NBER WORKING PAPER SERIES

MEDICAL INNOVATION AND HEALTH DISPARITIES

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Working Paper 28864
http://www.nber.org/papers/w28864

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2021, Revised November 2022

Previously circulated as "Innovation and Health Disparities During an Epidemic: The Case of HIV." *First version: May 22, 2021. This version: November 8, 2022. We are grateful for helpful suggestions and comments from seminar participants in the Hopkins Economics Applied Micro Brownbag Seminar, the Annual Health Econometrics Workshop, and the University of Copenhagen CEBI Workshop. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 28864
May 2021, Revised November 2022
JEL No. I12,I14,I20,J2,O31

ABSTRACT

Health-maximizing and welfare-maximizing behaviors can be at odds, especially among disadvantaged groups, generating health disparities. We estimate a lifecycle model of medication and labor supply decisions using data on HIV-positive men. We evaluate an effective HIV treatment innovation that had harsh side effects: HAART. Measured in lifetime utility gains, HAART disproportionately benefitted higher-education men. Lower-education men were more likely to avoid the side effects of HAART that interfered with work. A counterfactual mandate to use HAART improves health but increases inequality because low-education individuals work less. A counterfactual non-labor income subsidy increases HAART adoption and improves health among lower-education individuals.

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1 Introduction

Volumes of research across several disciplines document persistent health disparities across sociodemographic groups, such as race, ethnicity, gender identity, income or education. For example, people without a high school diploma are 6–7 times more likely to be in poor or fair health compared to those with a bachelor's degree or higher (Goldman and Smith, 2011). Explanations often point to prices and other barriers that restrict access to high quality medications, especially expensive new treatments. An alternative explanation, often posited in opposition to the access story, is that heterogeneous preferences drive variation in health investments and thus generate health disparities.

Focussing on these two channels presents a false dichotomy. The access explanation minimizes the role of individual decision-making. Meanwhile, the preference explanation downplays the circumstances, contexts and constraints under which individuals from different sociodemographic groups must make their choices. Both overlook how health-maximizing and welfare-maximizing behaviors can often be at odds—and that this can be especially true in the types of economic contexts disadvantaged individuals face, which can thus generate health disparities. For example, effective medication often has side effects that can interfere with an individual's ability to work, especially in the types of low-wage, physically taxing or inflexible jobs that are available to people with relatively low levels of human capital. In this case, health disparities do not arise from a lack of access to medication or by variation in preferences *per se*. Instead, they are driven by a tradeoff between health and work that is particularly salient for disadvantaged individuals.

Viewing health disparities in this way has natural implications for evaluating medical innovation, including its distributional impacts across sociodemographic groups. Compared to existing treatments, new drugs are often more effective at treating illness, but have harsher side effects. A new drug can thus widen the wedge between choices that maximize health (e.g., taking the effective new drug despite side effects) versus welfare (e.g., avoiding medication to remain at work), especially for disadvantaged groups for whom working while taking the state-of-the-art treatment becomes untenable. If so, more advantaged patients disproportionately benefit

from the new drug, which means medical innovation can exacerbate existing health disparities.

In this paper, we examine the interplay between innovation and health disparities. We develop a lifecycle model in which individuals make repeated medication and labor supply decisions to maximize their lifetime welfare. Treatments can improve long-run health and survival, but can also have immediate side effects that discourage employment and thus decrease consumption. As constructed, the model can rationalize behavior that leads health to deteriorate since individuals are not viewed as maximizing solely survival or some other measure of health. However, the model can easily accommodate the possibility that individuals may not face much of a tradeoff at all between health and welfare if, for example, utility-maximizing actions are fully compatible with behavior that improves health. Crucially, the model is fully interacted by education (dichotomized as a college degree or higher versus no college degree). This interaction means individuals with different levels of education may face different tradeoffs between health and welfare.

We estimate model parameters using rich data on treatment choices and labor supply decisions of HIV-positive men.[1] The estimated model reveals that side effects can disincentivize medication use directly (i.e., by lowering utility) and indirectly through their impact on the utility cost of work. The effect on work is stronger for people with less education, which means they face a more drastic tradeoff between medication use and work. Not surprisingly, using limited data on broad occupational categories, we show that lower-education HIV-positive men in our sample tend to work in jobs that are more physically demanding. This leads to less medication use, including later adoption of HAART, even after accounting for prices and baseline health. In contrast, out-of-pocket treatment costs and insurance have little impact on treatment use, largely because HIV drugs are generally covered and inexpensive for men in the sample we study.

A benefit of modeling lifetime utility is that it permits computation of the welfare impacts of HAART, measured as the difference in lifetime utility between the

[1]Data for this study come from the Multi-Center AIDS Cohort Study, which has followed a sample of men who have sex with men starting in the 1980s, when the AIDS epidemic began in the U.S. We introduce the data set in Section 2.

first year after HAART entered the market compared to the year before HAART was invented. Health disparities existed during the early years of the AIDS epidemic, when treatments were largely ineffective. For example, in the early 1990s the 6-month mortality rate for HIV-infected (henceforth: *HIV-positive* or *HIV+*) college graduate men was almost half that for HIV+ men without a college degree. Using our model, we find that while HAART drastically reduced mortality, improved health and increased welfare, its side effects, including their interaction with the utility cost of work, meant that the benefits of HAART disproportionately accrued to individuals with higher education. In other words, when we account for a broad set of factors — including labor supply — that drive health decisions, we find that the innovation increases inequality because it disproportionately benefits more advantaged patients. Decompositions show that there are several factors driving variation in the value of HAART, including higher earnings potential and lower baseline mortality rates for more highly educated individuals along with a stronger health-work tradeoff that leads to lower usage among those with less education.

We also use the estimated model to conduct two policy simulations. The first one illustrates the wedge between health and welfare. We simulate the effects of a 6-month HAART treatment mandate on health, welfare and labor supply.[2] This counterfactual casts doubt on the idea that full compliance with a health-improving treatment regimen is unequivocally positive. While mandating a treatment that comes with disabling side effects improves health, as expected, it reduces expected lifetime value. Value declines more for those with less education (2.8% compared to 1.4%), because they are less likely to be using treatment before the mandate. This is reflected in larger decreases in labor supply (4.1% compared to 1.6% for those with a college degree). When patients are forced to weigh many factors that affect utility, choices reflect that individuals may avoid treatment that generate health improvements if there is a high cost to compliance. In this scenario, the costs of treatment are uneven, so mandating treatment is more costly for those with less education, exacerbating welfare inequality.

Since differences in health behaviors (and resulting health disparities) follow-

[2]This policy is meant to simulate the results of a clinical trial, which may show improvements to health but fail to consider the tradeoffs associated with treatment.

ing an innovation are in part due to difficulties working while taking medication, policies affecting labor market structures may prove effective. To explore this possibility we analyze a second counterfactual policy that increases non-labor income.[3] In particular, we raise non-employment income by $10,000 over a six-month period (about 50 percent of the median person's income) and examine how agents in the model make health and employment decisions in response. Unsurprisingly, we show declines in employment as people move out of the labor market. We also find that higher-education people or those who were already using the most effective medication available, HAART, exhibit few changes in behavior. In contrast, relatively healthy HIV+ men with less education who are not using HAART increase their use of HAART by roughly 81% percent. Given how persistent good health is, this translates to a modest 0.2% percent rise in the probability of being healthy in the following period compared to the same group absent the policy. For men in relatively low health and not using medication, this policy change increases their probability of using HAART by 21% (since many would have gone onto HAART anyway) and of being healthy next period by 13%. The effects of the policy on health behaviors are smaller for those with more education, with college educated men in poor health who are not using medication experiencing an approximately 5% increase in the probability of being healthy next period. Our results show that policies affecting labor supply can reduce incentives to engage in behaviors that compromise health and improve population health, and we find these effects to be concentrated among disadvantaged groups.

This paper relates to a vast literature in public health and other fields that documents and examines the consequences of health disparities across socioeconomic or demographic groups (Adler and Rehkopf, 2008; Beer et al., 2011; Conti et al., 2010; Currie, 2009; Cutler et al., 2011; Goldman and Smith, 2011; Rubin et al., 2010; Williams and Jackson, 2005). In this literature, barriers to access are frequently identified as the culprit (Chang and Lauderdale, 2009; Lasser et al., 2006; Williams

[3]This policy is meant to mimic policies that many countries used during the Covid-19 pandemic, which is to pay people to not work. The primary motivation behind these policies was to support people who faced sudden unemployment with few prospects to find a new job. An additional consequence of this policy has been that some workers could choose to avoid risks associated with staying at work.

et al., 2010; Woolf et al., 2015). Another literature, however, discusses how health disparities may result from persistent differences in behavior across socioeconomic groups. Often, these differences are characterized as errors in judgment (e.g., impatience or present bias) and sometimes they are (implicitly) presented as reckless or careless choices (Adimora and Schoenbach, 2002; Robinson and Moodie-Mills, 2012).[4] Our findings show that persistent behavioral differences across sociodemographic groups can lead to different health outcomes, but need not reflect biases or carelessness. Rather they can reflect rational responses to prevailing circumstances, constraints and market conditions.

This paper complements the approach taken by the sociological literature on fundamental cause theory. This theory says that social factors such as socioeconomic status are "fundamental causes" of health that persist despite, or even because of, medical innovation (Link and Phelan, 1995; Phelan et al., 2010). Empirical studies based in this literature have found increased health disparities after innovations in cholesterol treatments (Chang and Lauderdale, 2009), respiratory treatments for infants (Frisbie et al., 2004), and multi-drug cocktails for HIV/AIDS (Rubin et al., 2010), among others (Glied and Lleras-Muney, 2008). While many of these papers point to access to medical care as a driver of this increased inequality, other factors such as the difficulty of complying with a complicated regimen are also considered (Chang and Lauderdale, 2009; Goldman and Lakdawalla, 2005). The structural model estimated in our paper allows us to quantify the impact of various factors from the financial costs of medication to the labor market impacts of physical ailments caused by treatment.

We also relate to literature examining ways to reduce health disparities. Policies studied in this literature include lowering health care prices to expand access for low-income groups, paying people to take care of their health, providing information about the risks and benefits of specific health-related behaviors, and making health care more convenient (Sommers et al., 2012; Thornton et al., 2016; Wherry and Miller, 2016; Gerber et al., 2005; Osborn et al., 2007; Avery et al., 2008). While

[4]For example, in the public health literature Stafford and Wood (2017) discusses how health behaviors among homeless populations that can appear careless can often be explained by the need to prioritize food and shelter.

some policies have been effective, others have had mixed success or even no impact at all (Sommers et al., 2012; Thornton et al., 2016; Wherry and Miller, 2016; Gerber et al., 2005). This likely reflects an incomplete understanding of the full set of factors underlying disparities, which thwarts efforts to close them. We argue that taking account of a broader set of factors, such as relationships between health behaviors and labor market conditions could lead to more effective policy. For example, if behaviors that maximize health also interfere with work, people may need to compromise their health in order to maintain their economic well-being (Cawley and Ruhm, 2012; Gilleskie, 1998).[5]

This approach to studying health decisions has its origins in the view that health is a form of human capital in which individuals invest through their choices (Grossman, 1972; Becker, 2007). One way to operationalize this insight is to build a structural model of dynamic decision-making (Arcidiacono et al., 2007; Chan et al., 2016; Crawford and Shum, 2005; Cronin, 2019; Cronin et al., 2020; Darden, 2017; Gilleskie, 1998; Chan and Hamilton, 2006; Papageorge, 2016). This framework is useful to understand health-related behaviors as it posits that individuals make health investments until the marginal costs of doing so exceed the benefits. Hence, risky health behaviors such as not using effective medications can be seen as *disinvestments* in health (Cawley and Ruhm, 2012). An implication is that rational individuals who face higher costs of health investments will exhibit worse health, and policies that lower these costs could reduce resulting health disparities by encouraging health investments (Gilleskie, 1998).

We are most closely related to papers applying insights from (Grossman, 1972) to health behaviors during the HIV epidemic (Chan et al., 2016; Hamilton et al., 2021; Lakdawalla et al., 2006; Papageorge, 2016). A goal of these papers is to investigate how medical innovation affects behavior and welfare. We depart from this work by constructing a framework to examine the distributional consequences of medical innovation, including the idea that medical innovation can reinforce existing health disparities. A central feature of the framework is to incorporate the

[5]Our paper also relates to recent work (see, e.g., (Jones and Klenow, 2016)) in macroeconomics showing that cross-country differences in GNP may over- or understate differences in economic welfare once disparities in health and leisure are taken into account.

idea that health is not the same as welfare, which has implications for how we evaluate medical innovation and health policy more generally.

The rest of the paper proceeds as follows. Section 2 describes the data and presents key empirical patterns. Section 3 presents the structural model and describes the estimation. Section 4 discusses our results regarding the value of innovation and our counterfactual simulations. Section 5 concludes.

2 Data and Descriptive Patterns

2.1 MACS data

Data for this paper come from the Multi-Center AIDS Cohort Study (MACS), an ongoing study beginning in 1984 following a sample of men who have sex with men semi-annually in four U.S. cities: Baltimore, Chicago, Pittsburgh and Los Angeles.[6] The study collects information on a series of individual health measures, medical treatments use (including HIV drugs), insurance and out-of-pocket payments for medicine. Importantly, the data contain an objective measure of immune system health, the CD4 count, as well as physical ailments such as nausea and vomiting. The study also collects labor market information including employment, income and occupation. It also contains the individuals' highest completed level of education. We split individuals into a higher-education group containing those who

[6]Data in this manuscript were collected by the Multicenter AIDS Cohort Study (MACS). MACS (Principal Investigators): Johns Hopkins University Bloomberg School of Public Health (Joseph Margolick, Todd Brown), U01-AI35042; Northwestern University (Steven Wolinsky), U01-AI35039; University of California, Los Angeles (Roger Detels, Otoniel Martinez-Maza, Otto Yang), U01-AI35040; University of Pittsburgh (Charles Rinaldo, Lawrence Kingsley, Jeremy Martinson), U01-AI35041; the Center for Analysis and Management of MACS, Johns Hopkins University Bloomberg School of Public Health (Lisa Jacobson, Gypsyamber D'Souza), UM1-AI35043. The MACS is funded primarily by the National Institute of Allergy and Infectious Diseases (NIAID), with additional co-funding from the National Cancer Institute (NCI), the National Institute on Drug Abuse (NIDA), and the National Institute of Mental Health (NIMH). Targeted supplemental funding for specific projects was also provided by the National Heart, Lung, and Blood Institute (NHLBI), and the National Institute on Deafness and Communication Disorders (NIDCD). MACS data collection is also supported by UL1-TR001079 (JHU ICTR) from the National Center for Advancing Translational Sciences (NCATS) a component of the National Institutes of Health (NIH) and NIH Roadmap for Medical Research. The contents of this publication are solely the responsibility of the authors and do not represent the official views of the National Institutes of Health (NIH), Johns Hopkins ICTR, or NCATS. The MACS website is located at http://aidscohortstudy.org/.

obtained a four year college degree or more and a lower-education group containing everyone else.

The initial enrollment of the MACS included 4,954 men. Our analysis focuses on the roughly half of them who are HIV+ and uses data starting in 1991 through 2003. After removing observations with missing data, we are left with 1,201 individuals comprising 11,290 observations across 13 years.[7] The panel structure of the data allows us to observe health and employment decisions during different phases of the AIDS epidemic, distinguished by the characteristics of available medications. A major change occurred when HAART hit the market in 1995. HAART is more effective than earlier treatments, which means it led to dramatic decreases in mortality, but it did so at the cost of severe side effects. This technological innovation shifted tradeoffs HIV+ patients faced between health and other factors affecting well-being such as employment. For example, while HAART extended life, its side effects led some patients using it to take time out of the labor market, thus reducing consumption. Since the sample consists of people with different levels of education, we are able to study the interaction between the introduction of medical innovations, education and decisions of work and health. In particular, we are able to study how the ensuing tradeoffs affect sociodemographic health disparities.

While there are many different HIV drugs, we follow Detels et al. (2001) and combine them into three categories: mono-therapy, combo-therapy, and HAART. Each category is characterized by its price, the likelihood that it improves underlying health (CD4 count) and its propensity to cause side effects. Similar to Chan et al. (2016) and Papageorge (2016), health is defined as an indicator of AIDS-level CD4 count, above or below 250. Below this threshold of immune system health, individuals are less able to fight off routine infections (AIDS), and mortality rates

[7] Specifically, we start with the full MACS sample of 139,288 observations for 7,175 individuals (including refresher samples). After restricting the sample to survey visits in the time period 1991–2003, we are left with 48,644 observations for 5,057 individuals. After removing HIV negative individuals and people with missing HIV status, we are left with 21,746 observations comprising 2,291 individuals. Removing individuals outside of the age range 30–65 leaves 20,937 observations from 2,185 people. We drop 1,098 observations from 390 non-white individuals from a refresher sample to the panel due to the sampling methodology used to select these individuals. Dropping observations with missing data leaves 11,352 observations for 1,203 individuals. Finally, we remove 62 observations with extreme outlier values for costs or who are recorded as using HAART before it was invented. This leaves 11,290 observations for 1,201 individuals.

spike (Hamilton et al., 2021). We also measure physical health by patient reports of physical ailments, which are a combination of symptoms of illness when CD4 counts are low and side effects of treatment. An individual is coded as suffering from physical ailments if he reports one of the following ailments for at least three days since their previous semi-annual interview: fatigue, diarrhea, headache, fever or sweating.[8] Employment decisions are likewise binary: individuals work full-time or not.[9] Work experience accumulated prior to the beginning of the survey equals the individual's potential experience: the number of years since the graduation age given education status. After the beginning of the survey, work experience is obtained using the observed employment history. Income, which we convert to year 2000 dollars, is a categorical variable that grows in increments of $10,000, with the highest value being $50,000 or more.

2.2 Summary Statistics

Summary statistics are presented in Table 1 for the full analysis sample and then separately by education level and era (pre- or post-HAART). The post-HAART is set to start with survey visit 24, roughly the second semester of 1995.[10] In the full sample 63% of the men have a college degree and the average age is 44. Individuals with less education are on average two years younger than those with a college degree. Due to the panel nature of the data, the population ages over time, with the average age increasing by 5 years between the pre- and post-HAART eras. In what follows we discuss health, mortality and choices of treatment and employment. Several key patterns emerge. HAART was a technological innovation that drastically decreased mortality and improved health. Yet, not everyone used HAART (or other treatments) as they also entailed toxic side effects that can make work difficult. Finally, education seems to make the health-work trade off more severe. This is consistent with the idea that lower-education individuals sort into occupations in which it is especially difficult to work with side effects. The structural model

[8] In previous work, results are robust to allowing ailments to vary by type or frequency (Papageorge, 2016).

[9] Individuals working part-time are classified as not working.

[10] Results are robust to treating either survey visit 25 or 23 as the first post-HAART visit.

developed in the section after is based on these patterns and takes into account the various tradeoffs HIV+ individuals face.

TABLE 1: Summary Statistics by Education and Era

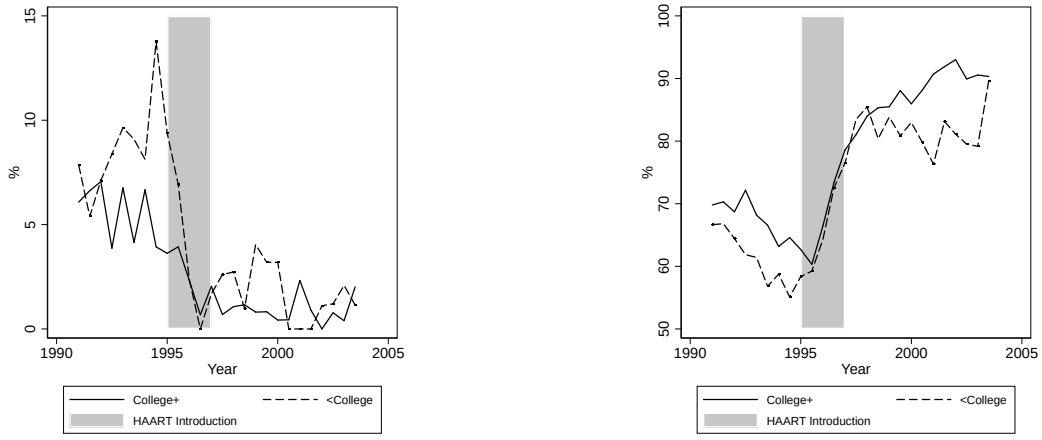
	All	<College		College+	
		Pre HAART	Post HAART	Pre HAART	Post HAART
College +	0.63	0.00	0.00	1.00	1.00
Age	44	40	45	42	47
Death	0.04	0.09	0.02	0.06	0.01
CD4 count	452	377	485	406	504
High CD4 ($\geq$ 250)	0.74	0.62	0.78	0.68	0.83
Treatment	0.71	0.54	0.75	0.57	0.85
Monotherapy	0.15	0.33	0.01	0.32	0.01
Combotherapy	0.20	0.21	0.16	0.26	0.18
HAART	0.36	0.00	0.58	0.00	0.66
Ailments	0.40	0.44	0.42	0.39	0.39
Full-time work	0.66	0.61	0.56	0.72	0.68
Income ($/half year)	19,938	15,373	14,780	22,290	21,902
Insurance	0.95	0.89	0.93	0.95	0.97
MOOP ($/half year)	245	159	210	198	326
Observations	11,290	1,785	1,708	3,380	4,417

Notes: The pre-HAART era contains observations from 1991 until mid 1995 (9 half-year periods), the post-HAART era contains observations from mid 1995 until mid 2003 (18 periods). Each entry represents the mean over person-visit observations for the given time period, except for education which is measured once per person. All measures are proportions, except age which is measured in years (30–64), CD4 count is a continuous measure and income and medical expenditures are in year 2000 dollars per half year. 11,290 person-visit observations for 1,201 individuals.

2.3 Health and Mortality

According to Table 1, the probability of dying in a given six-month period is higher for those with less education, regardless of whether HAART is available. For both education groups, HAART drastically reduces the probability of dying, from 9% to 2% for those with less than a college degree and from 6% to 1% for those with a college degree. Figure 1a shows mortality over time for higher- and lower-education men. The vertical bar (1995–1996) indicates HAART introduction.[11] The figure shows a precipitous drop in the probability of dying when HAART is introduced

[11] Since interviews were staggered it is not possible to pinpoint at which exact survey visit individuals first had access to HAART.



(A) Death **(B)** High CD4

FIGURE 1: Death Probability and CD4 Level Over Time

Notes: Panel (A) shows the probability of death in each period by educational attainment. Individuals with less education are more likely to die, especially before the introduction of HAART. Panel (B) shows the probability of having above AIDS level CD4 (>250) in each period by educational attainment. Individuals with less education are less likely to have high CD4 before and after the introduction of HAART.

for both education groups. Moreover, low-education individuals exhibit generally higher mortality rates.

TABLE 2: Medication Spell Characteristics by Education for Analysis Sample

	<College	College +	p-value
Ever use treatment	0.81	0.88	0.002
Share of survey visits using treatment	0.63	0.72	0.000
Ever use HAART	0.67	0.81	0.000
Share of survey visits using HAART (when available)	0.48	0.58	0.001
First used HAART	28.1	27.3	0.025
Treatment transitions (per visit)	0.17	0.17	0.718
Ever stopped HAART	0.21	0.27	0.060
Ever started HAART after stopping	0.17	0.20	0.278
Ever started HAART after stopping (conditional on stopping)	0.80	0.73	0.363

Notes: One observation per person for 1,201 individuals. Treatment in this context means using one of the three medications. Ever use treatment is an indicator for if the individual is observed using treatment during the sample period. The first visit where HAART was available is 24, so an individual first using HAART in visit 27 started approximately a year and a half after it was introduced. Ever stopped HAART means that the individual was observed using HAART and then later observed not using HAART.

Consistent with lower mortality rates, HAART introduction led to higher CD4 counts. Overall, the average sample CD4 count is 452, well above the threshold for transition from HIV to AIDS and reflects survivor bias. For both education

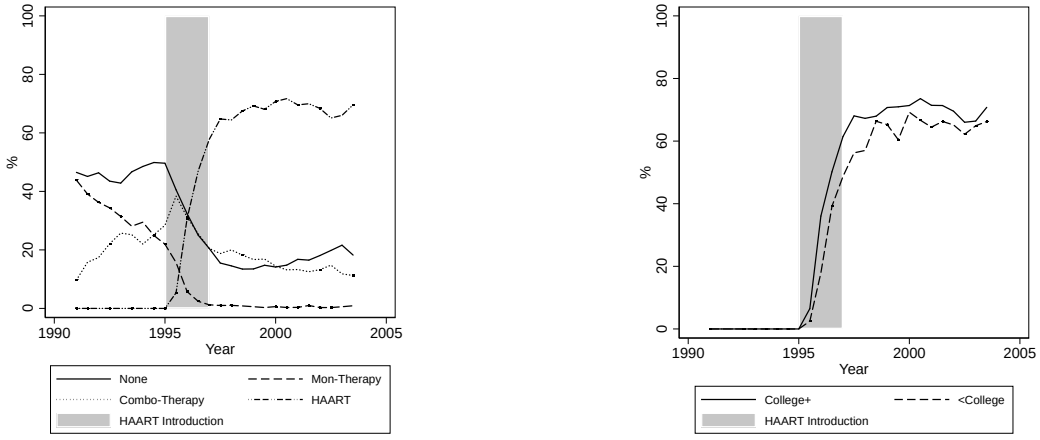
levels, CD4 counts are higher after HAART becomes available, increasing by 108 units for those with less education and 98 units for those with higher education. On average, those with less education are less healthy, but the differences across education level are small compared to the differences across eras. Another way to measure immune system health is to examine the probability of being above AIDS-level CD4 count. Both education groups exhibit drastic increases in the probability of high CD4 count once HAART is introduced: 62% to 78% in the lower- and 68% to 83% in the higher-education group. Figure 1b shows the probability of high CD4 count over time. It shows a clear and swift post-HAART increase in high CD4 count, though health disparities across education groups are evident.

To further understand factors driving health, Table A2 presents coefficient estimates from logistic regressions for being above an AIDS-level CD4 count.[12] The explanatory variables include current-period health (to capture persistence), a second-order polynomial in age, along with an era-specific time trend. We estimate this model for the full sample and then separately by education group. The estimates confirm that health is significantly worse for people with less education even after controlling for additional variables. In general, health is highly persistent. Age has a marginally significant positive association with health, which may reflect survivor bias. Finally, we find declining health in the pre-HAART era and improving health in the post-HAART era, which maps to the evolution of treatment quality. The slope of the post-HAART positive trend is larger for people in the higher-education group, suggesting they benefit more from the new technology. Next we discuss whether this facts reflect different usage patterns.

2.4 Treatment Choices and Employment Decisions

The introduction of HAART is associated with large changes in the treatment choices of HIV+ individuals. Returning to Table 1, while the probability of using any treatment increased post-HAART, consumption of older treatments, mono-therapy and combo-therapy, fell. After HAART becomes available, 58% of those with less than

[12] In this section, we present several descriptive regression models that are similar, but not identical, to the processes estimated for the model, which are presented in section B.3 and appendix C.



(A) Treatment **(B)** HAART

FIGURE 2: Treatment and HAART Use Over Time

Notes: Panel (A) shows the probability of using each treatment in each period. Before HAART was introduced, many individuals did not use any treatment. HAART was adopted quickly after it was introduced, causing a decrease in the use of monotherapy and in the share of individuals using no treatment. Panel (B) shows the probability of using HAART in each period by educational attainment. HAART was adopted more quickly by individuals with more education, and is used at higher rates by those individuals throughout the study period.

a college degree and 66% of those with a college degree use it. These shifts are illustrated in Figure 2a, which shows treatment choices over time. Prior to the introduction of HAART, a large portion of the sample (46% of the lower-education and 43% of the higher-education group) chose no treatment at all. Although pre-HAART treatments were not very effective, prices were generally low, suggesting other factors could help explain patient reluctance to consume treatment. Below, we argue that side effects is one such factor explaining low consumption of medications with limited effectiveness.

Of patients who used a treatment in the pre-HAART era, most were on monotherapy, which means they used one single drug to combat HIV. Starting in the late 1980s, recommended treatment regimens tended to include multiple drugs. This did not immediately improve effectiveness, but did lead to more side effects. Once HAART was introduced, treatment consumption patterns shifted dramatically. HAART use soared rapidly, reflecting its high level of effectiveness, as patients substituted away from both mono- and combo-therapy. HAART also attracted patients who had previously opted for no treatment. After its introduction, the probability of

using any treatment increased from 54% to 75% for those with less than a college degree and from 57% to 85% for those with a college degree or more.

While HAART did not produce fewer side effects than the previously available medications, it was much more effective at improving health. Still, differences across groups persist. Lower-education individuals report using HAART 58% of the time, while those with more education use it 66% of the time. Figure 2b shows that HAART adoption was slower among lower-education individuals, with usage rates converging at the end of our sample. While the majority of individuals use treatment, there is a significant minority who do not. Papageorge (2016) argues that this can be explained by side effects and their interaction with labor supply, showing that people cycle on and off of HAART depending on their health: getting off treatment in an effort to work while in relatively good health, and using live-saving medication when their health declines. The patterns here suggest that the work-side effects tradeoff may be more salient for individuals in the lower-education group, inducing even lower HAART consumption.

To provide further insight into treatment patterns, Table A2 shows the transition matrix for treatment choices by education level and HAART era. In general, we see a high degree of persistence over time, which suggests it may be costly to switch treatments or to go into or off treatment. For example, over 80% of individuals who are not using treatment will continue to not use treatment in the following period. Pre-HAART, 70% or more of those taking a given medication continue with the same medication in the following period, with a substantial minority switching between treatments. In the post-HAART era, however, many individuals switch from mono-therapy, combo-therapy or no therapy at all to adopt HAART. Relatively few individuals go off treatment in any given period.

To further explore treatment choices, we estimate a logit model to explain use of any treatment. Estimates in Table A3 show that even after controlling for factors including health and employment, individuals with less education are less likely to use treatment. Unsurprisingly, individuals already in good health are less likely to use treatment across education categories. Medication use declines over time until HAART is introduced. Thereafter, treatment use increases over time. In addition, we find that those who are working are also less likely to use treatment, and this

effect is larger for those with less education. This finding is consistent with lower-education individuals having a harder time working while using treatments with side effects. The structural model specified in the following section formalizes this idea by allowing the utility cost of work to vary by ailments and education.

Table 2 shows that higher-education individuals are more likely to ever be observed using treatment compared to lower-education people (88% versus 81%). They also spend more time on medication: higher-education individuals use medication in 72% of survey visits compared to 63% for lower-education people. Similarly, the higher-education group is more likely to use HAART at all and to spend more time using it. Figure 2b shows that those with less education are slower to adopt HAART when it becomes available. The average age of first survey visit at which those with a college degree start HAART is 27.25 (roughly the first semester of 1997). The corresponding number for those with less than a college degree is 28.07, approximately 5 months later. The probability of switching treatment in a given visit is not significantly different for different education groups. However, those with a college degree are marginally more likely to have stopped HAART. Among those that ever stop HAART, 80% of those with less than college and 73% of those with more than college will restart, though these differences in means are not significant.

One reason individuals may choose to forgo treatment is that these medications have side effects, such as fatigue, diarrhea, headaches and fever. As we have mentioned, these physical ailments could also be symptoms of illness. Hence, we understand ailments as being produced by both underlying health and treatment choices. According to Table 1, 40% of the sample suffers from ailments at any given time. Those with less education are slightly more likely to suffer from ailments compared to those with a college degree, 44% versus 39% respectively. The share of individuals suffering ailments does not differ significantly pre- and post-HAART. This is likely due to the adoption of effective medication with side effects: while more effective treatments decrease ailments through their effect on underlying health, their toxicity increases them so that there is no overall change.

To further understand what drives physical ailments, Table A4 presents coefficients from logistic regressions for *not* suffering ailments. These regressions are

performed for the full sample and separately by education group. Across education groups, HAART is associated with slightly more ailments than other medications, though all treatments increase the probability of ailments. The association between treatment use and ailments is slightly larger for those with more education. For all groups, high CD4 count is negatively associated with ailments. Interestingly, those with less education are less likely not to have ailments, even after controlling for health, treatment and time factors. This could reflect that individuals in different education groups may be using HAART somewhat differently. For example, higher-education individuals may be less likely to skip medication to avoid side effects or may use more effective HAART regimens that have harsher side effects.

Given that treatment decisions may affect or reflect employment decisions, we next consider what drives labor supply in the sample. On average, individuals work in 66% of the observed periods. Employment declines post-HAART for both groups as the cohort ages. In both the pre- and post-HAART eras individuals with less education are approximately 11 percentage points less likely to be employed. The transition matrix in Table A5 shows that unemployment is persistent, especially for those with less education. Among those who were not working in a given period, 90.8% of the lower-education individuals will not be working next period; the corresponding number for the higher-education individuals is 87.9%. Among those who are working this period, those with less education are somewhat more likely to stop working next period, though at both education levels employment is highly persistent.

Table A6 presents coefficients from a logistic regression with employment as the outcome variable controlling for a variety of factors. The regression is run for the overall sample and separately by education groups. Individuals with less education are less likely to work. Ailments decrease the probability of work, more so for those with less education. This is consistent with side effects making work difficult, especially for those with less education. Having a high CD4 count is associated with a higher probability of working, for all groups, while using medication is associated with a reduction in the probability of work. This effect is also larger for those with less education.

Several additional variables in the data set can shed light on the patterns de-

scribed above (Table 3). While individuals with less education are only slightly more likely to experience ailments, we hypothesize that ailments have different implications for the two education groups. Individuals with less education are significantly more likely to work in occupations that require manual labor, which likely makes work more difficult while experiencing side effects. Indeed, 22% of those with less than a college degree report stopping medications specifically because of side effects, compared to 19% of those with more education. Similarly, those with less education are more likely to report needing to change their job due to their HIV status (6% compared to 5%), though this event is relatively rare.

TABLE 3: Additional Characteristics by Education

	<College	College +	p-value
Changed job due to HIV	0.06	0.05	0.002
Stopped meds for side effects	0.22	0.19	0.019
Manual occupation	5.12	4.49	0.000

Notes: These questions are not asked of all participants in all visits so we have substantial missing data relative to analysis sample. Occupation is measured once at the beginning of data collection and not updated after that. We use occupation definitions from Autor et al. (2003). Occupations are scored by the amount of manual labor they require based on DOT task measures. Stopped meds is only measured for those taking medications in the given period. Changing jobs is asked regardless of employment.

Evidence until now suggests that ailments from side effects can help to explain treatment and employment decisions. In particular, individuals may stop using effective treatment with side effects to work. A natural question to ask is why people infected with a deadly virus would be willing to take such a risk. A key motivation seems to be to generate income as those with less education have lower incomes. Individuals with less than a college degree earn $15,373–14,780 on average per six-months (pre- and post-HAART), while those with a college degree earn $22,290–21,902 on average.[13] While incomes fall slightly for both groups post-HAART, likely because individuals age out of the workforce, the major difference is across education categories. Table A7 presents linear regression results for income overall and by education group. Individuals with less education have lower incomes even after controlling for employment, experience and health. Health is more important for income for those with less education, again suggesting that working while ill

[13]These numbers are averages of the upper and lower bounds of the income brackets

may be more difficult for those with less education.[14]

Overall, the empirical patterns suggest that HAART was an important but imperfect innovation. Treatments improves health but also cause side effects that can make work difficult. The model described below incorporates both the costs and benefits of treatment and its interactions with work.

3 Model

At every period, forward-looking, HIV+ individuals in our model maximize their expected lifetime utility by choosing what antiretroviral treatment to consume and whether to participate in the labor market. Their treatment choices affect their future health, which in turn affects their survival and future income. Although potentially beneficial for their future underlying health, treatment consumption can generate higher physical ailments and it directly increases current medical expenditures. The latter are also affected by insurance coverage, which is determined through a stochastic process that depends on labor market participation and health. Individuals have myopic expectations with regards to technological change. In other words, they are surprised by changes in technology that affect the health and ailments processes, and they always assume that the new technological regime is permanent.

3.1 State Variables and Choices

Individuals are denoted by the subindex i. They enter period (semester) t with a vector z_{it} of state variables including their age $a_{it-1} \in R_+$, their completed education captured by the indicator $s_i \in \{0,1\}$ that takes the value of 1 if they have college or more, their labor market experience $e_{it-1} \in R_+$, their prior treatment decision d^m_{it-1}, and their prior health status captured by the indicator $h_{it-1} \in \{0,1\}$ that takes the value of 1 if their prior health was higher than AIDS level. Individuals first enter the

[14] In addition to the side effects, cost barriers could prevent individuals from accessing medications. However, the vast majority of the sample is insured at any given time and medical expenditures are generally low relative to income. Those with less education are less likely to be insured, but even this group has a 91% insurance coverage rate. Even for those individuals who are not insured, HIV medications are generally available at low costs (Gable et al., 1996).

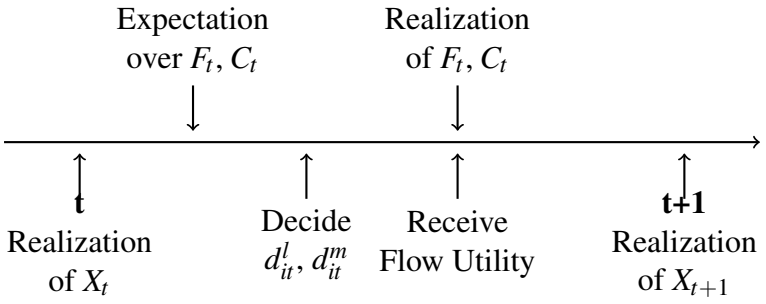


FIGURE 3: Timing of the Model

Notes: This figure shows the timing of the model including state variables and decisions. Treatment and work choices are made simultaneously not sequentially.

model at age $\underline{a}$ and age half-year at a time; they make choices until age $\bar{a}$.[15] Upon reaching age $\bar{a}$ individuals receive a termination payment equal to a bond whose yearly payment equals the monetary value of the flow utility obtained in the last period of life.

At every period individuals decide their labor market participation and their treatment. If they decide to work, the labor indicator d_{it}^l takes the value of 1. There are two eras in terms of treatment alternatives. In the first era ($t < \bar{t}$) there are three treatment alternatives: no treatment (d_{0it}^m), mono therapy (d_{1it}^m) and combo therapy (d_{2it}^m). In the second era ($t \geq \bar{t}$) an additional treatment alternative called HAART becomes available (d_{3it}^m). Treatments are mutually exclusive and individuals must choose one. Hence, the collection of treatment-specific indicators $d_{rit}^m \in \{0,1\}$ satisfies $\sum_{r=0}^{2+\mathbf{I}\{t\geq\bar{t}\}} d_{rit}^m = 1$. The treatment decision vector $d_{it}^m \in \{0,1\}^{3+\mathbf{I}\{t\geq\bar{t}\}}$ collects all the treatment-specific indicators. Labor and treatment choices are made simultaneously. Therefore, there are six labor-treatment alternatives available at any $t < \bar{t}$ and eight at any $t \geq \bar{t}$. At every period individuals receive a vector of alternative-specific preference shocks ε_{it} before making their choice. The preference shocks are distributed Type I Extreme Value and are independent and identically distributed across alternatives, individuals and over time.

[15] Hence, $a_{it} = a_{it-1} + 0.5$

3.2 Outcomes and Transitions

3.2.1 Health and Mortality

Physical wellbeing is characterized by health and ailments. While *health* refers to the state of the individual's immune system, *ailments* refer to all other afflictions that the individual may face conditional on their immune system health. Health, which has a direct effect on survival, is what efficacious treatments aim to improve.

Health. Health h_{it} is determined in a two-step process. First, individuals draw a health booster Δh_{it}, equal to one if CD4 increased or stayed the same, from a Bernoulli distribution with probability:

$$P[\Delta h_{it} = 1 | x_{it}^{\Delta h}] = \frac{exp(x_{it}^{\Delta h}\theta^{\Delta h})}{1 + exp(x_{it}^{\Delta h}\theta^{\Delta h})} \tag{1}$$

where $x_{it}^{\Delta h} \equiv [h_{it-1}, d_{it}^{m} \times h_{it-1}, a_{it-1}, a_{it-1}^{2}, s_i, \nu_t^{\Delta h}]$. The vector $x_{it}^{\Delta h}$ captures the efficacy of treatment alternatives d_{it}^{m} and its interaction with prior health and also permits variation by education and age. The scalar $\nu_t^{\Delta h}$ captures aggregate changes in health-boosting baseline technology at period t.

Second, individuals transition into their next period health level according to:

$$P[h_{it} = 1 | x_{it}^{h}] = \frac{exp(x_{it}^{h}\theta^{h})}{1 + exp(x_{it}^{h}\theta^{h})} \tag{2}$$

where $x_{it}^{h} \equiv [h_{it-1} \times \Delta h_{it}]$. The vector x_{it}^{h} captures the effect of prior health and treatment (indirectly through the health booster) on the transition into future health. This two-stage process allows us to capture both the absolute level and the trajectory of health without having to rely on a continuous health variable.[16]

[16]The two-stage process is preferred over a single discrete transition probability because it prevents drugs that keep healthy people healthy from being classified as ineffective.

Survival. Health has a direct effect on survival. At the beginning of every period after entry individuals face death with probability:

$$P[b_{it} = 1|x_{it}^b] = \frac{exp(x_{it}^b \theta^b)}{1 + exp(x_{it}^b \theta^b)} \tag{3}$$

where $x_{it}^b \equiv [h_{it-1}, a_{it-1}, h_{it-1} \times a_{it-1}, s_i, v_t^b]$. Survival depends on the individual's health, age and education level, as well as aggregate changes in survival-boosting technology. Current treatment consumption affects survival into next period indirectly through their effect on next period health h_{it}.

3.2.2 Ailments and Monetary Outcomes

Depending on their labor and treatment choices, at every period individuals realize their ailments, income, insurance coverage and medical expenditures. These outcomes are collected in the vector y_{it}.

Ailments. Toxic treatments with strong side effects increase the likelihood that an individual will suffer ailments. Denote $y_{it}^{ailments}$ as the no-ailments indicator that takes the value of 1 if the individual does not suffer ailments in period t. The probability of not suffering ailments is given by:

$$P[y_{it}^{ailments} = 1|x_{it}^{ailments}] = \frac{exp(x_{it}^{ailments} \theta^{ailments})}{1 + exp(x_{it}^{ailments} \theta^{ailments})} \tag{4}$$

where $x_{it}^{ailments} \equiv [h_{it-1}, d_{it}^m, a_{it-1}, a_{it-1}^2, s_i, v_t^{ailments}]$. The vector $x_{it}^{ailments}$ captures the side effects of treatment alternatives and it also controls for prior health, education and aging. The scalar $v_t^{ailments}$ captures aggregate changes in side effects baseline technology at period t.

Work Experience and Income. Individuals enter the model without prior work experience and endogenously accumulate work experience e_{it} in half-year incre-

ments as a function of their labor market participation:

$$e_{it} = e_{it-1} + 0.5d_{it}^{l} \tag{5}$$

Their labor market participation and experience determine their income according to:

$$y_{it}^{income} = x_{it}^{income}\theta^{income} + \varepsilon_{it}^{income} \tag{6}$$

where $x_{it}^{income} \equiv [d_{it}^{l}, h_{it-1}, a_{it-1}^{2}, a_{it-1}, e_{it-1}, e_{it-1}^{2}, s_i, s_i \times d_{it}^{l}, \nu_t^{income}]$ and $\varepsilon_{it}^{income}$ is an iid income shock with a conditional mean of zero. The biological processes of health evolution and aging affect individual productivity through a direct effect on income. These processes also affect income indirectly through the decision to participate in the labor market. The scalar ν_t^{income} captures aggregate changes in income.

Insurance Coverage and Medical Expenditures. Health insurance in the model is a stochastic outcome that is realized after an individual makes his choice at t. An individual draws insurance coverage with probability:

$$P[y_{it}^{insurance} = 1 | x_{it}^{insurance}] = \frac{exp(x_{it}^{insurance}\theta^{insurance})}{1 + exp(x_{it}^{insurance}\theta^{insurance})} \tag{7}$$

where $x_{it}^{insurance} \equiv [h_{it-1}, a_{it-1}, a_{it-1}^{2}, e_{it-1}, e_{it-1}^{2}, d_{it}^{l}, s_i, s_i \times d_{it}^{l}, \nu_t^{insurance}]$. By controlling for labor market participation and experience the vector $x_{it}^{insurance}$ captures the fact that health insurance is often employer-sponsored in the United States. The probability of insurance coverage also captures age, education and health effects. The scalar $\nu_t^{insurance}$ captures aggregate changes in insurance coverage. In turn, insurance coverage affects the amount of medical expenditures an individual pays out of pocket (MOOP) according to:

$$y_{it}^{expenses} = x_{it}^{expenses}\theta^{expenses} + \varepsilon_{it}^{expenses} \tag{8}$$

where $x_{it}^{expenses} \equiv [y_{it}^{income}, y_{it}^{insurance} \times d_{it}^{m}, h_{it}, y_{it}^{ailments}, h_{it} \times y_{it}^{ailments}, a_{it-1}, a_{it-1}^{2}, s_i, \nu_t^{expenses}]$ and $\varepsilon_{it}^{expenses}$ is an iid medical expenses shock with a conditional mean of zero.

3.3 Utility and the Value Functions

There is no borrowing or saving in the model. Individuals use the entirety of their current income for consumption c_{it} and medical expenses. Hence, the individual's budget constraint for period t is given by:

$$c_{it} = y_{it}^{income} - y_{it}^{expenses} \tag{9}$$

Individuals with education level s draw utility from their consumption $\tilde{u}(c_{it})$, their ailments and their treatment choices according to:

$$\begin{aligned} u(y_{it}, d_{it}, d_{it-1}^m, s) = \prod_{f \in \{0,1\}} \Big[& \tilde{u}(c_{it}) + \theta_{1sf}^u \cdot (1 - y_{it}^{ailments}) + \theta_{2sf}^u \cdot d_{it}^l \\ & + \theta_{3f}^u \cdot d_{0it-1}^m (1 - d_{0it}^m) \\ & + \theta_{4f}^u \cdot \left(1 - d_{0it-1}^m\right) \left(1 - (d_{it-1}^m \cdot d_{it}^m)\right) \\ & + \theta_{5f}^u \cdot \left(1 - d_{0it-1}^m\right) d_{0it}^m + \varepsilon_{it}(d_{it}) \Big]^{\mathbf{1}[y_{it}^{ailments} = f]} \end{aligned} \tag{10}$$

As equation (10) suggests, we allow all of the utility parameters to vary by ailments status, and parameters θ_{1sf}^u and θ_{2sf}^u to vary by education level. Hence, people with different education levels in our model may experience different disutility from working while ill (or well). The flow utility captures direct utility from ailments (θ_{1sf}^u), direct utility from work (θ_{2sf}^u) and switching cost for starting (θ_{3f}^u), changing (θ_{4f}^u) and stopping treatment (θ_{5f}^u). The utility from not suffering ailments θ_{1s0}^u is normalized to zero for both education levels. The flow utility also contains the idiosyncratic, alternative-specific, preference shock $\varepsilon_{it}(d_{it})$.

Value Function. Let z_{it} denote the observable part of the state vector. Upon reaching age $\bar{a}$, individuals no longer make choices and receive a bond that pays the monetary equivalent of their age $\bar{a}$ flow utility forever. The bond is their only source of utility from $\bar{a}$ forward. They discount the returns from this bond by their discount factor and their annual probability of survival that remains fixed at its age $\bar{a}$ level. Let $z_{it}(a)$ be the state of an individual when he is of age a and let $\mathbb{K}_t$ denote

the number of alternatives in the choice set at period t. Hence, his conditional value function (net of the taste shock) from choosing alternative $k \in \mathbb{K}_t$ at age $\bar{a}$ is given by:

$$v_{kit}(z_{it}(\bar{a})) = \left(\frac{1}{1-\delta(z_{it}(\bar{a}))}\right) u_k(y_{it}, d_{it}, d^m_{it-1}, s) \tag{11}$$

where $\delta(z_{it}(\bar{a})) \equiv \beta(1 - P[b_{it} = 1 | x^b_{it}, age_{it} = \bar{a}])$. For any age $a < \bar{a}$ his conditional value function is given recursively by:

$$v_{kit}(z_{it}(a)) = u_k(y_{it}, d_{it}, d^m_{it-1}, s) + \beta E_k[V_{it+1}(z_{it+1}(a+1)) | z_{it}(a)] \tag{12}$$

where E_k denotes the expectation of the state conditional on choosing alternative k. Given that the taste shocks are distributed Type I EV, the ex-ante value function $V_{it}(z_{it}(a))$ is given by:

$$V_{it}(z_{it}(a)) = \gamma + \ln\left(\sum_{k'=1}^{\mathbb{K}_t} \exp\{v_{k'it}(z_{it}(a))\}\right) \tag{13}$$

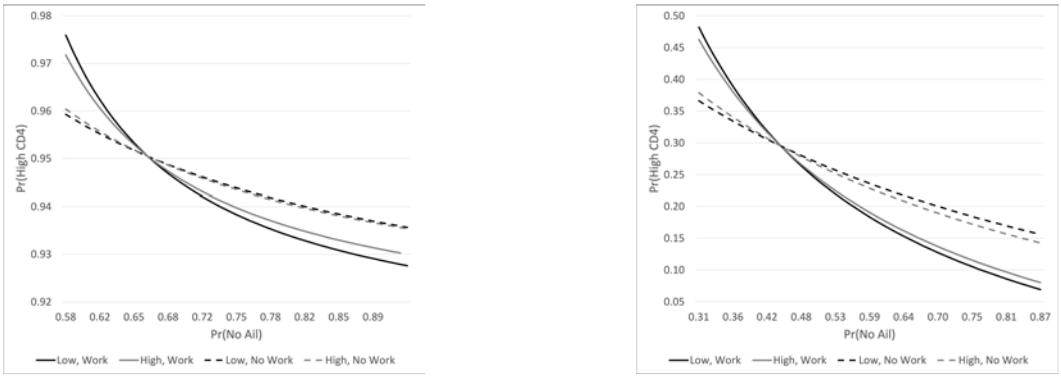
At any age $a \leq \bar{a}$ individuals choose an alternative $k \in \mathbb{K}_t$ to solve the discrete maximization problem:

$$\max_{k \in \mathbb{K}_t} \{v_{kit}(z_{it}(a)) + \varepsilon_{kit}\} \tag{14}$$

3.4 Estimation

To estimate the model, we follow a nested procedure. For a given set of proposed parameters, we use backwards induction to solve the dynamic programming problem for each set of state variables. The outer step uses the probabilities generated by this first step to search for parameters that maximize the likelihood of the data. We describe the estimation procedure, parameter estimates and model fit in detail in appendix B.

The estimated utility parameters (Table A8) show that the utility cost of ailments alone is not significantly different across education groups. However, when agents suffer from ailments, working decreases utility, and the disutility of working with ailments is higher for those with less than a college degree. Figures 4a and 4b plot



(A) High CD4 **(B)** Low CD4

FIGURE 4: Simulated Indifference Curves for Medications

Notes: This figure shows simulated indifference curves for medications that generate combinations of health and ailment probabilities. Panel (A) shows an agent with high CD4, Panel (B) shows an agent with low CD4. The point at which the indifference curves cross is the health and ailment probabilities from HAART for an agent with the given CD4 count and without a college degree. The simulated agent is 30 years old, has 10 years of work experiences and is in visit 26 (1996). In Panel (A), when working, the slope of the simulated indifference curve is smaller for those with more education, which means that they are more willing to experience side effects in exchange for health improvements. The across-education difference is present for agents forced to work, because the disutility of working with ailments is higher for those with less education. When not working, the slopes are approximately equal. In Panel (B), when working, the slope of the simulated indifference curve is smaller for those with more education, which means that they are slightly more willing to experience side effects in exchange for health improvements. The across-education difference is present for agents forced to work, because the disutility of working with ailments is higher for those with less education. When not working, the slope is higher for those with more education, because the utility cost of ailments absent work is higher.

indifference curves by education and employment to demonstrate differences in the health-ailment tradeoff, separately by health status. In addition to flow utility parameters, we estimate parameters for the health, survival and additional processes included in y_{it}. The estimated parameters for these processes are presented in Appendix C. Overall, the model predictions closely match the data (Table A9). Both the data and the model predict that agents will be employed 66% of the time. The results are similar for HAART use, with the model predicting HAART use in 33% of periods and the data showing HAART use in 36% of periods.

4 Results

4.1 The Value of HAART

HAART was an important innovation with major implications for HIV+ individuals. Figures 5a and 5b show total expected lifetime value for a 30 year old indi-

vidual on the best available treatment in each period by education status for those with high and low CD4 counts respectively. In our model, HAART is an unanticipated innovation, so by comparing expected lifetime value just before and just after it was introduced, we can see the impact it has on agents in the model. Table 4 shows expected lifetime value in 1995 and 1996 by health and education status for an individual on the best available treatment at the time. Regardless of health or education level, HAART's introduction had a large impact. HAART is more important for agents with a low CD4 count because this group is more in need of the positive health effects. However, since health is not permanent and HAART is beneficial for health regardless of current CD4 count, HAART's introduction increases value across the board. For agents with a low CD4 count, HAART's introduction is associated with a 176.6–236.1% increase in expected lifetime value, compared to an increase of 76.3–85.7% for those with a high CD4 count. In absolute terms, the gains were larger for those with more education because they are more likely to take advantage of the innovation. However, in percentage terms the innovation increased expected lifetime value somewhat more for those with less education because their expected lifetime value was lower to begin with.

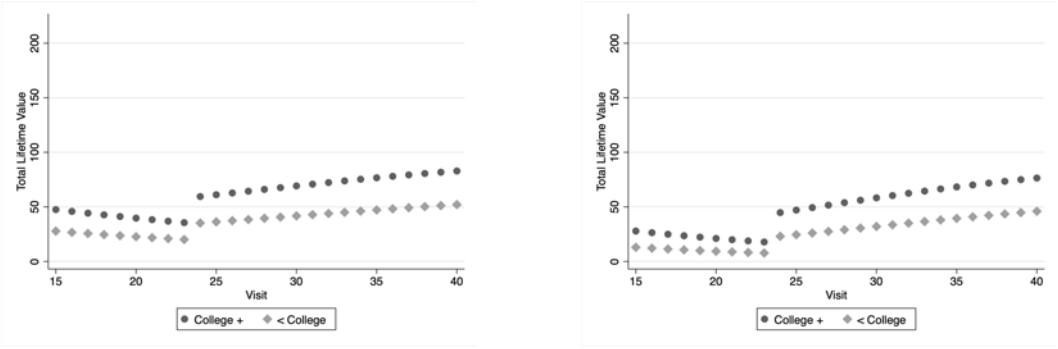
TABLE 4: Expected Total Lifetime Value

	<College		College+	
	Low CD4	*High CD4*	*Low CD4*	*High CD4*
Combotherapy (1995)	21.7	56.5	50.1	100.0
HAART (1996)	73.0	104.9	138.6	176.3
Absolute gain	51.3	48.4	88.5	76.3
Percent gain	236.1	85.7	176.6	76.3

Notes: Estimates from model simulations. Total expected lifetime value for a 30 year old male on best available treatment, 1995 (visit 23) versus 1996 (visit 26). High education, high CD4, Combotherapy normalized to 100.

4.2 Decomposing Differences in the Value of HAART

To understand why HAART was more important for those with more education, we decompose the differences in lifetime value in Table A10. Panel 1 replicates the results from Table 4, showing expected lifetime value pre- and post-HAART by education and health status. The following panels gradually cumulatively re-



(A) High CD4 **(B)** Low CD4

FIGURE 5: Expected Total Lifetime Value on the Best Available Treatment

Notes: This figure shows expected total lifetime value by visit and education for an agent with a high CD4 count (Panel A) or low CD4 count (Panel B) on the best available treatment. Before HAART was introduced in visit 24, combotherapy was the best available treatment. The simulated agent is 30 years old and has 10 years of work experience. Total value increases for both education levels when HAART is introduced, but the value change is larger for those with more education.

place processes and parameters faced by lower-education agents with those faced by higher-education agents. Panel 2 shows the effect of giving the lower-education group the income process of the higher-education group. Total lifetime value increases for those with less education, as would be expected, but does not come close to closing the gap in value. This suggests that lower incomes are not the primary reason why those with less education expect lower lifetime value. In panel 3, we also replace the insurance and medical expenditures processes, which actually decreases value for those with less education relative to just replacing the income process. This is because people with more education tend to have more out of pocket medical expenditures.

Changing the health (panel 4) and ailments (panel 5) process have small positive effects on lifetime value for those with less education, but the results again are not drastic. Changing the survival process in the next panel has a large impact for those with less education, who otherwise are much more likely to die, thus forgoing the value they otherwise would have received. This change helps more pre-HAART than post-HAART because the chances of death are higher in the pre-HAART period. Thus, changing this survival process not only closes most of the remaining gap between the education groups but also decreases the percent increase in value after HAART was invented for those with a low CD4 count. While we do not explore

the mechanisms that make those with less education more likely to die, it is likely that policy interventions could help boost survival for those with less education. Finally, panel 7 shows the effects of changing the structural utility parameters. This fully closes the gap (mechanically, as there are no other differences in the model). Since preferences are often deep individual characteristics, unlike with the other processes, it is less clear whether policy can close this part of the gap.

4.3 Treatment Effects versus Welfare

We use the model to simulate a counterfactual scenario aimed to show how improved health through treatment, akin to what might be shown in a clinical trial, does not necessarily lead to welfare improvements given the costs of treatments, such as side effects. This counterfactual casts doubt on the idea that full compliance with a health-improving treatment regimen is unequivocally positive. In fact, mandating a treatment that comes with disabling side effects reduces expected lifetime value even though, as expected, it improves health. In other words, the counterfactual illustrates the fundamental idea that patient choices reflect that health is only one among many factors that affect utility and that treatments that can improve health can leave patients worse off. Not only does a treatment mandate reduce lifetime value across the board, but it increases inequality, as it is more costly for those with less education. These results are both driven by and help to explain why full compliance is not observed in the data.

We construct expected lifetime value under the simulation by reducing the choice set to include only two alternatives, both entailing HAART treatment: full time and not full time. Clearly, this reduction in the choice set from eight choices (four treatment options times two work options) to two choices results in a mechanical decrease in value, even for those agents with a very high probability of choosing HAART, because the expected value of the utility shocks falls with the number of choices. This represents the loss of value associated with the loss of freedom of choice. Even for agents where HAART appears to be an obvious choice, a small share of individuals will forgo it due to idiosyncratic variation in preferences. By mandating HAART, we eliminate this option, reducing expected value. An alternate

method of conducting this simulation would be to let the choice-specific shock be a random variable defined as the maximum of four independent draws of the distribution of preference shocks to capture the role of freedom of choice. This method would mechanically increase value by the same amount for all agents relative to the first method, and would have no effect on the health and labor supply results of the simulation. We opt for the first method because removing the choice specific draws from unavailable choices more closely represents the scenario faced by individuals mandated to use treatments in settings like clinical trials. However, it is important to note that part of the reduction in value associated with the simulation is a mechanical result of the simulation methodology.

Table 5 shows expected lifetime value, the probability of a high CD4 count and the probability of employment across several 6-month mandate scenarios. The first panel shows results from the model with all choices intact, so agents can choose amongst three treatment options or choose not to use treatment. The second panel shows the effects of a HAART mandate where all agents are forced to use HAART for 6 months. The third panel shows a treatment mandate where agents can choose among the three treatments but cannot forgo treatment. The fourth panel shows a no-treatment mandate where agents are not able to use any treatments. We integrate over the distribution of states observed in the data in visit 30 (1998) to reflect the composition of the sample population.

Mandating HAART reduces expected lifetime value. Value declines less for those with a low CD4 count (0.3–0.9%) compared to those with a high CD4 count (1.6–3.1%) because they are likely to use HAART even without the mandate. Similarly, value declines more for those with less education (2.8% compared to 1.4%) because they are less likely to be using treatment before the mandate. While the mandate reduces welfare, it increases health because people are forced to use health-improving treatments. Health improves more for those with a low CD4 count (8.7–14.4%) because those with a high CD4 count were likely to remain healthy regardless. Health increases more for those with less education (1.7% compared to 1.0%), reflecting the larger increase in HAART use. HAART use comes with significant ailments, which inhibit work. Employment declines when HAART is mandated, especially for those with less education (4.1% compared to 1.6%). This is because

TABLE 5: Treatment Mandate

	All	<College			College +		
		All	Low CD4	High CD4	All	Low CD4	High CD4
Lifetime value, no mandate	100.0	65.6	52.8	68.6	113.6	88.1	117.6
Pr(High $CD4_{t+1}$), no mandate	0.84	0.82	0.27	0.94	0.86	0.28	0.95
Pr(Treatment), no mandate	0.87	0.83	0.94	0.80	0.89	0.97	0.88
Pr(HAART), no mandate	0.65	0.61	0.80	0.57	0.66	0.87	0.63
Pr(Work), no mandate	0.66	0.58	0.40	0.62	0.69	0.54	0.71
Lifetime value, HAART mandate	98.3	63.8	52.3	66.4	111.9	87.8	115.8
Percent change	-1.7	-2.8	-0.9	-3.1	-1.4	-0.3	-1.6
Pr(High $CD4_{t+1}$), HAART mandate	0.85	0.83	0.31	0.95	0.86	0.30	0.95
Percent change	1.2	1.7	14.4	0.9	1.0	8.7	0.6
Pr(Work), HAART mandate	0.64	0.56	0.39	0.59	0.68	0.54	0.70
Percent change	-2.2	-4.1	-2.7	-4.3	-1.6	-1.0	-1.7
Lifetime value, treatment mandate	99.5	64.9	52.6	67.7	113.1	88.0	117.1
Percent change	-0.5	-1.1	-0.3	-1.2	-0.4	-0.1	-0.4
Pr(High $CD4_{t+1}$), treatment mandate	0.85	0.82	0.28	0.95	0.86	0.29	0.95
Percent change	0.4	0.6	3.8	0.4	0.3	2.3	0.2
Pr(Work), treatment mandate	0.65	0.56	0.39	0.60	0.68	0.54	0.70
Percent change	-1.5	-2.8	-1.8	-3.0	-1.0	-0.7	-1.0
Lifetime value, no treatment	93.2	59.7	44.9	63.2	106.4	78.5	110.9
Percent change	-6.8	-9.0	-15.0	-7.9	-6.3	-10.9	-5.7
Pr(High $CD4_{t+1}$), no treatment	0.80	0.77	0.09	0.92	0.81	0.09	0.92
Percent change	-5.5	-6.1	-66.7	-2.1	-5.3	-68.5	-2.3
Pr(Work), no treatment	0.73	0.67	0.52	0.70	0.76	0.64	0.77
Percent change	11.1	15.4	29.3	13.4	9.6	18.4	8.6

Notes: Represents model predictions matched to data on observable state variables for visit 30. Value for "all, no mandate" normalized to 100.

those with less education find it more difficult to work while experiencing side effects of treatment.

Turning to the third panel, allowing agents to choose between treatments reduces the expected value loss from the mandate, but also reduces the health improvements because some individuals choose sub-standard treatments. The fourth panel shows that preventing people from accessing treatment reduces both value and health, but increases employment through the reduction in ailments that comes from forgoing treatment.

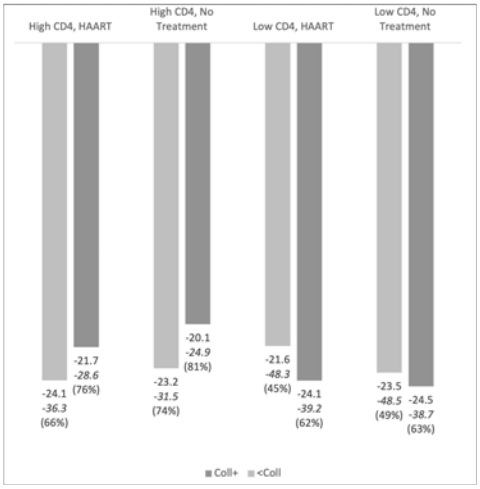
Appendix Tables A17 and A18 show counterfactual results removing the effect of medications on the ailment process. These results show that the negative effects

of the mandate are largely driven by the ailments caused by the treatment. Table A17 shows a counterfactual where none of the available treatments increase the probability of ailments, while Table A18 removes the ailment effects of HAART only. Removing the ailment effects of medication reduces the loss in value associated with a medication mandate. It also reduces the health improvements by increasing the baseline probability of medication use pre-mandate. Under this counterfactual, the medication mandate has almost no effect on labor supply because the agents do not face additional work-inhibiting ailments. In fact, Table A18 shows that in a scenario where HAART does not cause ailments but other treatments do, a HAART mandate actually slightly increases employment as agents switch from ailment-producing treatments to HAART.

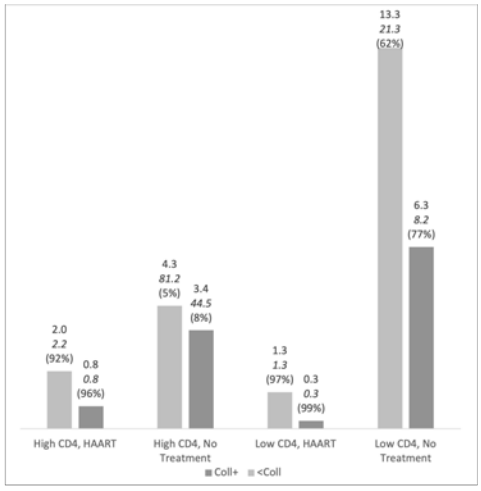
4.4 Social Determinants of Health

We use the estimated model to examine the effects of a targeted policy that increases by $10,000-per-six-months income for non-workers. We focus on the effect on employment, medication use and health. Figures 6a–6c show the effect of this policy change on the probability of working, using HAART and having a high CD4 count next period. The four sets of bars show four possible combinations of current-period health status and medication use, with each bar representing the percentage point change in the probability of the given outcome next period by education level. We also write the percent change in italics and the baseline probability of the outcome without the policy change in parentheses.

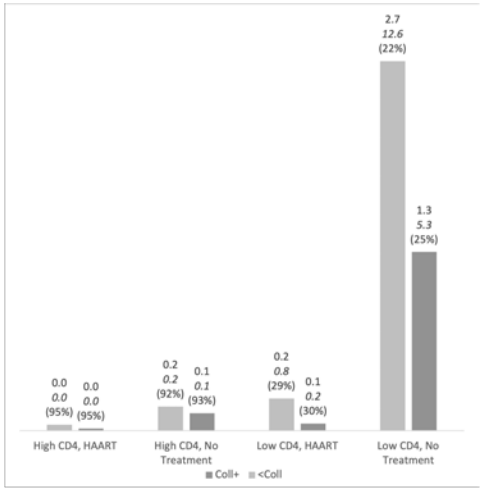
For all groups, increasing the amount of income they earn while not working leads to a decrease in the probability of work (Figure 6a). This change is relatively similar across the board in percentage point terms, but in percent change terms the decrease is larger for people with low CD4 counts and for those with less education. Across health and medication categories, people with less than a college degree are between 31 and 49 percent less likely to work after the policy, compared with a 25 to 39 percent decrease for those with a college degree or more. This disparity is the result of two mechanisms. First, people with less education might respond more because the policy represents a larger share of their potential income. Second, the



(A) Work



(B) HAART



(C) Health

FIGURE 6: Effects of a Non-Labor Income Subsidy

Notes: This figure shows the change in the probability of working (Panel A), the probability of using HAART (Panel B) and the probability of high CD4 (Panel C) in the next period for HIV+ men across four possible current-period health-treatment states given a $10,000-per-six-months increase in non-labor income for non-workers. Bars represent percentage point changes. Percent changes are in italics and baseline probabilities (absent the policy) are in parentheses.

estimated model parameters show that the disutility of working when experiencing side effects is larger for those with less education, perhaps due to the nature of their jobs. Thus, HIV+ men with less education are more likely to be on the margin such that the policy is enough to induce them to leave work.

In addition to the direct effects on employment, the increase in non-labor income induces people to take up HAART (Figure 6b). The policy allows people to stop working, which reduces incentives to avoid treatment with side effects. Even without the policy, the model predicts that people who are already using medication will often continue to use it. Consistently, the largest effects of the policy change on medication use are for those individuals who were not taking medication. Among those with AIDS-level CD4 counts not previously on medication, 62% of those without a college degree and 77% of those with a college degree will start using HAART without the policy change. The policy change increases that probability by 13.3 percentage points for the less educated group and by 6.3 percentage points for the more educated group. However, the largest proportional change is for those individuals with higher than AIDS-level CD4 counts, who are less likely to take-up HAART without the policy. After the policy change, the share of those with less than a college degree who will start HAART increases by 81.2%, from 5% to 9%. For those with more education, HAART use increases by 44.5%, from 8% to 11%.

Finally, the increases in medication use lead to increases in the probability of having a CD4 count above AIDS levels (Figure 6c). Health changes are concentrated among those who changed their treatment decisions, primarily individuals not previously using HAART. The probability of being healthy next period changes more for those who were unhealthy this period because those who were healthy are highly likely to be healthy next period, regardless of medication use. For individuals with AIDS-level CD4 counts who were not on treatment, the probability of having a high CD4 count next period increased by 12.6% for those with less than a college degree and by 5.3% for those with a college degree. The results of this policy simulation suggest that transfers can ease the burden of life-saving treatments, especially for those individuals for whom treatment makes work difficult. While the magnitudes of the health changes may be small, there are (unmodeled) externalities to even small changes to health status, as individuals on treatment are at

much lower risk of transmitting the virus.

People optimally engage in risk in ways that depend on sociodemographic differences. That people with less education face a more difficult tradeoff is perhaps as depressing as it is unsurprising. Yet, people do respond to incentives and policy can help. In the case of HIV, people who are very sick tend to use medication. Hence, increases in non-labor income have their biggest impacts on people who are not as sick, but who could still benefit from treatment. Understanding which segments of society have the most trouble engaging in health behaviors with positive externalities, such as lower infection risk, is crucial in the design of policies.

There are two key reasons why those with less education may respond more to this policy change. As mentioned above, their incomes are lower, so the $10,000 increase in non-labor income represents a larger change to their consumption, resulting in a stronger response. Additionally, lower-education individuals experience more disutility from working (with ailments), so it is easier to encourage them to leave work. Figures A1a–A1c replicate figures 6a–6c but hold the income process constant across education groups, while Figures A2a–A2c replicate figures 6a–6c removing differences in the disutility of work and ailments. For both sets of figures, we give the lower-education group the parameters for the higher-education group, meaning that the darker bars representing higher education do not change. Figures A1b and A1c show that changing the income process reduces the gap in response between those with more and less education, but it does not come close to eliminating the gap. Changing the parameters for the disutility of work and ailments also has the effect of reducing but not eliminating the gaps between the education groups. The effects on HAART use (Figure A2b) and health (Figure A2c) are comparable to the results of changing the income process. In both of these simulations, the probability of working does not meaningfully change from the results of the initial simulation (Figures A1a and A2a). These simulations suggest that both mechanisms are at play, so the effects of the policy are not solely due to the effects of differential income.

Table 6 shows the effects of the simulations shown in Figures 6a–6c across two periods. The first three rows of each panel show the impact of the simulated increase

in non-labor income in the following period.[17] The following three rows show the effects in the following period, a year out from baseline. For individuals who start with a high CD4 count, regardless of their treatment history, the probability of maintaining their health status is high. Those who start the simulation on HAART are already highly likely to continue with the treatment, so the policy change does not have a large effect on their treatment choice. For those individuals with a high CD4 count who were not using treatment before, the simulation induces a large change to HAART use at both time $t+1$ and $t+2$. This group would not have been likely to switch to HAART in the absence of the intervention because they were already highly likely to stay healthy regardless of treatment choice. Thus, one year after the policy is introduced the probability of using HAART is 7.9 percentage points higher than it would be in the absence of the policy for those with less than a college degree and 6.1 percentage points higher for those with a college degree. However, because health is highly persistent, this translates to only small gains in health.

Individuals with low CD4 have a lot to gain from using HAART, even in the absence of the policy intervention. For those already using HAART, the policy therefore has a very small effect on HAART use, since these individuals would have continued the treatment with a 97–99% probability at $t+1$ and a 94–97% probability at $t+2$. Given this pattern, the policy change does not have a meaningful impact on health. However, for those individuals with low CD4 and no treatment use at time t, the impacts are larger. In the absence of the policy, 63% of those with less education and 78% of those with a college degree would have started HAART in $t+1$, while 81% and 91% would have started HAART by $t+2$, respectively. With the policy intervention, HAART take-up happens faster, with 76% of those with less education and 84% of those with a college degree starting HAART in $t+1$. Thus, while the health impacts of the policy attenuate over time, the policy change does induce individuals to improve their health sooner than they otherwise would have.

[17] Small differences from Figures 6a–6c are due to simulation error.

TABLE 6: Non-Labor Income Subsidy

		<College				College+			
		No Subsidy	Subsidy	PP Δ	% Δ	No Subsidy	Subsidy	PP Δ	% Δ
High CD4, on HAART									
$t+1$	Work	66.7	42.2	-24.5	-36.7	76.8	54.9	-21.8	-28.4
	HAART	91.9	93.9	1.9	2.1	95.5	96.3	0.8	0.8
	Health	95.0	95.0	0.0	0.0	95.1	95.1	0.0	0.0
$t+2$	Work	65.2	41.3	-24.0	-36.7	75.2	53.2	-22.0	-29.3
	HAART	85.1	88.8	3.7	4.3	91.7	93.1	1.5	1.6
	Health	91.6	91.7	0.1	0.1	91.9	92.0	0.1	0.1
High CD4, no treatment									
$t+1$	Work	74.4	51.3	-23.1	-31.1	81.1	60.8	-20.3	-25.0
	HAART	5.1	9.3	4.3	84.0	7.3	11.0	3.7	50.4
	Health	92.6	92.7	0.1	0.1	92.7	92.8	0.1	0.1
$t+2$	Work	71.4	47.3	-24.1	-33.8	78.8	58.0	-20.9	-26.5
	HAART	13.4	21.3	7.9	58.9	18.1	24.2	6.1	33.7
	Health	87.7	88.2	0.5	0.6	88.2	88.5	0.3	0.4
Low CD4, on HAART									
$t+1$	Work	45.2	23.0	-22.2	-49.2	62.1	37.6	-24.5	-39.5
	HAART	96.5	97.7	1.2	1.3	98.8	99.1	0.3	0.3
	Health	29.2	29.4	0.1	0.5	30.0	30.1	0.1	0.2
$t+2$	Work	50.6	28.6	-22.0	-43.5	65.4	42.2	-23.2	-35.5
	HAART	93.8	95.9	2.1	2.2	97.4	98.1	0.6	0.7
	Health	48.4	48.8	0.4	0.8	49.7	49.8	0.1	0.2
Low CD4, no treatment									
$t+1$	Work	48.1	24.9	-23.2	-48.2	63.0	38.5	-24.5	-38.9
	HAART	62.9	76.3	13.4	21.3	77.6	83.8	6.2	8.0
	Health	22.3	25.1	2.9	12.9	25.7	26.9	1.2	4.6
$t+2$	Work	50.8	28.2	-22.6	-44.4	65.4	41.9	-23.4	-35.8
	HAART	81.0	89.9	8.9	11.0	91.3	94.6	3.2	3.6
	Health	41.6	45.1	3.5	8.4	46.0	47.1	1.2	2.5

Notes: This table shows the effects of a simulated permanent $10,000 per-six-months increase in income for non-workers. Each panel of the table shows the results for a different combination of starting health and treatment for a 30 year old individual in 1996 by education level. Columns 1 and 5 show results without the subsidy (for those without and with a college degree respectively), while columns 2 and 6 include the subsidy. The following columns show the percentage point and percent difference with and without the subsidy. The first three rows of each panel show results for one period ahead, while the following rows show results for two periods ahead. We simulate 20,000 observations to reduce simulation error, though $t+1$ values differ slightly from Figures 6a–6c due to simulation error.

5 Conclusion

This paper develops a model for assessing variation in the value of medical innovation across sociodemographic groups. The model captures how health-maximizing and welfare-maximizing behaviors can be at odds. Health-welfare tradeoffs can be particularly salient for disadvantaged individuals because various features of their lives—such as their work conditions—make health investments particularly costly.

We argue that this approach to modeling patient behavior aids in our understanding of tradeoffs agents face that lead them to optimally choose behaviors that exacerbate health disparities. Effective policy could modify these tradeoffs to reduce health disparities.

We use the model to study an HIV treatment innovation, HAART, which was introduced in the mid-1990s. While HAART was far more effective than earlier treatments, it had harsh side effects, which interfered with employment, especially so for patients with less education, who are more likely to sort into physically taxing or less flexible jobs. As a result, HAART provided less value (measured as gains in lifetime utility) for people with less education, thus exacerbating existing inequality. Policies that make it easier to use medications, including those that directly target the health-work tradeoff, could increase uptake and broaden the set of patients who benefit from medical innovation.

While our focus is on HIV, we view the AIDS epidemic as a useful historical analogy that provides lessons for other health contexts. A recent example is COVID-19. Like HIV, COVID-19 has unequal consequences in part because protective health actions imply different costs for different groups. In the case of HIV, effective medication has side effects that make work difficult, especially for less educated people. In the case of COVID-19, staying at home has been more difficult for people in cramped housing or who could not tele-work. In both contexts, a useful starting point—one that can contribute to risk mitigation—is to understand the health-welfare tradeoffs that people in different circumstances face and to design policy accordingly.

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For Online Publication Appendix to Medical Innovation and Health Disparities

A Appendix: Additional Tables

TABLE A1: Next Period High CD4 by Education

	All	<College	College+
<College	-0.238		
	(0.075)		
Health (h_{it})	4.310	4.401	4.253
	(0.073)	(0.130)	(0.088)
Age (a_{it})	0.082	0.030	0.087
	(0.052)	(0.093)	(0.065)
Age^2 (a_{it}^2)	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)
Pre-HAART ν_t	-0.086	-0.071	-0.093
	(0.014)	(0.025)	(0.017)
Post-HAART ν_t	0.062	0.054	0.068
	(0.009)	(0.016)	(0.011)
Constant	-3.250	-2.795	-3.131
	(1.171)	(2.029)	(1.472)
Observations	10,858	3,305	7,553

Notes: Standard errors in parentheses. Logit models for 1,201 individuals in the sample. Health is defined as CD4>250.

TABLE A2: HIV Treatment Choice Transitions

		Time $t+1$				
		No treatment	Monotherapy	Combotherapy	HAART	Observations
		Pre-HAART, <College				
Time t	No treatment	85.9	9.9	4.2	–	838
	Monotherapy	8.3	73.2	18.6	–	628
	Combotherapy	7.5	19.5	73.1	–	319
		Pre-HAART, College+				
Time t	No treatment	88.1	8.6	3.3	–	1,477
	Monotherapy	6.5	69.6	23.9	–	1,141
	Combotherapy	3.4	21.4	75.2	–	762
		Post-HAART, <College				
Time t	No treatment	82.8	0.9	5.3	11.0	463
	Monotherapy	9.4	28.1	40.6	21.9	35
	Combotherapy	2.7	0.7	67.6	29.1	308
	HAART	2.6	0.1	4.1	93.2	902
		Post-HAART, College+				
Time t	No treatment	80.6	0.5	6.4	12.4	758
	Monotherapy	1.0	30.0	33.0	36.0	103
	Combotherapy	2.1	1.3	67.5	29.0	858
	HAART	1.5	0.2	4.3	94.1	2,698

Notes: This table presents a transition matrix for medication choices by HAART era and education level. Before HAART, medication use/non-use was highly persistent. After HAART individuals using other medications often switch to HAART.

TABLE A3: Treatment Use by Education

	All	<College	College+
<College	-0.352		
	(0.049)		
Health (h_{it})	-1.228	-1.125	-1.289
	(0.064)	(0.100)	(0.082)
Insurance ($y_{it}^{insurance}$)	0.960	0.952	0.978
	(0.095)	(0.136)	(0.131)
Work (d_{it+1}^{l})	-0.288	-0.334	-0.264
	(0.052)	(0.084)	(0.066)
Age (a_{it})	0.098	0.012	0.160
	(0.035)	(0.058)	(0.044)
Age^2 (a_{it}^2)	-0.001	0.000	-0.002
	(0.000)	(0.001)	(0.000)
Pre-HAART ν_t	-0.128	-0.107	-0.139
	(0.010)	(0.017)	(0.012)
Post-HAART ν_t	0.064	0.054	0.070
	(0.006)	(0.010)	(0.007)
Constant	-1.342	0.158	-2.695
	(0.783)	(1.274)	(0.994)
Observations	10,858	3,305	7,553

Notes: Standard errors in parentheses. Logit models for 1,210 in the sample. Treatment is an indicator for whether the individual is taking any medication. Health indicates CD4>250.

TABLE A4: No Ailments by Education

	All	<College	College+
<College	-0.213		
	(0.044)		
Health (h_{it})	0.908	1.068	0.831
	(0.049)	(0.085)	(0.060)
Monotherapy	-0.355	-0.145	-0.463
	(0.066)	(0.112)	(0.083)
Combotherapy	-0.508	-0.427	-0.559
	(0.060)	(0.106)	(0.074)
HAART	-0.563	-0.487	-0.612
	(0.063)	(0.112)	(0.076)
Age (a_{it})	-0.109	-0.105	-0.123
	(0.031)	(0.054)	(0.039)
Age^2 (a_{it}^2)	0.001	0.001	0.001
	(0.000)	(0.001)	(0.000)
Pre-HAART ν_t	-0.022	-0.015	-0.025
	(0.009)	(0.016)	(0.011)
Post-HAART ν_t	0.010	0.024	0.006
	(0.005)	(0.010)	(0.006)
Constant	2.823	2.157	3.335
	(0.701)	(1.188)	(0.880)
Observations	10,858	3,305	7,553

Notes: Standard errors in parentheses. Logit models for 1,201 individuals in the sample. No ailments is an indicator for if the individual suffered no ailments in the period. Health indicates CD4>250.

TABLE A5: Employment Choice Transitions

		Time $t+1$		
		<College		
		Not Working	Working	Observations
Time t	Not working	90.8	9.3	1,377
	Working	9.1	90.9	2,002
		College+		
		Not Working	Working	Observations
Time t	Not working	87.9	12.1	2,239
	Working	7.1	92.9	5,369

Notes: This table presents a transition matrix for employment choices by education level. Working is defined as full time work.

TABLE A6: Full Time Work by Education

	All	<College	College+
<College	-1.136		
	(0.056)		
Ailments ($y_{it}^{ailments}$)	-0.964	-1.167	-0.868
	(0.046)	(0.081)	(0.056)
Health (h_{it+1})	0.861	0.846	0.854
	(0.053)	(0.091)	(0.065)
Treatment ($d_{it+1}^{m} \neq 0$)	-0.114	-0.167	-0.085
	(0.054)	(0.088)	(0.068)
Age (a_{it})	-0.065	-0.298	0.028
	(0.041)	(0.075)	(0.054)
Age^2 (a_{it}^2)	-0.001	0.001	-0.002
	(0.000)	(0.001)	(0.001)
Experience (e_{it})	0.129	0.146	0.126
	(0.011)	(0.022)	(0.014)
Experience^2 (e_{it}^2)	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)
Pre-HAART ν_t	-0.004	-0.011	-0.001
	(0.010)	(0.017)	(0.012)
Post-HAART ν_t	0.015	0.013	0.018
	(0.006)	(0.010)	(0.007)
Constant	2.934	6.840	0.819
	(0.856)	(1.517)	(1.135)
Observations	10,858	3,305	7,553

Notes: Standard errors in parentheses. Logit models for 1,201 individuals in the sample. Health indicates CD4 >250.

TABLE A7: Income by Education

	All	<College	College+
<College	-5.309		
	(0.180)		
Health (h_{it})	1.126	1.313	1.044
	(0.181)	(0.303)	(0.226)
Work (d^l_{it+1})	9.417	9.657	9.287
	(0.166)	(0.281)	(0.205)
Age (a_{it})	0.727	0.800	0.733
	(0.132)	(0.232)	(0.172)
Age^2 (a^2_{it})	-0.006	-0.007	-0.005
	(0.001)	(0.002)	(0.002)
Experience (e_{it})	0.136	-0.038	0.191
	(0.036)	(0.067)	(0.045)
Experience^2 (e^2_{it})	-0.003	-0.000	-0.004
	(0.001)	(0.001)	(0.001)
Pre-HAART ν_t	-0.018	-0.008	-0.024
	(0.032)	(0.056)	(0.040)
Post-HAART ν_t	-0.104	-0.087	-0.113
	(0.018)	(0.032)	(0.021)
Constant	-7.143	-11.241	-8.072
	(2.762)	(4.745)	(3.591)
Observations	10,858	3,305	7,553

Notes: Standard errors in parentheses. Linear regression models for 1,201 individuals in the sample. Income is in thousands of year 2000 dollars per half year. Health indicates CD4>250.

TABLE A8: Estimated Structural Utility Parameters

Definition	Parameter	Estimate	Standard Error
No ailments	$\theta^u_{1,f=1}$	0	–
Ailments	$\theta^u_{1,f=0}$	-2.13	0.132
Ailments, college +	$\theta^u_{1,f=0,s=1}$	-0.22	0.139
Work, no ailments	$\theta^u_{2,f=1}$	1.03	0.063
Work, no ailments, college +	$\theta^u_{2,f=1,s=1}$	0.11	0.074
Work, ailments	$\theta^u_{2,f=0}$	-2.73	0.085
Work, ailments, college+	$\theta^u_{2,f=0,s=1}$	0.76	0.104
Start treatment, no ailments	$\theta^u_{3,f=1}$	0.25	0.485
Start treatment, ailments	$\theta^u_{3,f=0}$	-1.64	0.38
Change treatment, no ailments	$\theta^u_{4,f=1}$	-4.98	0.122
Change treatment, ailments	$\theta^u_{4,f=0}$	1.49	0.135
Stop treatment, no ailments	$\theta^u_{5,f=1}$	-9.39	0.467
Stop treatment, ailments	$\theta^u_{5,f=0}$	3.18	0.449

Notes: Parameters are for equation (10). $\theta_{1,f=1}$ is set to 0. f=1 means no ailments. s=1 means college+. Standard errors calculated using the delta method.

TABLE A9: Model Fit

		Pr(Work)		Pr(HAART)	
Healthy	College+	Data	Model	Data	Model
0	0	0.39	0.42	0.25	0.29
1	0	0.66	0.64	0.31	0.26
0	1	0.52	0.56	0.31	0.38
1	1	0.75	0.73	0.40	0.35
All		0.66	0.66	0.36	0.33

Notes: Estimates from model simulations compared with data from analysis sample. Comparison is facilitated by matching on all observable state variables.

TABLE A10: Value Decomposition

	<College		College+	
	*Low CD*4	*High CD*4	*Low CD*4	*High CD*4
All education differences				
Combotherapy (1995)	21.7	56.5	50.1	100.0
HAART (1996)	73.0	104.9	138.6	176.3
Absolute gain	51.3	48.4	88.5	76.3
Percent gain	236.1	85.7	176.6	76.3
Same Income Process				
Combotherapy (1995)	31.2	76.2	50.1	100.0
HAART (1996)	97.2	136.8	138.6	176.3
Absolute gain	66.0	60.6	88.5	76.3
Percent gain	211.6	79.6	176.6	76.3
+Insurance & MOOP				
Combotherapy (1995)	31.1	76.0	50.1	100.0
HAART (1996)	97.0	136.5	138.6	176.3
Absolute gain	65.9	60.5	88.5	76.3
Percent gain	211.7	79.6	176.6	76.3
+Health				
Combotherapy (1995)	31.4	76.7	50.1	100.0
HAART (1996)	97.9	137.4	138.6	176.3
Absolute gain	66.4	60.8	88.5	76.3
Percent gain	211.3	79.3	176.6	76.3
+Ailments				
Combotherapy (1995)	34.3	83.7	50.1	100.0
HAART (1996)	106.7	148.8	138.6	176.3
Absolute gain	72.4	65.1	88.5	76.3
Percent gain	211.3	77.8	176.6	76.3
+Survival				
Combotherapy (1995)	46.5	93.5	50.1	100.0
HAART (1996)	129.9	165.7	138.6	176.3
Absolute gain	83.4	72.2	88.5	76.3
Percent gain	179.3	77.3	176.6	76.3
+Utility Parameters				
Combotherapy (1995)	50.1	100.0	50.1	100.0
HAART (1996)	138.6	176.3	138.6	176.3
Absolute gain	88.5	76.3	88.5	76.3
Percent gain	176.6	76.3	176.6	76.3

Notes: Estimates from model simulations. This table decomposes the value of HAART by education group by gradually changing processes and parameters to give the agents with lower education the processes and parameters of those with higher education. Panel 1 shows results with all differences intact, as in Table 4. Total expected lifetime value for a 30 year old male on best available treatment, 1995 (visit 23) vs 1996 (visit 26). High edu, high CD4, combotherapy normalized to 100.

B Appendix: Estimation

In this section we first specify some of the details of the empirical implementation of the model. Then we present the estimation method and briefly discuss identification. We finish the section by discussing parameter estimates and model fit.

B.1 Empirical Implementation

Individuals enter the model at age $\underline{a} = 30$ and make choices until age $\bar{a} = 65$. The period $\bar{t}$ at which HAART is introduced is the first semester of 1996. The health booster variable Δh_{it} is an indicator constructed from the continuous measure of health (i.e. the CD4 count) and takes the value of one if $CD4_{it} \geq CD4_{it-1}$ and zero otherwise. In other words, the health booster captures health improvement that can occur within a health state h_{it}. The aggregate processes for technological change in health and ailments and the aggregate processes for income and medical expenses are captured using era-specific linear time trends. Hence, ν_t in all processes it appears is given by:

$$\nu_t = [t \cdot \mathbf{I}\{t < \bar{t}\}, t \cdot \mathbf{I}\{t \geq \bar{t}\}] \tag{15}$$

Finally, we specify the flow utility from consumption $\tilde{u}(c_{it})$ to be linear but divide consumption, which is already in thousands of dollars, by 10 for ease of computation, i.e. $\tilde{u}(c_{it}) = \frac{c_{it}}{10{,}000}$.

B.2 Estimation and Identification

Let θ^{xy}, the vector that collects all parameters governing processes and transition probabilities, be $\theta^{xy} \equiv [\theta^{\Delta h}, \theta^{h}, \theta^{b}, \theta^{ailments}, \theta^{income}, \theta^{insurance}, \theta^{expenses}]$, and let θ^{u} be the vector of parameters of the flow utility function. We estimate the model parameters $\theta = [\theta^{u}, \theta^{xy}]$ following a nested procedure. In the inner step, given a set of proposed parameters, we use backwards induction to solve the dynamic programming problem for each set of observable state variables. This procedure generates choice probabilities that maximize utility given the parameters. The search algorithm in the outer step uses the probabilities generated by the inner step to search for the parameters that maximize the likelihood of the data. The likelihood contri-

bution of each individual is:

$$L_i(\theta) = \prod_{t=1}^{T_i} P(d_{it}|X_{it};\theta) \times \prod_{t=1}^{T_i} f(X_{i,t+1}|X_{it}, d_{it};\theta^{xy}) \tag{16}$$

where f denotes the density function derived from the processes. Because the log likelihood is additively separable, we estimate the processes separately from the utility parameters in a first step to reduce computational burden while retaining consistency. In the second step, we search for the utility parameters using the nested procedure described above.

Our first stage processes are identified by their data counterparts. In particular, the evolution of health as well as treatment effects are identified off of the panel variation in CD4 counts for individuals with different levels of initial health and different treatment choices. The variation in the data that identifies flow utility parameters comes from observed conditional choice probabilities. For example, the disutility of ailments is identified by differences in choices by ailment status, given state variables. Additionally, because HAART is a quasi-experimental, unexpected intervention that occurs in the middle of our panel of data, this unanticipated variation in the set of available treatments to choose from helps identify utility parameters. We assume the discount factor $\beta = \sqrt{0.95}$ and we normalize the parameter $\theta^u_{1s,f=1}$ to zero. Given data on transitions and choices, as well as the choices of β, the distributional assumption of taste shocks and the flow utility normalization, identification follows from the arguments made by Magnac and Thesmar (2002) showing that under these assumptions there will be a unique parameter vector that maximizes the likelihood function.

B.3 Parameter Estimates

This section presents estimates of preference parameters and parameters governing outcomes and transitions. Table A8 presents estimates of the utility parameters θ^u along with standard errors calculated using the delta method. $\theta^u_{1,f=0}$ represents the disutility of ailments for those with less than a college degree, while the sum of $\theta^u_{1,f=0}$ and $\theta^u_{1,f=0,s=1}$ represents the disutility of ailments for those with a college

degree. The utility cost of ailments alone is not significantly different across education groups, though parameter estimates suggest a higher disutility of ailments for those with more education. Regardless of educational attainment, individuals not suffering from ailments get utility from work (rows 4 and 5), and there is no difference in this utility across educational categories. However, when agents suffer from ailments, working decreases utility (rows 6 and 7). For those with less than a college degree, the disutility of working with ailments is -2.73 ($\theta^u_{2,f=0}$) while for those with more education the cost is less, -1.97 ($\theta^u_{2,f=0}$+$\theta^u_{2,f=0,s=1}$). This is in line with the reduced form results showing larger impacts of ailments on work for those with less education.

Given that individuals with less education have a stronger aversion to ailments when working, we would expect the tradeoff between health and ailments to differ across education groups. Figures 4a and 4b plot indifference curves by education and employment for the health-ailment tradeoff, separately by health status. The point at which the indifference curves cross represents the health and ailments probabilities generated by HAART for a higher-education agent. For both high and low CD4 agents, individuals with less education are more willing to trade health for ailments when working. The cross-education differences appear when agents are working because the disutility of working with ailments is larger for those with less education. When agents are not working, the tradeoff is approximately the same for both education groups, with those with more education actually slightly less willing to make the tradeoff. When working, the difference across education groups is larger for high CD4 agents, because for low CD4 agents, health is critical.

The utility function includes switching costs for starting, changing and stopping treatment. These switching costs vary by ailment status but not by education. Stopping treatment (without ailments) is the most costly, followed by switching among treatments. For both stopping and changing treatments, the costs are lower (benefits are higher) when individuals suffer from ailments. This may be because the medication transitions are made in service of attempting to reduce ailments, or that doctors are more supportive of treatment changes when treatments are causing ailments. The relationship reverses when starting treatments, perhaps because beginning a treatment reinforces ailments.

In addition to flow utility parameters, we estimate parameters for the health, survival and additional processes included in y_{it}. The estimated parameters for these processes are presented in Appendix C. Table A11 shows the estimates for the two-step health process. The estimated parameters suggest that all medications increase the probability of health improvements, with HAART being the most effective. The difference between HAART and other medications is especially pronounced for individuals in poor health. In the second stage of the process, both previous period health and health improvements are associated with current period health. There is no statistically significant relationship between health and education, though the parameter estimate suggests a positive relationship between education and health improvements.

Table A12 shows parameter estimates for the death process. Individuals with a high CD4 count are much less likely to die, though that relationship weakens as individuals age. Before HAART, the probability of dying increased over time, but post-HAART the probability decreases over time. The parameter estimates for the no ailments process are shown in Table A13. Individuals in good health are less likely to suffer ailments. All three treatment options reduce the probability of no ailments, but HAART produces more ailments than mono-therapy or combo-therapy. Individuals with less education are more likely to suffer ailments.

Parameter estimates from the income process show that employment and education have strong positive relationships with income (Table A14). In addition, health is associated with higher incomes, and income falls over time. Age and experience are also associated with increases in income, though the increases slow over time. Table A15 shows parameter estimates for the insurance process. Employment is associated with a significant increase in the probability of insurance coverage, as is higher education. A high CD4 count is associated with a decrease in the probability of insurance perhaps capturing slight adverse selection. In all, the vast majority of those in the sample are covered by insurance. Medical expenditures increase with income and decrease when insured (Table A16). Unsurprisingly, both medication usage and ailments are generally associated with increased medical costs. In line with the results shown in Table 1, individuals with less education have lower medical expenditures, but the difference is not large.

B.4 Model Fit

Table A9 shows the model predicted probabilities of work and HAART use for the sample compared to the actual probabilities from the data. To construct the comparison, we match choice probabilities from the model to state variables in the data. Overall, the model predictions closely match the data. Both the data and the model predict that agents will be employed 66% of the time. The results are similar for HAART use, with the model predicting HAART use in 33% of periods and the data showing HAART use in 36% of periods. When fit is disaggregated by health and education, the model performs less well. The model slightly over-predicts employment among unhealthy people and slightly under-predicts employment among healthy people, but both the model and data show that healthy individuals work more and that those with less education work less. The model slightly under-predicts medication use among those with a high CD4 count and over-predicts it among those with a low CD4 count. While the data show that individuals with a high CD4 count are more likely to use HAART, the model predicts that these individuals are slightly less likely to use treatment.[18] Both the model and the data show that individuals with less education are less likely to use treatment.

[18] In results available by request, we show that this pattern is robust to various specification changes such as the inclusion of additional or different switching costs, changes to the process inputs and alternate specifications of consumption utility. We also show that specifications including unobserved heterogeneity in the utility function produce very small probabilities of a second type (below 5%), evidence against the inclusion of unobserved utility heterogeneity.

C Appendix: Process Estimates

TABLE A11: Health Process

	Δh_{it}
Health (h_{it-1})	0.071
	(0.111)
Health X Monotherapy $\left(h_{it-1} \cdot d^m_{1it}\right)$	0.108
	(0.077)
Health X Combotherapy $\left(h_{it-1} \cdot d^m_{2it}\right)$	0.443
	(0.067)
Health X HAART $\left(h_{it-1} \cdot d^m_{1it}\right)$	0.632
	(0.063)
Low Health X Monotherapy $\left((1-h_{it-1}) \cdot d^m_{1it}\right)$	0.016
	(0.136)
Low Health X Combotherapy $\left((1-h_{it-1}) \cdot d^m_{2it}\right)$	0.414
	(0.127)
Low Health X HAART $\left((1-h_{it-1}) \cdot d^m_{3it}\right)$	1.356
	(0.136)
Age (a_{it-1})	0.043
	(0.030)
Age^2 (a^2_{it-1})	-0.001
	(0.000)
Pre-HAART ν_t	-0.043
	(0.009)
Post-HAART ν_t	-0.001
	(0.005)
<College	-0.019
	(0.044)
Constant	-1.375
	(0.684)
	Health h_{it}
Health (h_{it-1})	5.332
	(0.313)
Health Booster X Low Health $\left(\hat{\Delta h}_{it} \cdot (1-h_{it-1})\right)$	4.649
	(0.362)
Health Booster X Health $\left(\hat{\Delta h}_{it-1} \cdot h_{it}\right)$	3.164
	(0.532)
Constant	-4.065
	(0.207)
Observations	10,858

Notes: Parameter estimates for two-step health process for structural model. Health is defined as CD4>=250.

TABLE A12: Death Process

	Death b_{it+1}
Health (h_{it})	-6.881
	(1.034)
Age (a_{it})	0.020
	(0.008)
Age X Health ($a_{it} \cdot h_{it}$)	0.083
	(0.022)
<College	0.417
	(0.107)
Pre-HAART ν_t	0.028
	(0.019)
Post-HAART ν_t	-0.111
	(0.019)
Constant	-2.799
	(0.368)
Observations	11,290

Notes: Parameter estimates for survival process for structural model. This process has more observations than the others because people who die between t & t+1 are not included in other processes.

TABLE A13: No Ailment Process

	No Ailments $\left(1 - y_{it}^{ailments}\right)$
Health (h_{it-1})	0.908
	(0.049)
Monotherapy	-0.355
	(0.066)
Combotherapy	-0.508
	(0.060)
HAART	-0.563
	(0.063)
Age (a_{it-1})	-0.109
	(0.031)
Age^2 (a_{it-1}^2)	0.001
	(0.000)
Pre-HAART ν_t	-0.022
	(0.009)
Post-HAART ν_t	0.010
	(0.005)
<College	-0.213
	(0.044)
Constant	2.823
	(0.701)
Observations	10,858

Notes: Parameter estimates for ailment process for structural model. The outcome is equal to one if the individual does *not* experience ailments.

TABLE A14: Income Process

	Income y_{it}^{income}
Experience (e_{it-1})	0.144
	(0.039)
Experience^2 (e_{it-1}^2)	-0.003
	(0.001)
Age (a_{it-1})	0.743
	(0.144)
Age^2 (a_{it-1}^2)	-0.005
	(0.002)
Health (h_{it-1})	1.211
	(0.199)
Work (d_{it}^l)	9.934
	(0.217)
<College	-6.665
	(0.306)
<College X Work	1.540
	(0.365)
Pre-HAART ν_t	-0.027
	(0.035)
Post-HAART ν_t	-0.112
	(0.019)
Constant	-8.634
	(3.022)
Variance of y_{it}^{income}	67.322
	(0.984)
Observations	10,858

Notes: Parameter estimates for income process for structural model. Income in $1000 of year 2000 dollars per half year.

TABLE A15: Insurance Process

	Insurance $y_{it}^{insurance}$
Health (h_{it-1})	-0.596
	(0.112)
Age (a_{it-1})	-0.236
	(0.083)
Age^2 (a_{it-1}^2)	0.003
	(0.001)
Experience (e_{it-1})	0.061
	(0.020)
Experience^2 (e_{it-1}^2)	-0.001
	(0.000)
Work (d_{it}^l)	0.787
	(0.126)
<College	-0.868
	(0.136)
<College X Work	-0.025
	(0.175)
Pre-HAART ν_t	-0.033
	(0.018)
Post-HAART ν_t	0.057
	(0.012)
Constant	7.257
	(1.729)
Observations	10,858

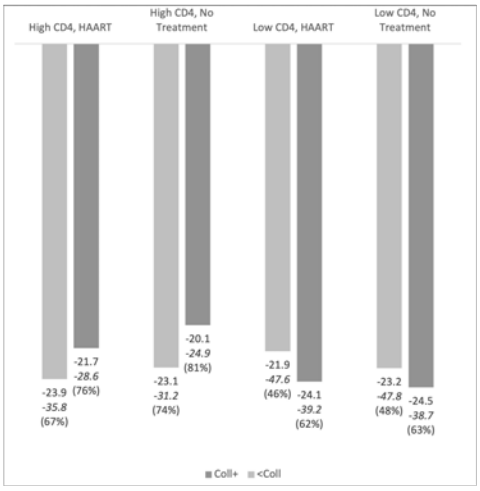
Notes: Parameter estimates for insurance process for structural model. Insurance is a binary indicator for health insurance coverage.

TABLE A16: Medical Out of Pocket Process

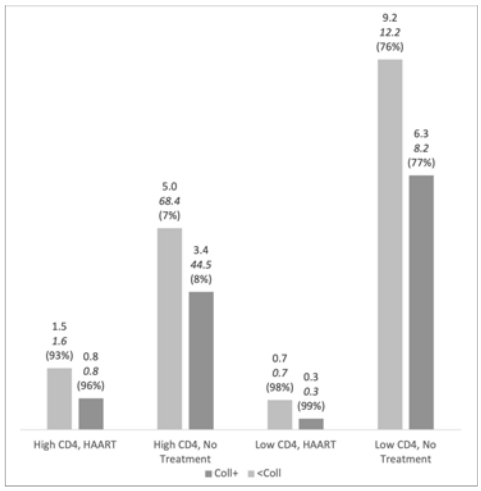
	Medical OOP Expenses $y_{it}^{expenses}$
Income $\left(y_{it}^{income}\right)$	0.008
	(0.001)
Insurance $\left(y_{it}^{insurance}\right)$	-0.081
	(0.035)
Insurance X Monotherapy $\left(y_{it}^{insurance} \cdot d_{1it}^{m}\right)$	0.173
	(0.018)
Insurance X Combotherapy $\left(y_{it}^{insurance} \cdot d_{2it}^{m}\right)$	0.249
	(0.016)
Insurance X HAART $\left(y_{it}^{insurance} \cdot d_{3it}^{m}\right)$	0.261
	(0.016)
No insurance X Monotherapy $\left((1-y_{it}^{insurance}) \cdot d_{1it}^{m}\right)$	0.274
	(0.074)
No insurance X Combotherapy $\left((1-y_{it}^{insurance}) \cdot d_{3it}^{m}\right)$	-0.187
	(0.077)
No insurance X HAART $\left((1-y_{it}^{insurance}) \cdot d_{3it}^{m}\right)$	-0.164
	(0.067)
Health (h_{it})	-0.037
	(0.018)
No Ailments $(1-y_{it}^{ailments})$	-0.096
	(0.022)
Health X Ailments $\left(h_{it} \cdot y_{it}^{ailments}\right)$	-0.039
	(0.025)
Age (a_{it})	0.005
	(0.008)
Age^2 (a_{it}^2)	-0.000
	(0.000)
<College	-0.051
	(0.012)
Pre-HAART ν_t	0.002
	(0.002)
Post-HAART ν_t	0.009
	(0.001)
Constant	-0.197
	(0.187)
Variance of $y_{it}^{expenses}$	0.278
	(0.004)
Observations	10,858

Notes: Parameter estimates for medical out of pocket expenditure process for structural model. Medical out of pocket expenses (MOOP) in $1000 of year 2000 dollars per half year.

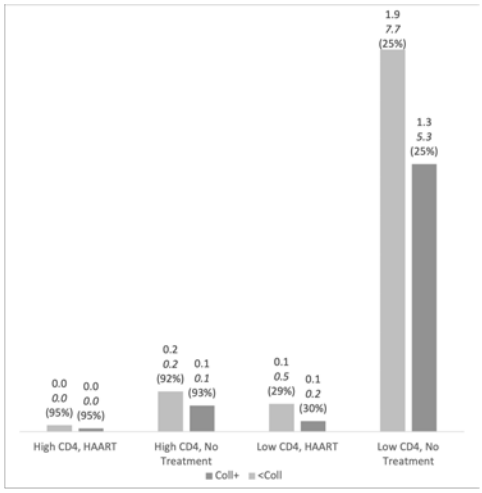
D Appendix: Non Labor Income Simulations



(A) Work



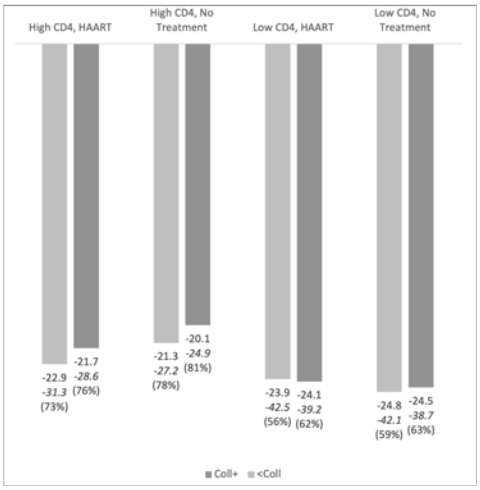
(B) HAART



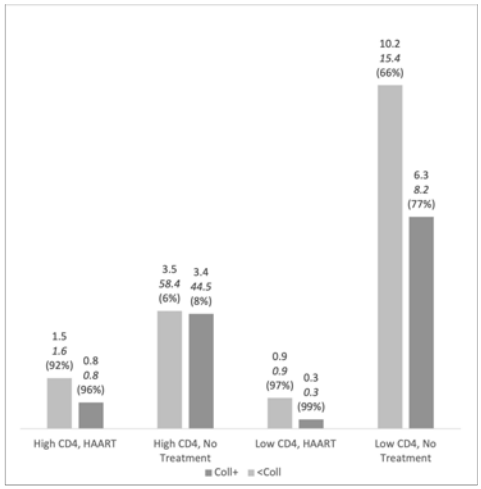
(C) Health

FIGURE A1: Effects of a Non-Labor Income Subsidy (Same Income Process)

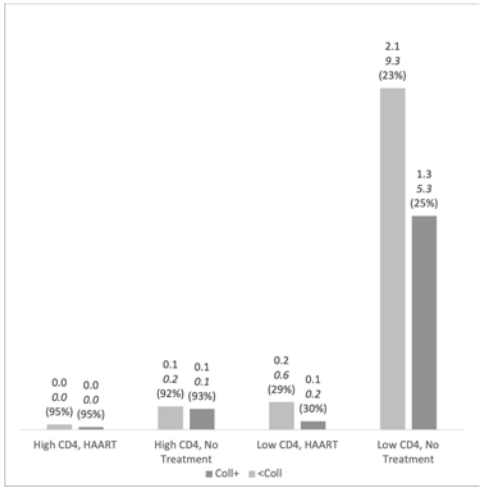
Notes: This figure shows the change in the probability of working (Panel A), the probability of using HAART (Panel B) and the probability of high CD4 (Panel C) in the next period for HIV+ men across four possible current-period health-treatment states given a $10,000-per-six-months increase in non-labor income for non-workers, removing education differences in the income process. Bars represent percentage point changes. Percent changes are in italics and baseline probabilities (absent the policy) are in parentheses.



(A) Work



(B) HAART



(C) Health

FIGURE A2: Effects of a Non-Labor Income Subsidy (Same Utility of Work and Ailments)

Notes: This figure shows the change in the probability of working (Panel A), the probability of using HAART (Panel B) and the probability of high CD4 (Panel C) in the next period for HIV+ men across four possible current-period health-treatment states given a $10,000-per-six-months increase in non-labor income for non-workers, removing education differences in the utility of work and ailments. Bars represent percentage point changes. Percent changes are in italics and baseline probabilities (absent the policy) are in parentheses.

E Appendix: Mandate Simulations

TABLE A17: Treatment Mandate Simulation—Treatments Do Not Ever Cause Ailments

	All	<College			College +		
		All	Low CD4	High CD4	All	Low CD4	High CD4
Lifetime value, no mandate	118.6	81.7	67.2	85.0	133.2	104.6	137.7
Pr(High $CD4_{t+1}$), no mandate	0.85	0.82	0.29	0.95	0.86	0.29	0.95
Pr(Treatment), no mandate	0.92	0.89	0.97	0.87	0.93	0.98	0.93
Pr(HAART), no mandate	0.74	0.73	0.92	0.69	0.75	0.93	0.72
Pr(Work), no mandate	0.73	0.67	0.51	0.70	0.75	0.64	0.77
Lifetime value, HAART mandate	117.5	80.5	67.0	83.7	132.0	104.4	136.4
Percent change	-1.0	-1.4	-0.3	-1.6	-0.9	-0.1	-0.9
Pr(High $CD4_{t+1}$), HAART mandate	0.85	0.83	0.31	0.95	0.86	0.30	0.95
Percent change	0.7	0.9	5.6	0.6	0.6	4.4	0.4
Pr(Work), HAART mandate	0.73	0.67	0.51	0.70	0.75	0.64	0.77
Percent change	-0.02	-0.03	-0.02	-0.03	-0.01	-0.01	-0.01
Lifetime value, treatment mandate	118.4	81.4	67.1	84.6	133.0	104.5	137.5
Percent change	-0.2	-0.4	-0.1	-0.4	-0.1	0.0	-0.2
Pr(High $CD4_{t+1}$), treatment mandate	0.85	0.83	0.30	0.95	0.86	0.29	0.95
Percent change	0.3	0.4	1.8	0.3	0.2	1.1	0.2
Pr(Work), treatment mandate	0.73	0.67	0.51	0.70	0.75	0.64	0.77
Percent change	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00
Lifetime value, No treatment	109.3	73.4	57.7	77.0	123.4	93.5	128.2
Percent change	-7.9	-10.1	-14.1	-9.4	-7.3	-10.6	-6.9
Pr(High $CD4_{t+1}$), No treatment	0.80	0.77	0.09	0.92	0.81	0.09	0.92
Percent change	-6.0	-6.9	-69.3	-2.4	-5.6	-69.8	-2.5
Pr(Work), No treatment	0.73	0.67	0.52	0.70	0.75	0.64	0.77
Percent change	0.1	0.1	0.3	0.1	0.1	0.2	0.1

Notes: Represents model predictions matched to data on observable state variables for visit 30. Value for "all, no mandate" in Table 5 normalized to 100.

TABLE A18: Treatment Mandate Simulation—HAART Does Not Ever Cause Ailments

	All	<College			College +		
		All	Low CD4	High CD4	All	Low CD4	High CD4
Lifetime value, no mandate	117.6	80.6	66.6	83.8	132.3	104.2	136.7
Pr(High $CD4_{t+1}$), no mandate	0.85	0.82	0.29	0.95	0.86	0.29	0.95
Pr(Treatment), no mandate	0.92	0.89	0.97	0.86	0.93	0.98	0.92
Pr(HAART), no mandate	0.80	0.79	0.93	0.75	0.81	0.95	0.78
Pr(Work), no mandate	0.72	0.66	0.51	0.69	0.75	0.64	0.76
Lifetime value, HAART mandate	117.0	79.9	66.5	83.0	131.6	104.1	136.0
Percent change	-0.5	-0.8	-0.2	-1.0	-0.5	-0.1	-0.5
Pr(High $CD4_{t+1}$), HAART mandate	0.85	0.83	0.31	0.95	0.86	0.30	0.95
Percent change	0.6	0.8	4.5	0.5	0.5	3.1	0.4
Pr(Work), HAART mandate	0.73	0.67	0.51	0.70	0.75	0.64	0.77
Percent change	1.1	1.4	0.8	1.5	1.0	0.4	1.1
Lifetime value, treatment mandate	117.4	80.2	66.6	83.4	132.1	104.2	136.5
Percent change	-0.2	-0.4	-0.1	-0.5	-0.2	0.0	-0.2
Pr(High $CD4_{t+1}$), treatment mandate	0.85	0.83	0.30	0.95	0.86	0.30	0.95
Percent change	0.3	0.5	1.8	0.4	0.3	1.1	0.2
Pr(Work), treatment mandate	0.72	0.66	0.51	0.69	0.75	0.64	0.76
Percent change	-0.1	-0.2	0.0	-0.3	-0.1	0.0	-0.1
Lifetime value, no treatment	108.4	72.3	57.1	75.8	122.6	93.1	127.3
Percent change	-7.9	-10.3	-14.3	-9.6	-7.3	-10.7	-6.9
Pr(High $CD4_{t+1}$), no treatment	0.80	0.77	0.09	0.92	0.81	0.09	0.92
Percent change	-6.1	-7.0	-69.6	-2.5	-5.7	-70.1	-2.6
Pr(Work), no treatment	0.73	0.67	0.52	0.70	0.75	0.64	0.77
Percent change	1.2	1.5	1.1	1.6	1.1	0.6	1.2

Notes: Represents model predictions matched to data on observable state variables for visit 30. Value for "all, no mandate" in Table 5 normalized to 100.