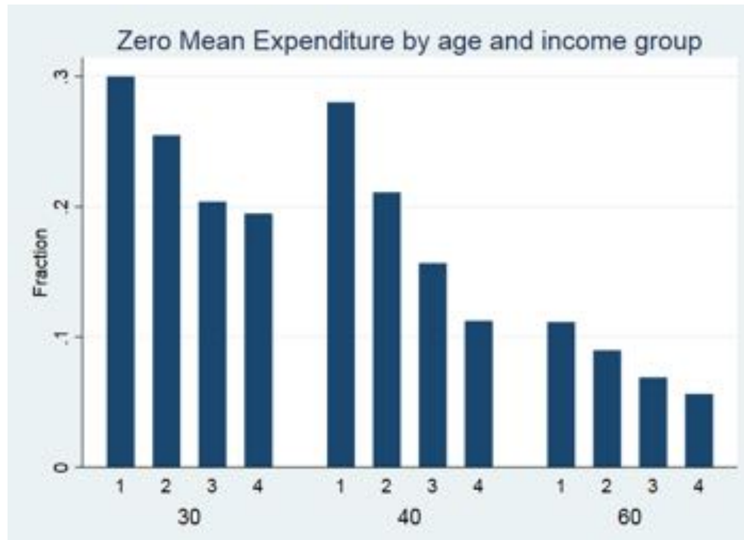
Using the 2000 wave from NLMS, we find that about 40% of those in bottom 20% of family distribution are uninsured. Figure 5 documents the uninsured rates by age and family income.

Figure 5: Fraction Uninsured by Income and Age



Source: NLMS-MDAC

Figure 6: Fraction Zero Expenditure



Source: NHIS-MEPS

Fact 5. More fraction of poor have zero medical spending but they also have very high expenditures

In table 1, we document the distribution of medical expenditures for 1st-4th quartile based on family income. We note that p25 in bottom quartile spend zero total medical expenditure in the entire year. At the same time, the p99 of the expenditure distribution is $40,771 for bottom quartile while it is $26,763 for top quartile. We find that a bigger fraction, 28%, of those in bottom income distribution have zero medical expenditure, compared to only 11% of those in top quartile of income as documented in figure 6. In table 2 we look at non-zero expenditure distribution and find that while median rich (p50 in quartile 4) spend more on medical expenses in a year, p75 and p99 of quartile 1 is much higher than p75 and p99 of rich quartile 4 individuals. In summary, while larger fraction of poor have zero medical spending but they also have thicker tails in expenditure distribution.

Table 1: Expenditure by Income: Age 35-45

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

Source: NHIS-MEPS

Table 2: Expenditure w/o 0 by Income: Age 35-45

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

Source: NHIS-MEPS

Fact 6. Rich individuals go to the doctor in a much healthier state

Table 3: Poor: Visit Decision by Health

	No Visit	Visit	Total
Poor	3.6	96.4	100.0
Fair	7.2	92.8	100.0
Good	14.9	85.1	100.0
Very Good	17.8	82.2	100.0
Excellent	21.8	78.2	100.0
Missing	70.9	29.1	100.0
Total	12.9	87.1	100.0

Source: NHIS-MEPS

Table 4: Rich: Visit Decision by Health

	No Visit	Visit	Total
Poor	1.7	98.3	100.0
Fair	4.8	95.2	100.0
Good	6.5	93.5	100.0
Very Good	7.3	92.7	100.0
Excellent	9.2	90.8	100.0
Missing	76.7	23.3	100.0
Total	7.7	92.3	100.0

Source: NHIS-MEPS

In table 3 we document whether a person in bottom family income quartile goes to the doctor in a given year conditional on his self-reported health status at the beginning of the year. In table 4 we do the same for the rich. While more than 90% of those in top quartile report going for a medical visit – even in excellent and very good health – those in bottom family income quartile, reach that level of visits only in their poor and fair health. These results suggests 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.

Fact 7. Going to the doctor "kills" poor, while improves rich individuals' health

In table 5 and 6 we look at the annual transitions in health for individuals in the first quartile of family income distribution conditional on medical visit. Table 5 shows that amongst the bottom income individuals who reported no medical visit, 10.5% of those in poor health in period 1 had very good health in period 2 while 28.9% of those in poor health stayed in poor health. While among those who reported a medical visit, only 4.1% of those in poor health in period 1 had very good or excellent health in period 2. At the same time, about 38% of those in poor health stayed in poor health.

We then look at the annual transitions in health for individuals in the fourth quartile of family income distribution conditional on medical visit in table 7 and 8. Table 5 shows that amongst the top income individuals who reported a medical visit, 8.5% of those in poor health in period 1 had very good or excellent health in period 2. At the same time, about 21.5% of those in poor health stayed in poor health.

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

Table 5: Poor: Transition in Health, Age 35-52 No Visit

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

Source: NHIS-MEPS

Table 6: Poor: Transition in Health, Age 35-52 Visit

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

Source: NHIS-MEPS

Table 7: Rich: Transition in Health, Age 35-52 No Visit

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

Source: NHIS-MEPS

Table 8: Rich: Transition in Health, Age 35-52 Visit

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

Source: NHIS-MEPS

3.2 Other Patterns

Exercise Time by Income and Age

We use the 2015 wave of the American Time Use Survey (ATUS) to document weekly time spent in exercise, working, leisure and sleeping by age and income. We also use the 2015 Eating and Health module to document fraction of people who exercise by age and income. ATUS data is collected in the following manner: a subsample is drawn from Current Population Survey (CPS) respondents, who have completed the eighth (final) month of the CPS. A person above the age of 15 is randomly chosen from the selected household and are contacted within a few months of the completion of CPS. The respondents are asked to provide a 24 hour time diary, in which the previous day is recorded in 15 minute intervals. These are then organized into detailed activity codes by ATUS. The Eating and Health Module data files contain additional information related to eating, meal preparation and health.

We divide this sample into 3 income groups low, middle and high based on their percentile in the income distribution. We see that lower fraction of low income group individuals report that they exercise figure 18. The (mean) weekly exercise time for low income individuals of age 50 was 1.6 hours as compared to 3.4 hours for high income group as seen in figure 19. The pattern was robust to all age group and sex. However, there are some relevant issues here with respect to using the exercise variable. It does not include exercise that might done in the form of walking to work or any work activity which is manual intensive.

County Level Patterns

The Food Environment and Food Access Atlas, released in August 2015, collects statistics on three broad categories food choices (access to grocery stores, fast food etc.), health and well-being (diabetes and obesity rates), and community characteristics (poverty, income). We use it to document county level estimates of uninsured across the poorest counties (defined as the counties with the highest number of people below FPL) as well as patterns of their food and health behavior. We see that poorest of the counties were also the ones with highest number of uninsured individuals as well as the ones with lower fraction of diabetic patients going for a hemo-test as shown in table 13 and 15. In table 14, we document that poor counties have fewer stores per 1000 population, higher milk price compared to the national average, lower soda price and higher per capita fast food consumption.

4. Model

We first describe the model in which we assume that health is common knowledge at all times. As the individuals age, their health deteriorates. There is a stochastic component of health which can be thought of as getting infected by antigens in day-to-day life. This stochastic component can be thought of as consisting two parts: continuous deterioration/betterment of health and sudden illnesses. Individuals show symptoms of underlying disease(s) and their sudden illness depends on their symptoms. We can think of the symptoms as cough and mild fever which make individuals more susceptible to major illness such as pneumonia . Individuals exercise, knowing that it would help them maintain a healthy life and increase longevity and also avail medical treatments to improve their health. Other than the standard consumption-saving decisions, individuals face two crucial decisions: whether or not to buy private insurance at the actuary fair premium and subsequently, given their insurance status and wealth, when to go for a medical visit and invest in their health.

4.1 Individual's problem

We model health capital h_t in a parsimonious way and it follows a Levy process as described in (1).

$$dh_t = -\delta(e)hdt + \sigma^A h_t dZ_t^A - (1-\delta(x))h_t dN_t \tag{1}$$

$$dx_t = \sigma^B dZ_t^B \tag{2}$$

$$(\lambda(x), \delta(x)) = \begin{cases} \lambda^H, \delta^H \text{ if } x \geq \bar{x} \\ \lambda^L, \delta^L \text{ if } x < \bar{x} \end{cases} \tag{3}$$

Thus the model assumes that health naturally deteriorates at the rate $\delta(e)$ that depends on the amount of exercise that the individual engages in. An alternative interpretation of e could be smoking or other bad behavior or a combination of exercise and smoking: while exercise reduces the rate of natural deterioration, smoking or bad behavior increases it. There is a Brownian motion component that has zero variance as h goes to zero. The third element is a Poisson (with intensity $\lambda^i(x)$), that reduces the stock of health when there is a shock by $(1-\delta^i(x))h_t$. The process x_t capture symptoms and the behavior of the parameters $(\delta^i(x), \lambda^i(x))$ capture the assumption that when symptoms are "good" the probability of a health shock decreases and, conditional on one occurring, the consequences are less severe.

The budget constraint is standard and given by

$$dw_t = \left(rw_t + \theta_i(h)y(1-e-\ell) - c_t - p\right)dt$$

Here $\theta_i(h)$ is individual specific productivity which is an increasing function of health, ℓ is leisure, c is consumption and p is the health insurance premium. For clear illustration, we shut down the labor productivity channel for the results below.

Timing

Individuals are born with different initial wealth and productivity θ_i and initial health (note that we the initial health and wealth are assumed uncorrelated) and die when hit by the death poisson. Productivity is assumed constant across time. At time t, individuals of productivity θ_i observe their wealth w_t, and health h_t and decide whether or not to get a health insurance, I of premium p each period. For simplicity, a health insurance contract is drawn until the individual gets the treatment, after which the insurance contract is re-written. In this section, we would take the premium p as given. In the next section, we model the insurance firm's problem to endogenously determine the premium. Individuals observe their health h_t, wealth w_t, symptoms x_t and their (endogenous) insurance status and choose the optimal time to invest in their health capital by paying a fixed cost k.

Given their decision to invest in health capital, they choose the medical expenditure m_t which increases their health capital as described in equation 6 and their wealth as in equation 5. Put differently, the individuals determine their optimal stopping time to visit the doctor by paying a fixed monetary cost k. When they visit they doctor, they choose optimal medical expenditure m_t to invest in their health capital using a Cobb-Douglas technology with Total Factor Productivity (TFP) A and intensities α and $1-\alpha$ of m and h respectively. Note that in the current version of the model, there is no information asymmetry. In particular, we assume that individuals observe their health capital with/without medical visit. We leave more interesting version in which health capital cannot be observed perfectly, for later.

By Øksendal and Sulem (2005, Theorem 1.19), the solution to Levy SDEs (1 - **??**) exists and is unique under the assumptions of at most linear growth and Lipschitz continuity. Individual's problem can be written compactly as,

$$V(w_0, h_0, x_0, I_0) = \max_{c_s, \tau} E[\int_0^\tau e^{-\rho s} u(c_s, h_s) ds + e^{-\rho\tau} V^*(w', h', x', I')] \tag{4}$$

$$\begin{aligned} w' &= w - mq(I_0) - k && (5) \\ h' &= h + Am^\alpha h^{1-\alpha} && (6) \\ x' &= x_0 && (7) \end{aligned}$$

$$V^*(w', h', x', I') = \begin{cases} \max_{m, I'} \{V(w', h', x', I')\} \text{ if } mq(I_0) + k \leq w \; \& \; h' < h^*(age^9) \\ -\infty \text{ otherwise} \end{cases} \tag{8}$$

Claim: Optimal stopping would be $\tau(w, h, x, I)$.

Following Øksendal and Sulem (2005, Theorem 3.2) Integrovariational Inequality for Optimal Stopping, the maximization problem in 4 is same as solving the following HJBII in (9).

As described earlier, insurance is modeled from one stopping time to another. Thus, we can optimize on notation by ignoring I as a state variable. We will solve the value function for two insurance regimes and pick the maximum for different levels of health and wealth for optimal insurance choice.

$$\begin{aligned} \min\Big\{ &\rho V(w, h, x) - \max_c \{u(c, h) + V_w[\theta_i y + rw - c - p]\} - V_h[-\delta(e)h] \\ &- \frac{1}{2} V_{hh} \sigma^2 h^2 (1-h)^2 - \frac{1}{2} V_{xx} \sigma_B^2 - \lambda(x)[V(w, h\delta(x), x) - V(w, h, x)] \\ &- \lambda^H(h)[V^T - V(w, h, x)], V(w, h, x) - V^*(w', h', x') \Big\} = 0 \end{aligned} \tag{9}$$

As a first step in this section, we also ignore the time use component and assume that individuals derive utility from consumption and health in the functional form of equation (10)

$$u(c, h) = \frac{c^{1-\gamma}}{1-\gamma} + \omega \frac{h^{1-\sigma}}{1-\sigma} + B \tag{10}$$

[9] Note that for the ease of notation, we have suppressed age (a state variable). The only way age affects individuals decision is their ability to invest in health capital.

4.2 Insurance Company's Problem

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

$$I(w_0, h_0, x_0, p_0) = E[\int_0^{\tau} e^{-rs} p_0 ds + e^{-r\tau}(-m(w, h, x, p_0))] \tag{11}$$

subject to:

$$\begin{aligned} dh_t &= -\delta(e)hdt + \sigma^A h_t(1 - h_t)dZ_t^A - (1 - \delta(x))h_t dN_t && (12) \\ dx_t &= \sigma^B dZ_t^B && (13) \\ dw_t &= [\theta_i y(1 - e - l) + rw_t - c_t - p_0]dt && (14) \\ (\lambda(x), \delta(x)) &= \begin{cases} \lambda^H, \delta^H \text{ if } x \geq \bar{x} \\ \lambda^L, \delta^L \text{ if } x < \bar{x} \end{cases} && (15) \end{aligned}$$

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

$$\begin{aligned} rI(w, h, x, p_0) = p_0 + I_w[\theta_i y + rw - c - p_0] + I_h[-\delta(e)h] + \frac{1}{2} I_{hh}\sigma^2 h^2(1 - h)^2 + \frac{1}{2} I_{xx}\sigma_B^2 \\ + \lambda(x)[I(w, h\delta(x), x) - I(w, h, x))] \quad + \lambda^H(h)[0 - I(w, h, x))] \end{aligned} \tag{16}$$

$I(w, h, x, p_0)$ is the value of the insurance firm who is in contract with an individual for insurance premium p_0, whose wealth is w, health is h, symptoms is x. Value matching condition at exogenous stopping time for the firm is:

$$\lim_{w,h,x} I(w, h, x, p_0) = -m(w, h, x, p_0) \tag{17}$$

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

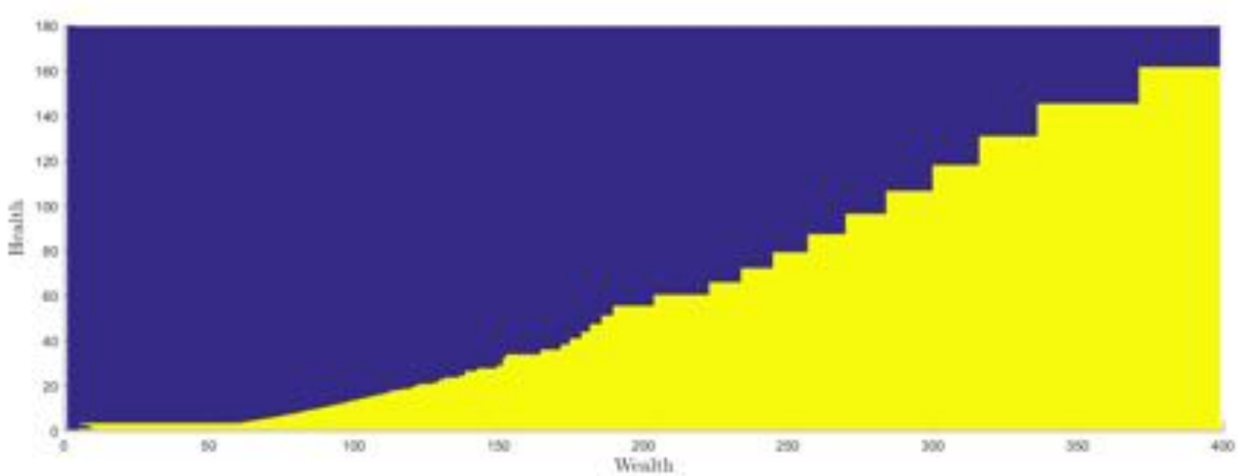
Since the firm is not choosing stopping time optimally, there would be no smooth pasting condition.

4.3 Solution: Baseline

We solve the model numerically as described in section 9 (Numerical Appendix). As mentioned earlier, as a first step, we solve the individual's problem for an exogenous premium. Based on the calibration described in table 17, we solve the consumer's optimal stopping time problem and present it in table 7. There are a few things to note:

- Because of the fixed cost, very low wealth individuals don't go to see the doctor, they

Figure 7: Policy Function: Optimal Stopping Time



Source: Model
Note: Yellow denote the optimal stopping region as a correspondance from wealth and health

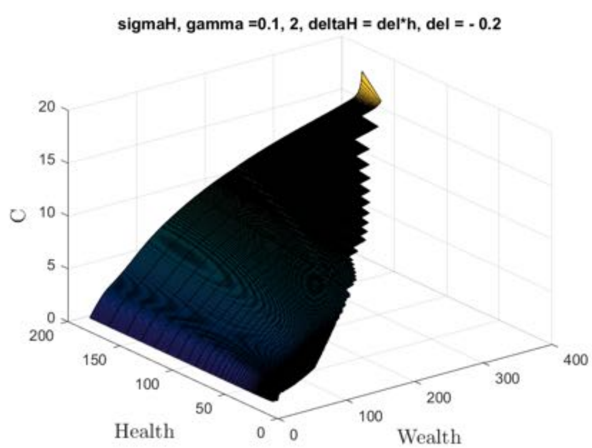


Figure 8: Policy Function: Consumption

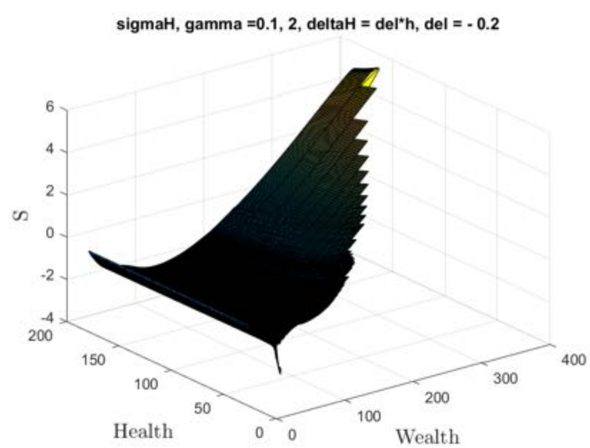


Figure 9: Policy Function: Savings

would wait for them to accumulate higher wealth by saving or once their health deteriorates further.

- There is a threshold health for each level of wealth, w, $h^*(w)$, such that if the health deteriorates below that threshold, the individuals go see the doctor. This threshold is increasing in wealth, i.e. wealthy individuals go see a doctor at a much higher health state compared to the poor individuals.

- Since the returns to medical investment depend on not just the technology but also the health, poorer individuals aren't able to improve their health even by spending the same amount of money, i.e. they don't get the bang for the buck.

Comparative Statistics If the fixed cost, k, goes up, the health threshold as a function of wealth shifts down, i.e. for same level of wealth, individuals lower their cutoff below which they go to the doctor. At the same time, conditional on going to the doctor, the expenditures shift up. This is intuitive since because of increased fixed cost, individuals go to doctor less frequenctly and spend more in each time.
High income individuals have a higher cutoff health as a function of wealth, i.e. for same level of wealth, individuals with higher level of income go sooner to the doctor.
As the overall productivity of medical technology improves, individuals go more frequently to the doctor and get better health even after paying the same amount of money. This also reduces the health inequality as described in table 9. Note that this requires an improvement in the productivity throughout rather than new technologies as discussed earlier. Full quantitative version of the model will have this dimension.

When $\delta(E)$ goes up, i.e. health depreciates faster, our model generates less frequency of medical investment. This is being generated because of substitutability between consumption and health in the utility function, i.e. if one good goes down, individuals substitute it with consumption. Full quantitative version of the model will allow for flexibility in complementarity between health and consumption which will be estimated using the data.

Table 9: Comparative Statistics: Productivity Increase

	Percentile of (Initial) Wealth		
	Bottom Third	Middle Third	Top Third
Life Expectancy	29.57	31.38	32.08
Medical Expenditure	2.50	2.70	2.98
Frequency of Visit	0.03	0.05	0.07

Notes: Life-expectancy is conditional on surviving until age 45. Frequency of visit is the fraction visiting the doctor per year in the simulation.

4.4 Calibration and Result

See table 17 for the initial set of parameters picked up for the model. The calibration is currently under-progress. The model is able to explain about 6 years in the gap in life-expectancy between the bottom third and top third wealth group as described in table 10. The model does well in predicting the relative similar levels of medical spending across wealth groups and also is able to capture overall increasing pattern of the frequency of visit by wealth.

Table 10: Baseline Model Patterns

	Percentile of (Initial) Wealth		
	Bottom Third	Middle Third	Top Third
Life Expectancy	22.13	24.44	28.73
Medical Expenditure	2.90	3.01	3.25
Frequency of Visit	0.03	0.05	0.10

Notes: Life-expectancy is conditional on surviving until age 45. Frequency of visit is the fraction visiting the doctor per year in the simulation.

5. Policy Experiment: Universal Health Insurance

Using the baseline model parameters, we can perform a policy experiment of Universal Health Insurance: what would happen to the health inequality, spending and frequency of visits if we were to give everyone a health insurance with 50% co-pay (fixed cost k) and 30% risk sharing (making $q(I_0) = 0.3$). To make the government budget balanced, we impose a flat 20% income-tax. We present the results in 11 where we see that such a policy leads to about 50% reduction in health inequality between the income groups. Importantly, such a policy is accompanied by slight increase in frequency of medical visits, where the increase at the lower income group is about 40% while at the top is 20%. The key implication is being driven by the change in stopping time function as shown in 28. The threshold h^* below which individuals go for a checkup, for each level of wealth, is higher than the one in baseline.

Table 11: Policy Experiment: Universal Health Insurance

	Percentile of (Initial) Wealth		
	Bottom Third	Middle Third	Top Third
Life Expectancy	28.91	31.69	32.43
Medical Expenditure	5.15	5.54	5.93
Frequency of Visit	0.05	0.08	0.12

Notes: Life-expectancy is conditional on surviving until age 45. Frequency of visit is the fraction visiting the doctor per year in the simulation.

6. Cross-validation: Insurance and Mortality

6.1 National Longitudinal Mortality Survey (NLMS)

National Longitudinal Mortality Survey (NLMS) is a longitudinal survey to study the differentials in mortality rates by socio-economic status and demographics. We use the Public Use Microdata Sample (PUMS) which is a multi-stage stratified sample of non-institutionalized population of the U.S. It is uniquely important for our purposes because it matches subsample of Census Bureau data from Current Population Surveys (CPS) with death certificate information to identify the mortality status and cause of death. In NLMS-PUMS version 5, we get three normalized waves for 1983, 1993, 2003 where they track the cause of death for 6 years starting the date of interview or one 1990 wave where they track the cause of death for 11 years.

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

6.2 Effect of Medicaid on Mortality

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

$$\alpha^{RD}(z^*) = \frac{P(Y_{t+6} = 1|z = 2) - P(Y_{t+6} = 1|z = 1)}{P(Medicaid = 1|z = 2) - P(Medicaid = 1|z = 1)} \tag{18}$$

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 12).

Table 12: Effect of Insurance on Mortality

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

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard Errors are in brackets.
Note: Outcome variable is mortality in the next 6 years across all columns. Marginal effects are tabulated. PSMxx stands for nearest neighbor Propensity Score Matching, RDxx stands for Regression Discontinuity, Logitxx shows the marginals of a simple logistic regression of whether or not an individual dies at the end of 6 years on insurance status, education, age, age sq, income, income square and sex (some of which have been suppressed from the table). xx denotes the corresponding wave number of NLMS, where 6a represents early 1980s, 6b represents early 1990s and 6c represents early 2000s.

6.3 Effect of Private Insurance on Mortality

We first estimate a logit regression of mortality on insurance, age, education and income. The exact specification is described in table 12 column 1, 3 and 5 for three waves of NLMS. Our reduced form regression specification in table suffers from potential selection problem. In particular, the decision to take up health insurance may not be random and the there could be idiosyncratic gains from treatment. In order to get around the selection problem, we use the propensity score matching estimator a la Heckman et al. (1998)[10]. Following Caliendo and Kopeinig (2008), our parameter of interest is the average treatment on the treated $\alpha^{ATT} = E[Y(1)|D=1] - E[Y(0)|D=1]$, where D is a dummy for insurance and Y is the probability of dying in the next 6 years[11]. We make the following identifying assumptions:

Assumption 1 (Conditional Independence Assumption): $Y(0), Y(1) \perp D|P(X)$

Assumption 2 (Common Support Assumption): $0 < P(D=1|X) < 1$

The estimator can be written as:

$$\alpha^{ATT}_{PSM} = E_{P(X)|D=1}\{E[P(Y_{t+6}=1)|D=1, P(X)] - E[P(Y_{t+6}=0)|D=0, P(X)]\} \tag{19}$$

We use nearest-neighbor matching and check for common support assumption in figure 23, 24 and 25 and leave out the bins without overlap to ensure that common support assumption is not violated. Our propensity score specification is the following:

$$P(D=1|age, sex, income) = \beta_0 + \beta_1 \text{ x } age + \beta_2 \text{ x } sex + \beta_3 \text{ x } income + \beta_4 \text{ x } education \tag{20}$$

Standard errors were calculating following Abadie and Imbens (2016) work on propensity score matching. Note that our matching estimate could still have some selection problem. In particular, we can only match based on observables. However, the selection could also be happening because of unobservables. As described in table 12, 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.

7. Conclusion

The paper investigates the role of insurance and technological progress on the rising health inequality across income groups in the US and finds a robust and economically significant effect of insurance on mortality outcomes. We then write down a parsimonious macro model with endogenous health capital in which individuals decide insurance take-up decision, the timing to visit the doctor and invest in their health capital to generate the patterns we see in data. A simple version of the model is able to explain about 50% of the gap in life-expectancy across income groups observed in data. In our model, consistent with the pattern in data, uninsured individuals, having deferred the treatment aren't able to reap the benefits of the technological

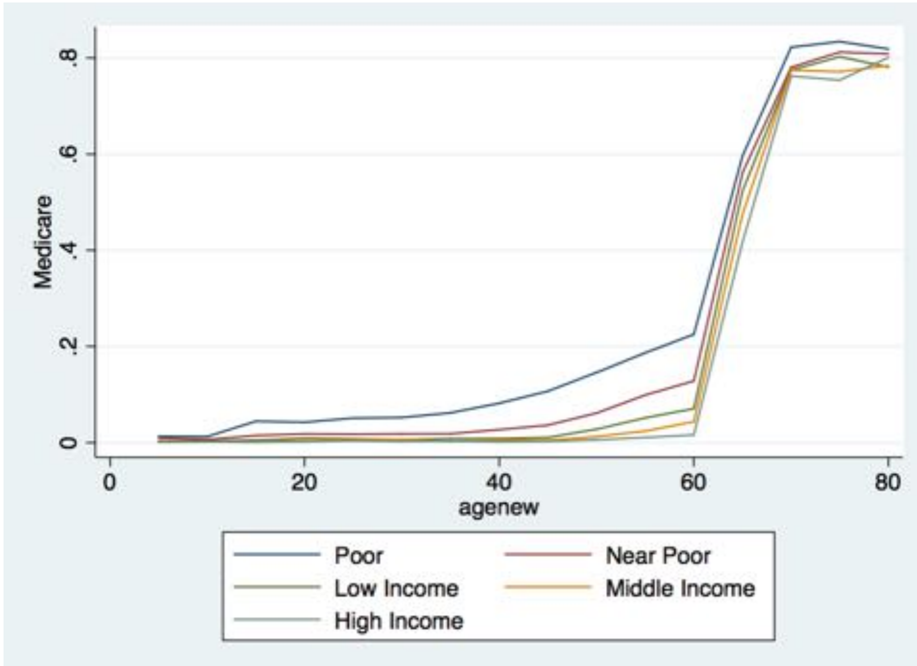
[10]See Heckman et al. (1998), Todd (1999) and Blundell and Dias (2009) for a detailed overview of the alternative approaches.

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

progress, thus resulting in poorer outcomes. The policy simulation with a plausible public health insurance scheme reduces the disparity in health outcomes to half. Our preliminary findings, suggest that public insurance could go a long way in ensuring health equity in the US.

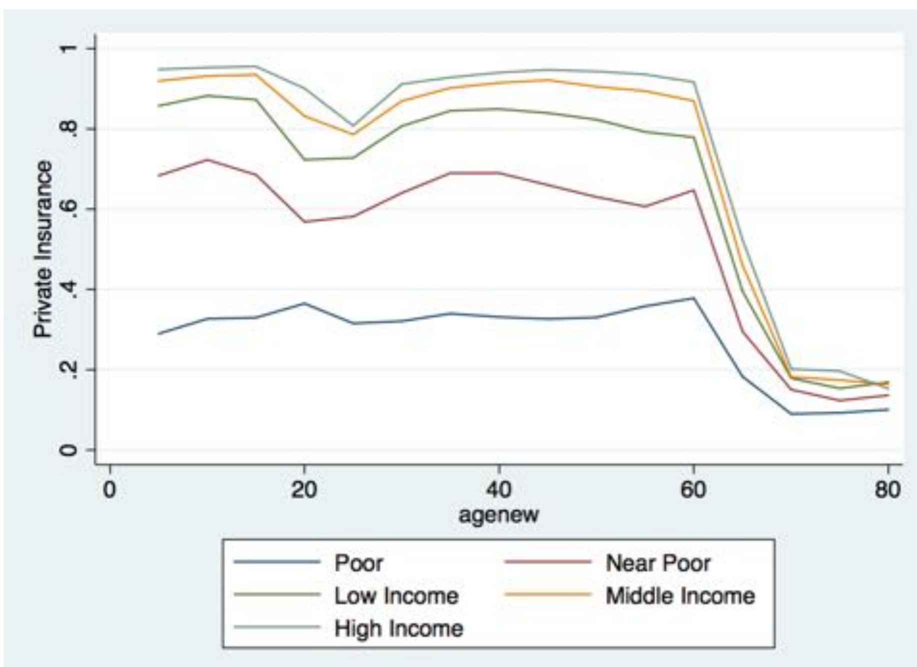
8. Figures

Figure 10: Fraction with Medicaid by Income



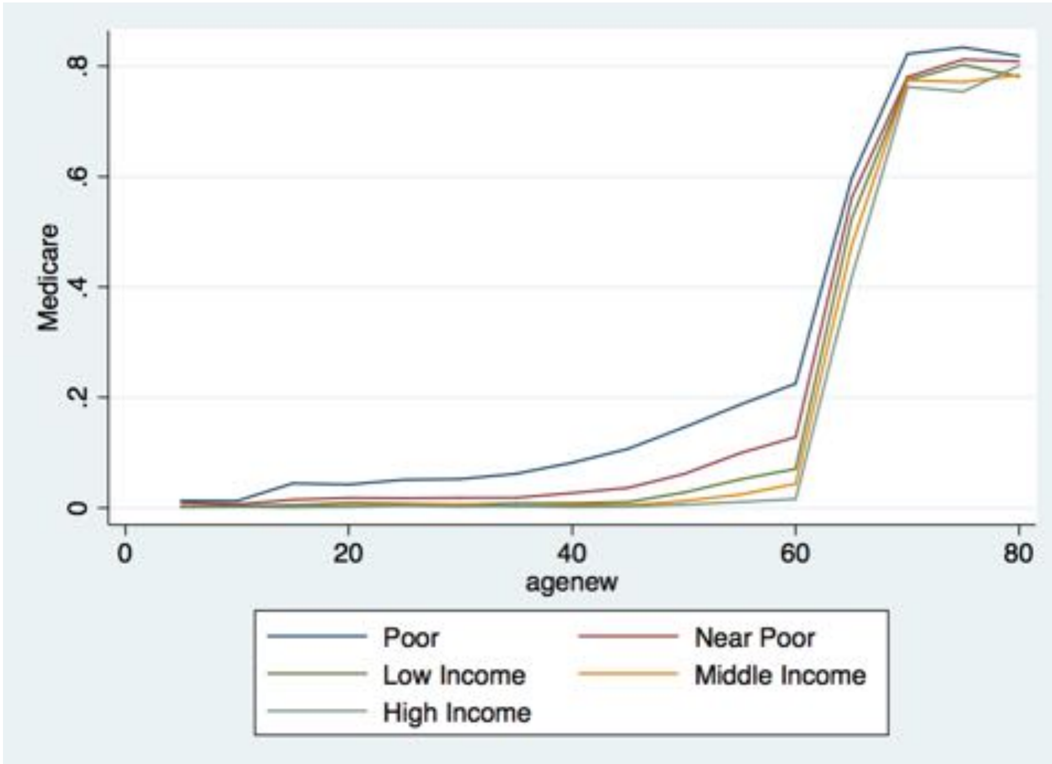
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 11: Fraction with Private Insurance by Income and Age



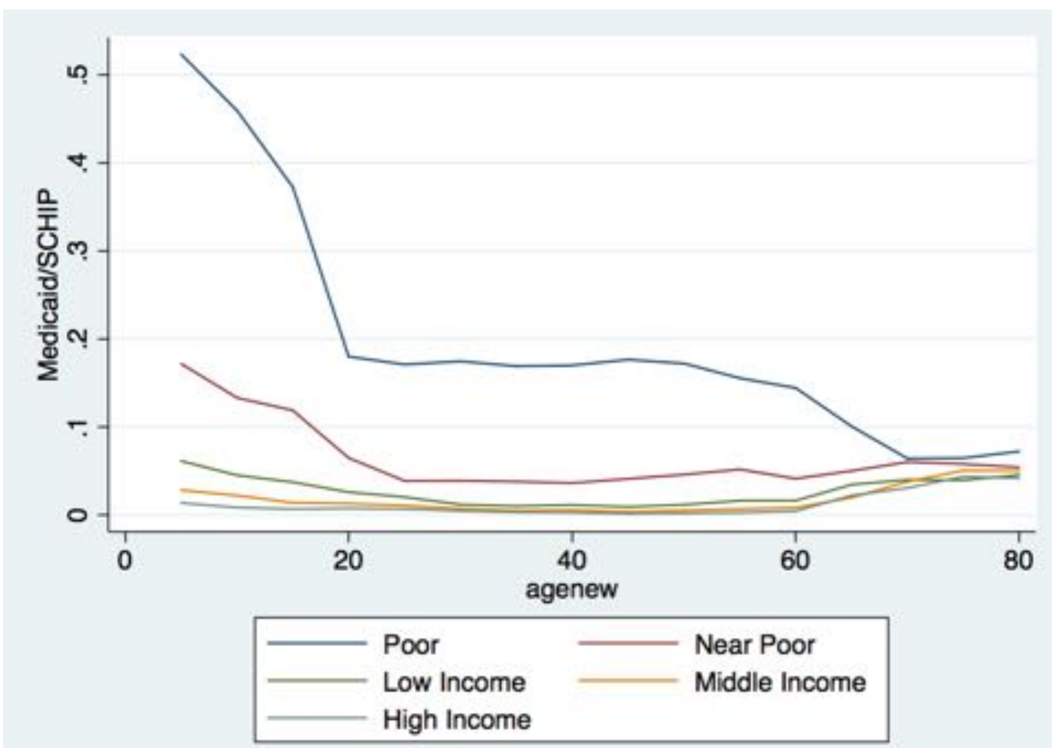
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 12: Fraction with Medicare by Income



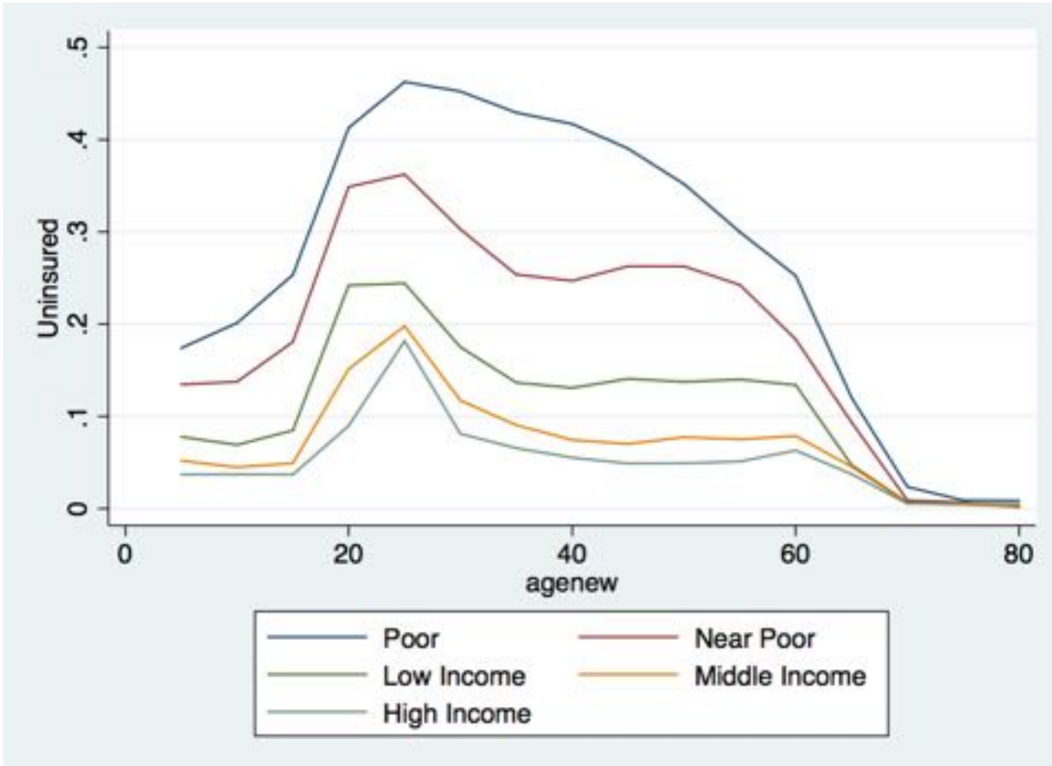
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 13: Fraction with Medicaid and SCHIP by Income and Age



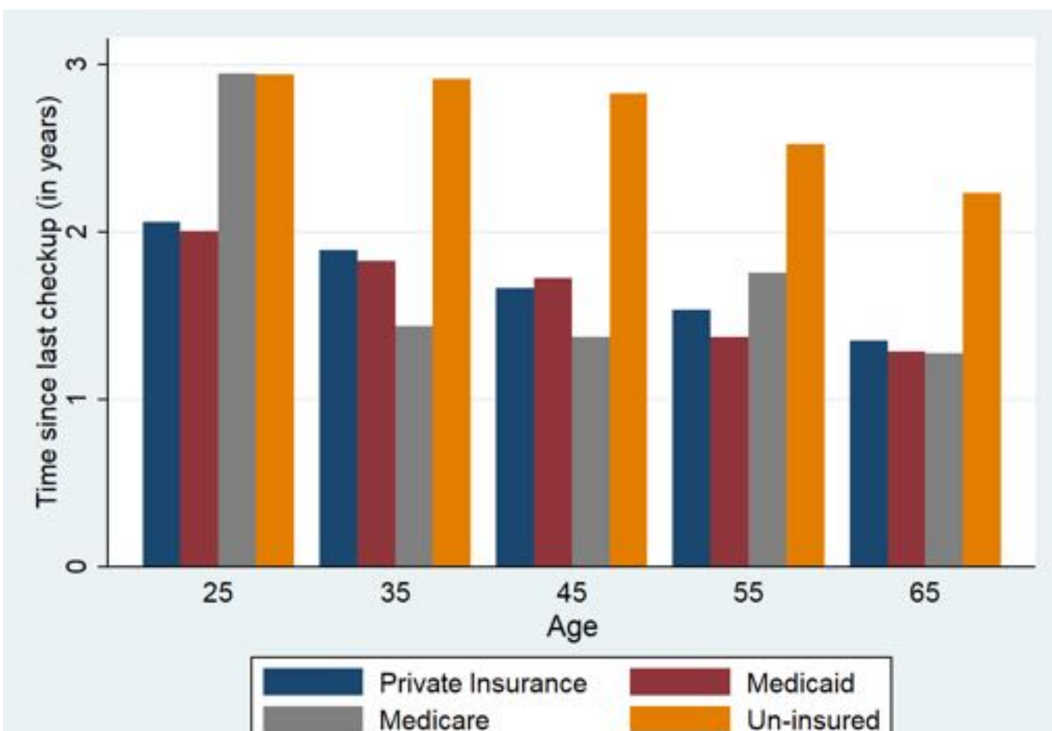
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 14: Fraction Uninsured by Income and Age



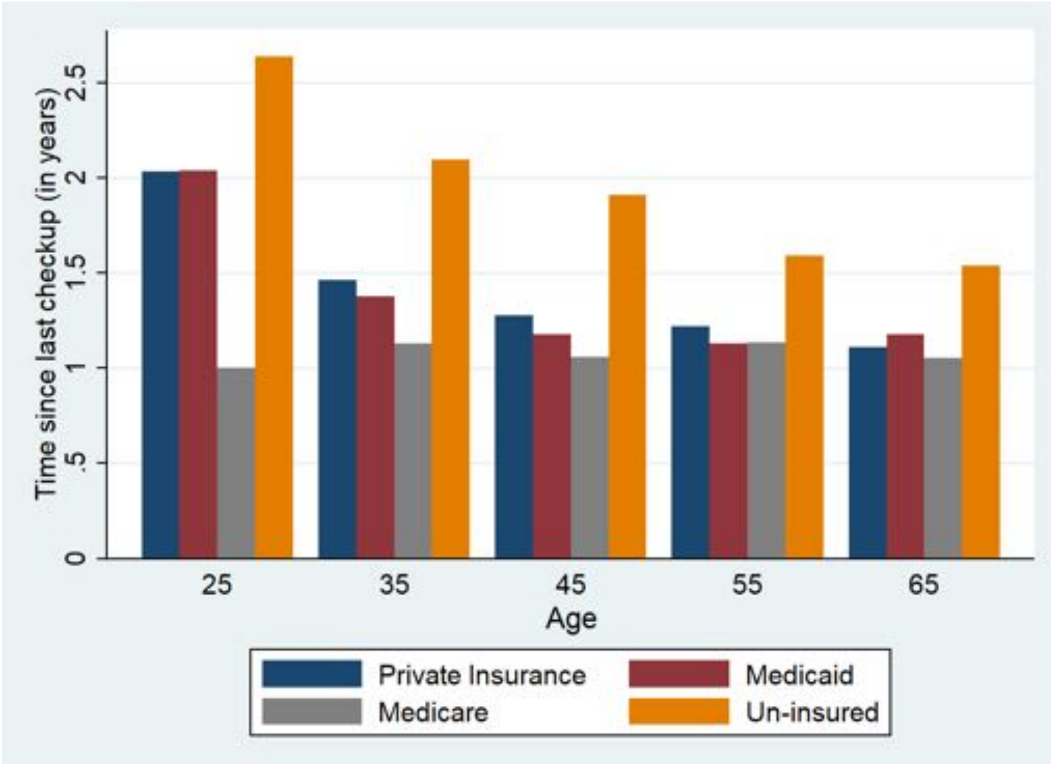
Source: Author's Calculation based on NLMS Data (early 2000s Wave)

Figure 15: Time Since Checkup (in years)



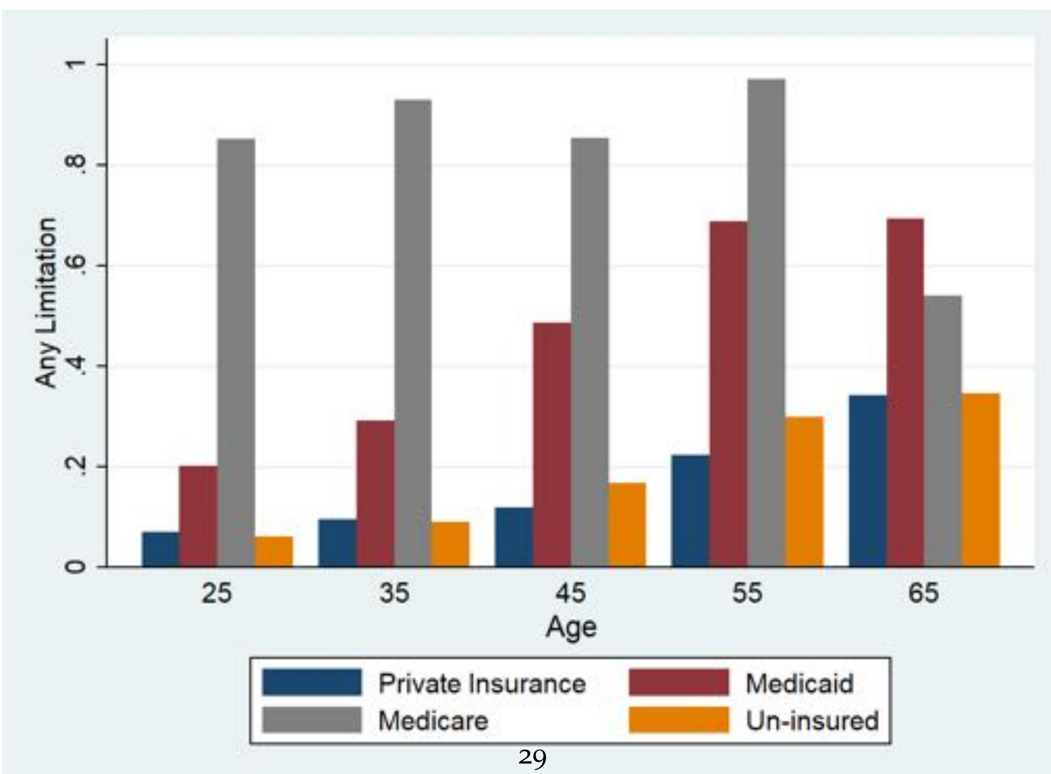
Source: Author's Calculation based on MEPS Data

Figure 16: Time Since Cholesterol Checkup (with pre-existing condition)



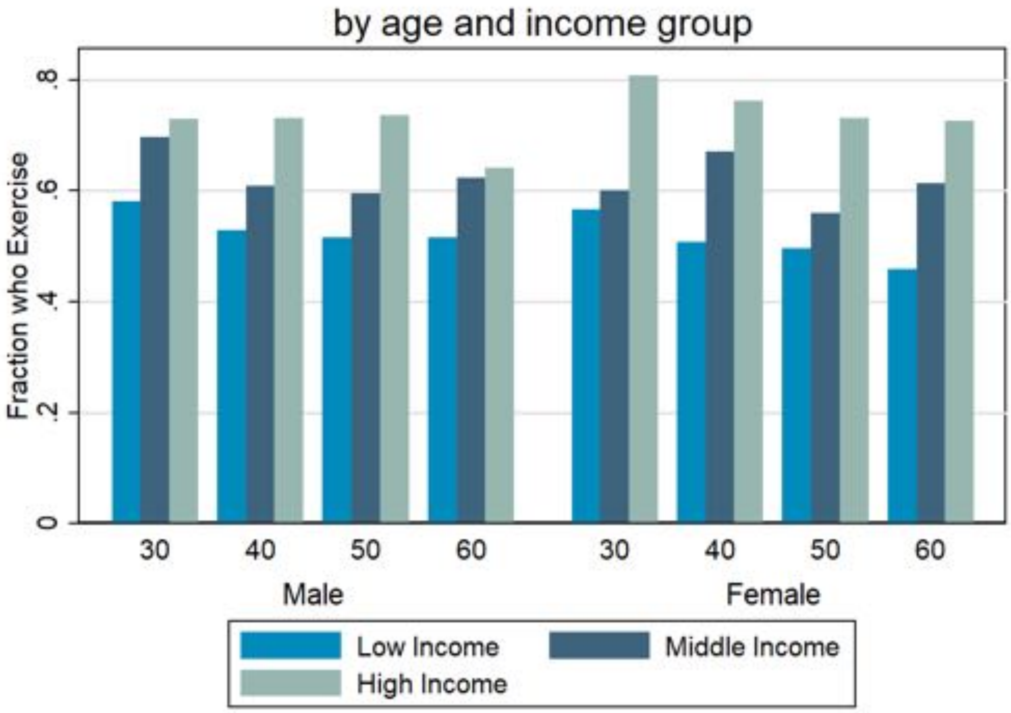
Source: Author's Calculation based on MEPS Data

Figure 17: Any Limitation by Age and Insurance Status



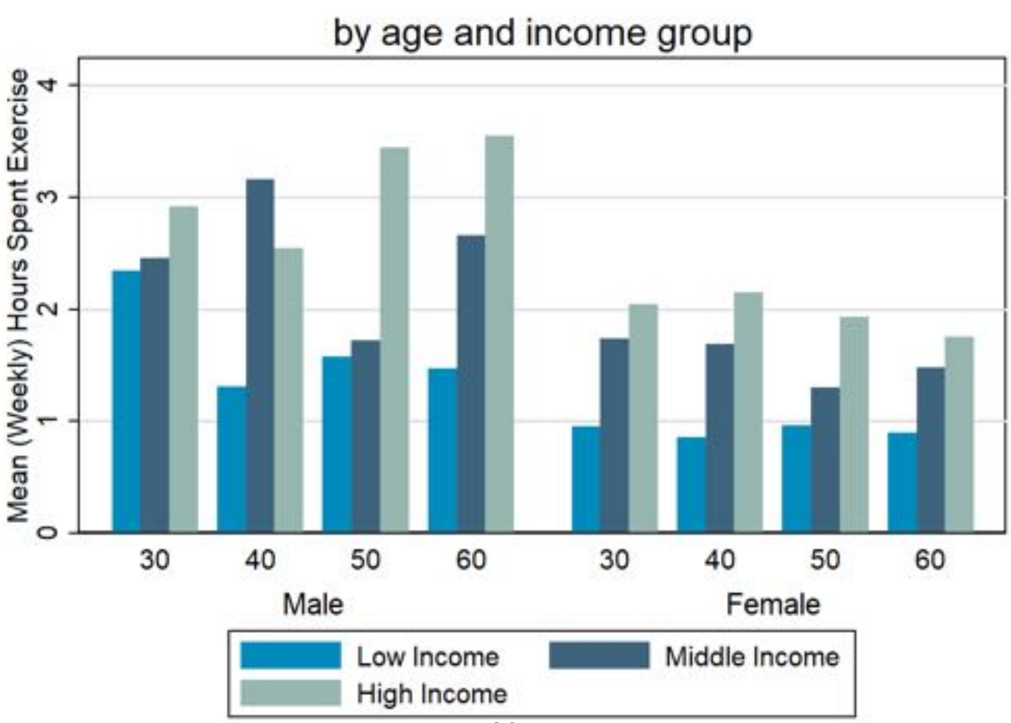
Source: Author's Calculation based on MEPS Data

Figure 18: Fraction Who Exercise by Age and Income



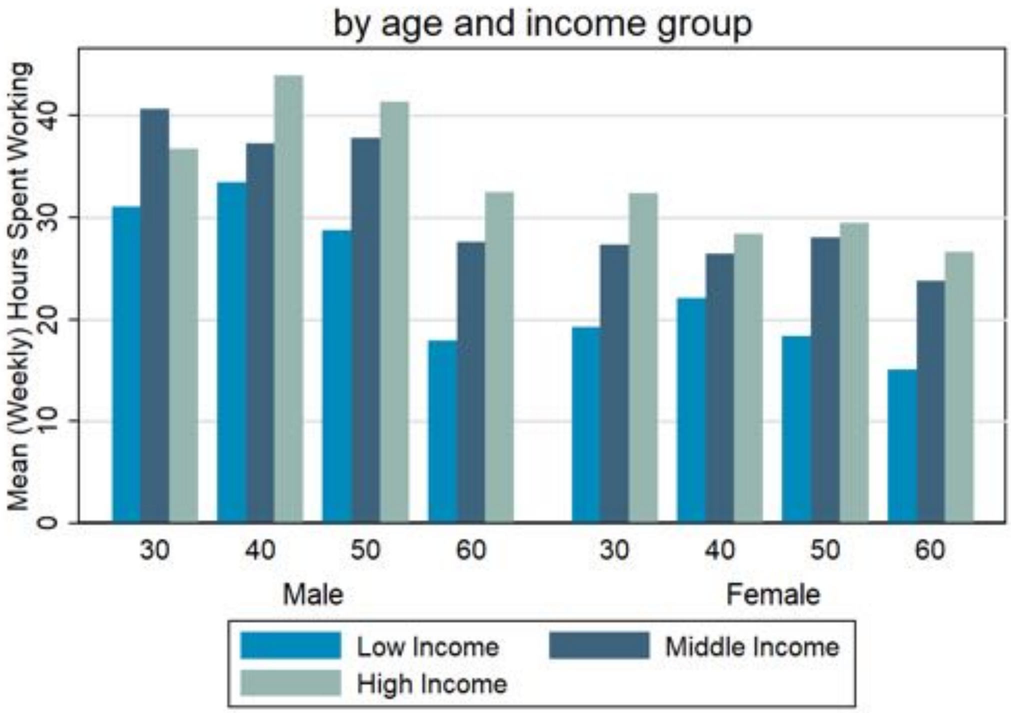
Source: Author's Calculation based on ATUS Eating and Health Module 2015 Data

Figure 19: Weekly Exercise Time by Age and Income



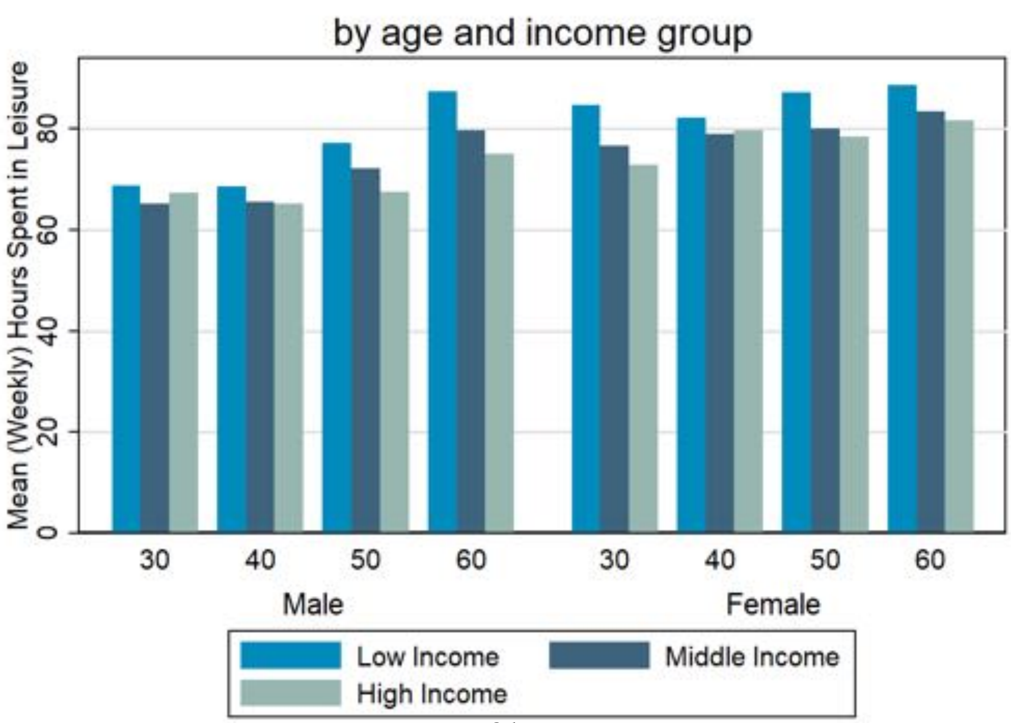
Source: Source: Author's Calculation based on ATUS 2015 Data

Figure 20: Weekly Working Time by Income and Age



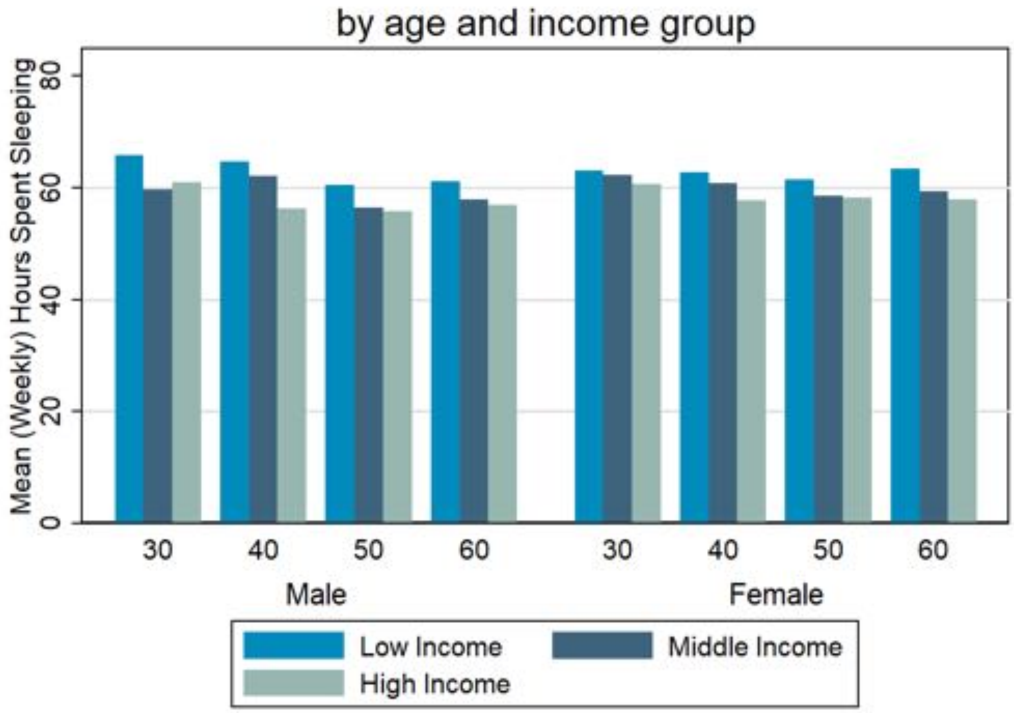
Source: Author's Calculation based on ATUS 2015 Data

Figure 21: Weekly Leisure Time by Age and Income



Source: Author's Calculation based on ATUS 2015 Data

Figure 22: Weekly Sleeping Time by Income and Age



Source: Author's Calculation based on ATUS 2015 Data

Figure 23: Support for Propensity Score Matching, Wave 6a

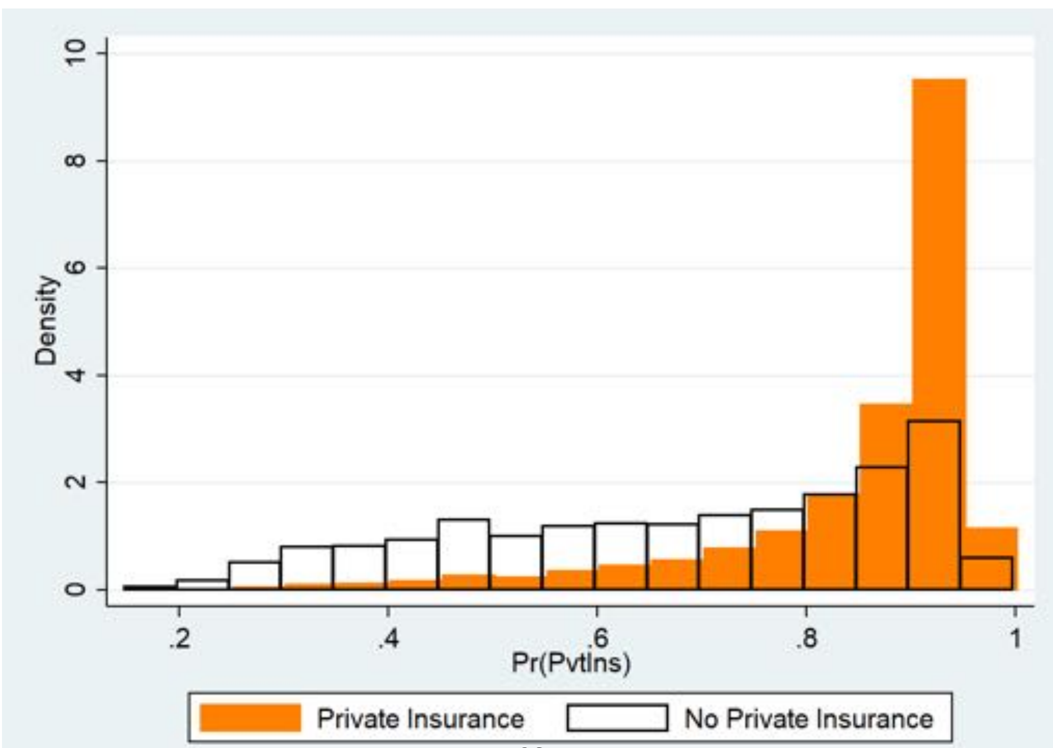


Figure 24: Support for Propensity Score Matching, Wave 6b

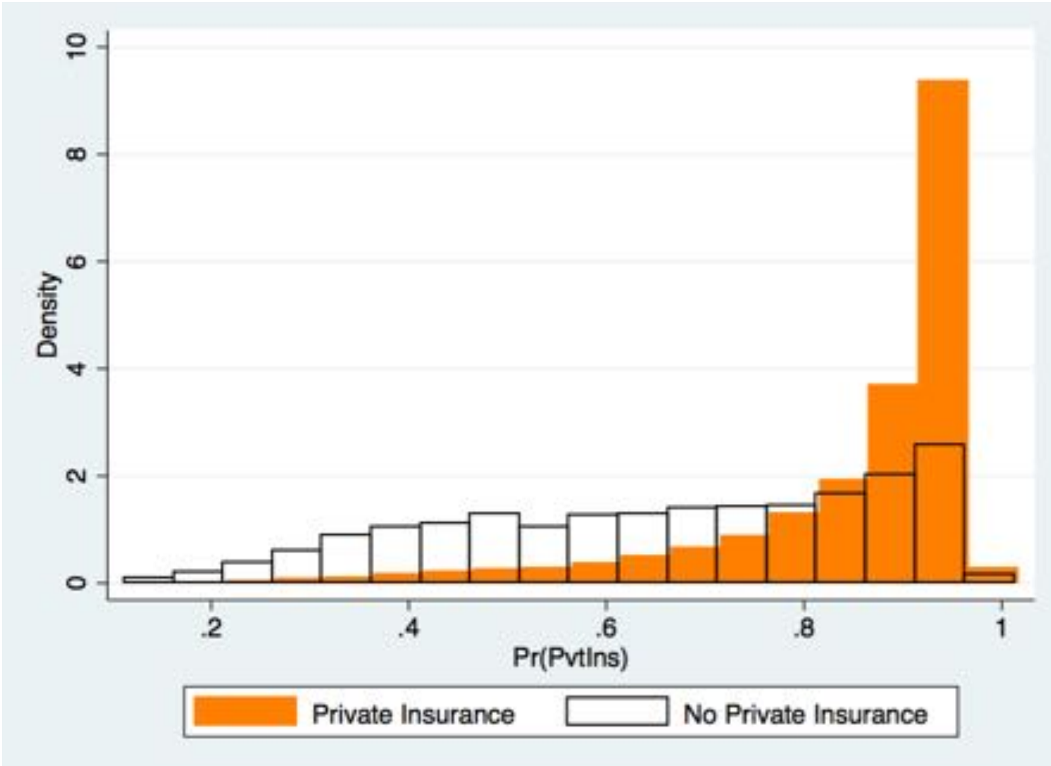


Figure 25: Support for Propensity Score Matching, Wave 6c

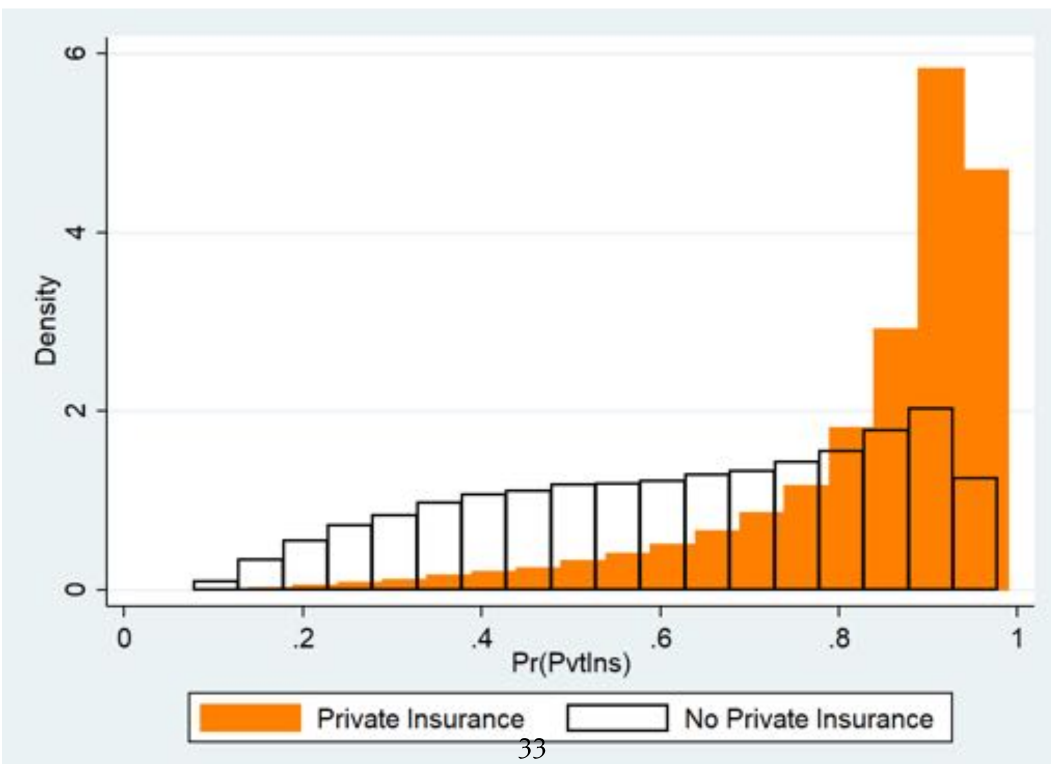
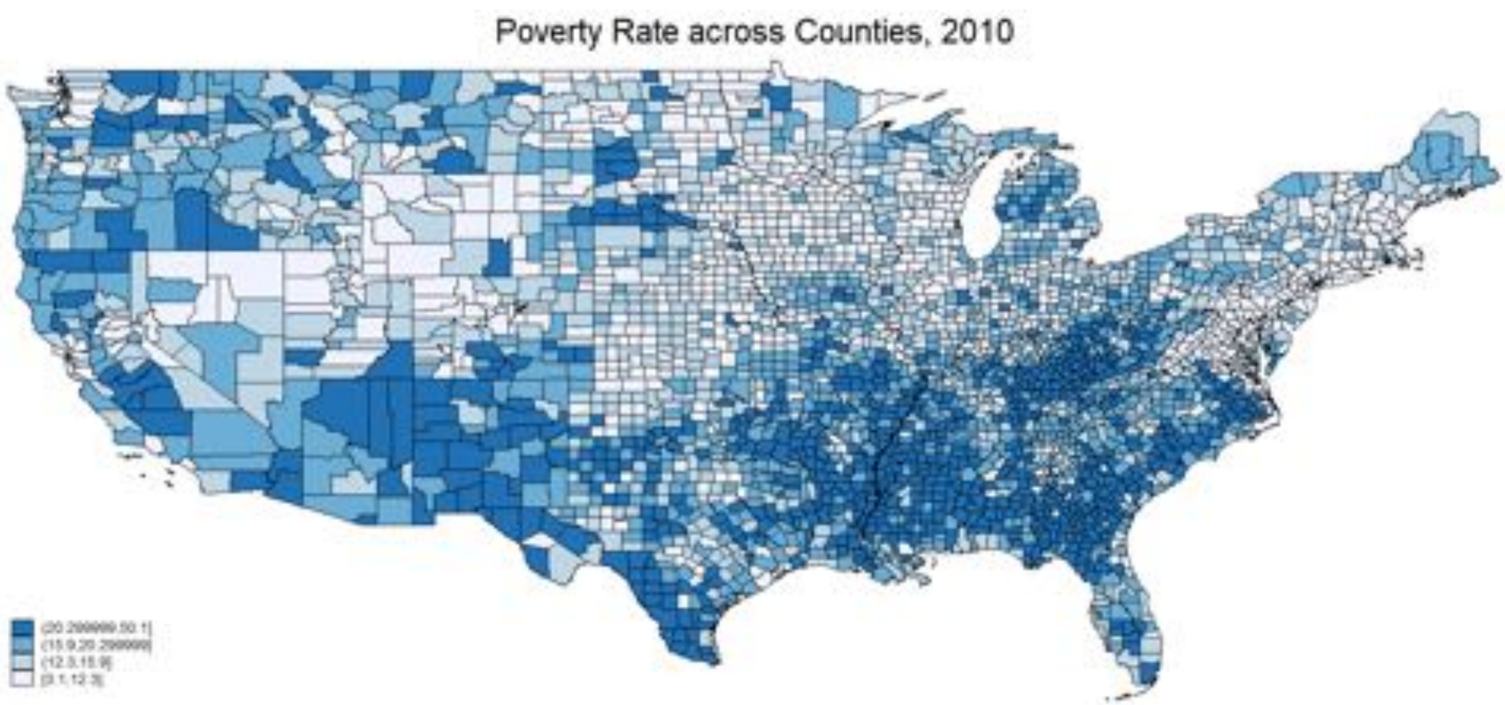


Figure 26: Grocery Stores across Counties, 2007

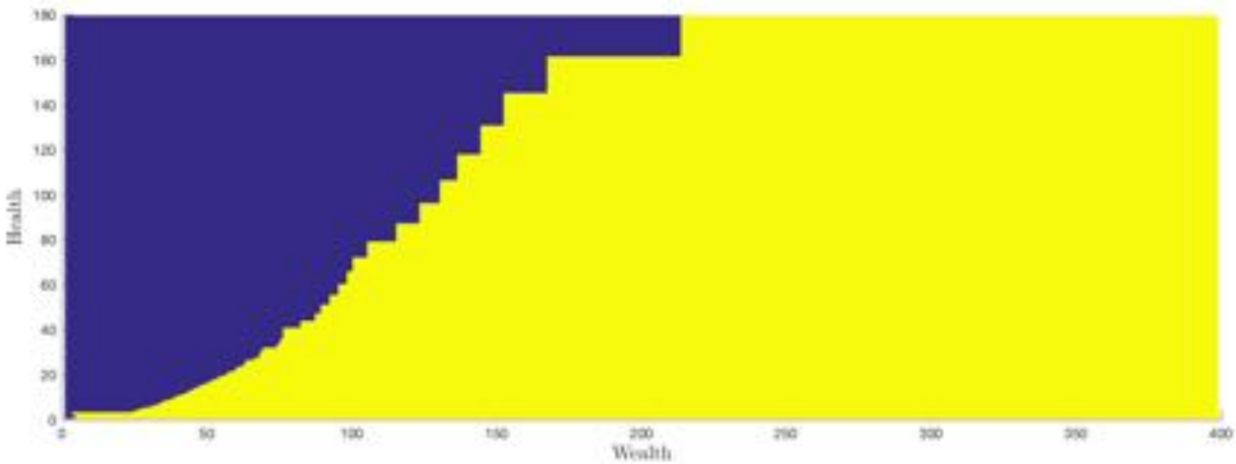
Source: Author's Calculation based on Food Environment and Food Access Atlas 2015

Figure 27: Poverty Rate across Counties, 2010



Source: Author's Calculation based on Food Environment and Food Access Atlas 2015

Figure 28: Counterfactual Policy Function: Optimal Stopping Time under Universal Health Insurance



Source: Model

Note: Yellow denote the optimal stopping region as a correspondance from wealth and health

9. Tables

Table 13: Health Outcome Across Counties

	% Uninsured	% Diabetic with Hemotest
% BPL: Medium	4.2097***	-0.4912**
	[0.1973]	[0.2450]
% BPL: High	7.6040***	-3.1133***
	[0.2024]	[0.3475]
% Uninsured: Medium		-1.2442***
		[0.2620]
% Uninsured: High		-3.5056***
		[0.3296]
Constant	14.5802***	86.3983***
	[0.1345]	[0.1596]

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard Errors are in brackets.
Baseline: Counties with low fraction of population Below Poverty Line and low fraction of uninsured

Table 14: Access to Food Across Counties

	Stores per 1000	Milk Price	Soda Price	Fast Food exp pc
% BPL: Medium	-0.1222***	0.0069	-0.0070**	22.2692***
	[0.0353]	[0.0053]	[0.0027]	[4.3013]
% BPL: High	-0.3426***	0.0697***	-0.0163***	56.6994***
	[0.0313]	[0.0050]	[0.0025]	[4.0020]
Constant	1.4059***	0.9473***	0.9995***	615.3544***
	[0.0264]	[0.0038]	[0.0019]	[3.0817]

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard Errors are in brackets.
Baseline: Counties with low % of population Below Poverty Line

Table 15: Health Outcome Across Counties

	%Obese	%Diabetic	%Food Insecurity
% BPL: Medium	1.3492***	1.2407***	1.2477***
	[0.1664]	[0.0768]	[0.0965]
% BPL: High	3.8604***	2.7035***	2.2341***
	[0.1770]	[0.0882]	[0.0986]
Constant	28.8308***	9.4045***	12.3097***
	[0.1213]	[0.0507]	[0.0701]

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard Errors are in brackets.
Baseline: Counties with low % of population Below Poverty Line

Table 16: List of Variables

Variable	Meaning
h	Health Capital
w	Wealth
x	Symptoms
e	Exercise Time
l	Leisure Time
c	Consumption
m	Investment in Medical Technology
I	Indicator Variable for Health Insurance

Table 17: List of Parameters

Parameter	Meaning	Value
$\bar{x}$	Symptoms Cutoff	-0.5
θ_i	Productivity of Individual i	1
y	Income	1
r	Risk Free Rate	0.05
ρ	Discount rate	0.06
$\delta(e)$	Deterioration of health as a function of exercise time	0.2 (constant for now)
$\delta^H(\delta^L)$	Fraction of Health Left in regime H(L)	0.5(0.8)
$\lambda^H(\lambda^L)$	Probability of Jump in regime H(L)	0.3(0.05)
σ^A	sd associated with the diffusion term of health capital	multiple values
σ^B	sd associated with the diffusion term of symptoms	0.5
k	Fixed Cost Associated with Health Investment	2
$q(I)$	Co-pay Fraction	1 (no insurance)
p	Health Insurance Premium	0
A	Medical Technology TFP	0.5
α	Cobb Douglas Intensity	0.7
ω	Intensity of Health in Utility	0.2
γ	Curvature of Utility Function w.r.to. c	2
B	Making Flow Utility Positive	0
V^T	Exit Value	-90
σ	Curvature of utility w.r.to. health	1.051

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Appendix

Numerical Appendix

Writing the HJBII described in section [to be added].

$$\min\Big\{\rho V(w,h,x) - \max_c\{u(c,h) + V_w[\theta_i y + rw - c - p]\} - V_h[-\delta(e)] - \frac{1}{2}V_{hh}\sigma^2 h^2(1-h)^2 \\ - \frac{1}{2}V_{xx}\sigma_B^2 - \lambda(x)[V(w,h\delta(x),x) - V(w,h,x))], V(w,h,x) - V^*(w',h',x')\Big\} = 0 \tag{1}$$

$$u(c,h) = \frac{(c^\omega h^{1-\omega})^{1-\gamma}}{1-\gamma} + B \tag{2}$$

$$u_c(c,h) = \omega(c^\omega h^{1-\omega})^{-\gamma} c^{\omega-1} h^{1-\omega} \tag{3}$$

FOC w.r.t. c

$$V_w = u_c(c,h) \tag{4}$$

$$c = \left[\frac{V_w}{\omega h^{(1-\omega)(1-\gamma)}}\right]^{\frac{1}{\omega-1-\omega\gamma}} \tag{5}$$

Algorithm for solving HJBII[12]

(See Appendix of Achdou et al. (2017) for a detailed discussion) We use the implicit method described by Moll [TO BE ADDED]. Refer to his notes for a detailed discussion on the alternative methods for numerically solving HJBVI.

$$\text{Standard HJB: } \rho V = u + \vec{A}V \tag{6}$$

$$\text{HJBII: } \min\{\rho V - u - \vec{A}V, V - V^*\} = 0 \tag{7}$$

Equivalently,

$$(V - V^*)'(\rho V - u - \vec{A}V) = 0 \tag{8}$$

$$V \geq V^* \tag{9}$$

$$\rho V - u - \vec{A}V \geq 0 \tag{10}$$

$$\text{Let } z = V - V^*,\ \vec{B} = \rho\vec{I} - \vec{A} \text{ and } q = -u + \vec{B}V^* \tag{11}$$

[12]I am grateful to Benjamin Moll for generously providing his codes and detailed notes on HACT website.

Thus, the system becomes an Linear Complementary Problem (LCP)

$$(z)'(\vec{B}z + q) = 0 \tag{12}$$
$$z \geq 0 \tag{13}$$
$$\vec{B}z + q \geq 0 \tag{14}$$

Writing HJB in discrete version

$$\frac{V_{i,j,k}^{n+1} - V_{i,j,k}^{n}}{\Delta} + \rho V_{i,j,k}^{n+1} = u(c_{i,j,k}^{n}) + V_{w}^{n+1}[s_{i,j,k}^{w,n}] + V_{h}^{n+1}[s_{i,j,k}^{h,n}] + \frac{1}{2}V_{hh}^{n+1}\sigma_A^2 h^2(1-h)^2 \tag{15}$$
$$+ \frac{1}{2}V_{xx}^{n+1}\sigma_B^2 + \lambda(x)[V_{i,j',k}^{n} - V_{i,j,k}^{n}]$$

$$\begin{aligned}
\partial_{w,B}V_{i,j,k} &= \frac{V_{i,j,k} - V_{i-1,j,k}}{\Delta w} && (16)\\
\partial_{w,F}V_{i,j,k} &= \frac{V_{i+1,j,k} - V_{i,j,k}}{\Delta w} && (17)\\
\partial_{hh}V_{i,j,k} &= \frac{V_{i,j+1,k} - 2V_{i,j,k} + V_{i,j-1,k}}{(\Delta h)^2} && (18)\\
\partial_{xx}V_{i,j,k} &= \frac{V_{i,j,k+1} - 2V_{i,j,k} + V_{i,j,k-1}}{(\Delta x)^2} && (19)\\
\partial_{h,B}V_{i,j,k} &= \frac{V_{i,j,k} - V_{i,j-1,k}}{\Delta h} && (20)\\
\partial_{h,F}V_{i,j,k} &= \frac{V_{i,j+1,k} - V_{i,j,k}}{\Delta h} && (21)\\
j' &= j\delta(x) && (22)
\end{aligned}$$

$$\begin{aligned}
s_{i,j,k}^{w,n,B} &= [\theta_i y + rw - c^{B,n} - p] && (23)\\
s_{i,j,k}^{w,n,F} &= [\theta_i y + rw - c^{F,n} - p] && (24)\\
s_{i,j,k}^{h,n} &= [-\delta(e)] && (25)
\end{aligned}$$

$$\begin{aligned}
V_w(w_i, h_j, x_k)s_{i,j,k}^{w,n} &\approx \partial_{w,B}V_{i,j,k}(s_{i,j,k}^{w,n,B})^- + \partial_{w,F}V_{i,j,k}(s_{i,j,k}^{w,n,B})^+ && (26)\\
V_h(w_i, h_j, x_k)s_{i,j,k}^{h,n} &\approx \partial_{h,B}V_{i,j,k}(s_{i,j}^{h,n}) && (27)
\end{aligned}$$

Thus,

$$\frac{V^{n+1}_{i,j,k} - V^{n}_{i,j,k}}{\Delta} + \rho V^{n+1}_{i,j,k} = u(c^{n}_{i,j,k}) + \frac{V^{n+1}_{i,j,k} - V^{n+1}_{i-1,j,k}}{\Delta w}(s^{w,n,B}_{i,j,k})^{-} + \frac{V^{n+1}_{i+1,j,k} - V^{n+1}_{i,j,k}}{\Delta w}(s^{w,n,F}_{i,j,k})^{+}$$
$$+ \frac{V^{n+1}_{i,j,k} - V^{n+1}_{i,j-1,k}}{\Delta h}(s^{h,n,B}_{i,j,k})^{-} + \sigma_A^2 h^2(1-h)^2 \frac{V^{n+1}_{i,j+1,k} - 2V^{n+1}_{i,j,k} + V^{n+1}_{i,j-1,k}}{2(\Delta h)^2} \quad (28)$$
$$+ \frac{V^{n+1}_{i,j,k+1} - 2V^{n+1}_{i,j,k} + V^{n+1}_{i,j,k-1}}{2(\Delta x)^2}\sigma_B^2 + \lambda(x)[V^{n}_{i,j',k} - V^{n}_{i,j,k}]$$

$$V^{n+1}_{i,j,k} : Y_{i,j} = \left[\frac{(s^{w,n,B}_{i,j,k})^{-} - (s^{w,n,F}_{i,j,k})^{+}}{\Delta w}\right] \quad (29)$$
$$yy_{i,j} = \left[\frac{(s^{h,n,B}_{i,j,k})^{-}}{\Delta h} - \frac{\sigma_A^2 h^2(1-h)^2}{(\Delta h)^2}\right] \quad (30)$$
$$yyy_{i,j} = \left[-\frac{\sigma_B^2}{(\Delta x)^2}\right] \quad (31)$$
$$V^{n+1}_{i,j-1,k} : XJ_{i,j} = \left[-\frac{(s^{h,n,B}_{i,j,k})^{-}}{\Delta h} + \frac{\sigma_A^2 h^2(1-h)^2}{2(\Delta h)^2}\right] \quad (32)$$
$$V^{n+1}_{i+1,j,k} : Z_{i,j} = \left[\frac{(s^{w,n,F}_{i,j,k})^{+}}{\Delta w}\right] \quad (33)$$
$$V^{n+1}_{i-1,j,k} : X_{i,j} = \left[-\frac{(s^{w,n,B}_{i,j,k})^{-}}{\Delta w}\right] \quad (34)$$

$$V^{n+1}_{i,j+1,k} : YJ_{i,j} = \left[\frac{\sigma_A^2 h^2(1-h)^2}{2(\Delta h)^2}\right] \quad (35)$$
$$V^{n+1}_{i,j,k+1} : ZK_{i,j} = \left[\frac{\sigma_B^2}{2(\Delta x)^2}\right] \quad (36)$$
$$V^{n+1}_{i,j,k-1} : XK_{i,j} = \left[\frac{\sigma_B^2}{2(\Delta x)^2}\right] \quad (37)$$

Converting into implicit method for Value Function Iteration,

$$\min\left\{\frac{V^{n+1} - V^{n}}{\Delta} + \rho V^{n+1} - u(V^{n}) - \vec{A}(V^{n})V^{n+1}, V^{n+1} - V^{*}(V^{n})\right\} = 0$$