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Barton Hamilton
Andrés Hincapié
Emma C. Kalish
Nicholas W. Papageorge

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Innovation and Health Disparities During an Epidemic: The Case of HIV
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ABSTRACT

We examine whether medical innovation can reinforce existing health disparities by disproportionately benefiting socioeconomically advantaged patients. The reason is that less advantaged patients often do not use new medications. This may be due to high costs of new drugs, but could also reflect differences in how side effects of new treatments interact with labor supply. To investigate, we develop a dynamic lifecycle model in which the effect of medical treatment on labor supply varies across sociodemographic groups. We estimate the model using rich data on treatment choices and employment decisions of men infected with HIV. In the model, treatments can improve long-run health, but can also cause immediate side effects that interact with the utility cost of work. Estimates indicate that HIV-infected men often forego medication to avoid side effects, in part to remain employed. This effect is stronger for people with fewer years of education, leading to lower use of treatment and worse health outcomes. As a result, while a breakthrough HIV treatment - known as HAART - improved lifetime utility for all patients, it disproportionately benefitted those with higher levels of completed education, thereby reinforcing existing inequality. A counterfactual subsidy that increases non-labor income reduces employment for all education groups, but only increases adoption of HAART and improves health among lower-education individuals, who face a starker health-work tradeoff.

Barton Hamilton
Olin Business School
Washington University in St. Louis
Campus Box 1133
One Brookings Dr.
St. Louis, MO 63130
hamiltonb@wustl.edu

Andrés Hincapié
Department of Economics
University of North Carolina at Chapel Hill
CB # 3305 Gardner Hall
Chapel Hill, NC 27599
andres.hincapie@unc.edu

Emma C. Kalish
Johns Hopkins University
ekalish1@jhu.edu

Nicholas W. Papageorge
Department of Economics
Johns Hopkins University
3400 N. Charles Street
Baltimore, MD 21218 and
IZA
and also NBER
papageorge@jhu.edu

1 Introduction

Research across several disciplines documents 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 bachelors degree or higher (Goldman and Smith, 2011). Health disparities reinforce existing economic inequality and are costly to society through a variety of channels, including public health care expenditures, gaps in employment and lower labor market productivity (LaVeist et al., 2011; Nanney et al., 2019).

Health disparities also have implications for how we should assess the impact of medical breakthroughs, including their societal value (Horne et al., 2015). Given health gaps across socio-demographic groups, an accessible and widely-adopted innovation could presumably reduce inequality by disproportionately benefitting sicker people who tend to be more disadvantaged. However, many new medications are not widely accessible (Chang and Lauderdale, 2009; Glied and Lleras-Muney, 2008). For example, low-income patients may be unable to afford effective but pricey new treatments. This not only reinforces existing health disparities, but also implies that the value of medical innovation varies across socio-demographic groups. Often, however, such variation is ignored and an innovation is valued using the number of patients and life-years gained per patient (Murphy and Topel, 2006; Testa and Simonson, 1996). Yet, for people who cannot afford a new treatment, its value is essentially nil.

Understanding variation in the value of medical innovation across sociodemographic groups requires a broad assessment of reasons why new treatments are often not widely adopted by disadvantaged patients. Costs are one crucial factor, but there are other important barriers to adoption that are often neglected (Chang and Lauderdale, 2009; Glied and Lleras-Muney, 2008; Groeneveld et al., 2006). Consider the link between medical innovation, health investments and labor supply (Garthwaite, 2012). New drugs often have side effects that make work difficult, which means that individuals face a health-work tradeoff that compels them to take risks with their health by refraining from using effective treatments (Papageorge, 2016). To the degree that this tradeoff is starker for more disadvantaged groups, it constitutes a channel through which the benefits of medical innovation are limited to more advantaged patients, potentially reinforcing existing inequality. This channel also means that simply lowering costs of treatment may not be enough to reduce health disparities. Rather, policies affecting employment or labor market structures may be required.[1]

This paper investigates sociodemographic differences in the value of medical innovation in the

[1] The Covid-19 pandemic also highlights the interaction between labor market choices and health disparities, since many low income employees were unable to work from home and so faced greater exposure to coronavirus through their jobs (Cevik et al., 2020; Lou et al., 2020; Papageorge et al., 2021).

context of the AIDS epidemic that began in the United States in the 1980s. We use HIV and the AIDS epidemic as an historical analogy to draw lessons about health behaviors and pandemics in general, including the current health crisis.[2] Like the Covid-19 pandemic, the AIDS epidemic exacerbated existing health disparities. For example, in the early 1990s the 6-month mortality rate for HIV-infected (henceforth: *HIV-positive* or *HIV+*) college graduate men was less than half that for HIV+ men without a college degree. Moreover, the AIDS epidemic allows us to investigate whether a breakthrough medical treatment (in this case, the introduction of HAART, or highly active anti-retroviral treatment) eliminates education-related health disparities.[3] If disparities do indeed persist after this innovation, does this reflect individual factors such as limited access to treatment, medication preferences, labor market concerns, or a combination of these channels?

Using individual-level panel data covering the period from 1990-2008, we construct and estimate a lifecycle model of repeated medication and labor supply decisions. The introduction of HAART in 1996 marked a massive improvement in effectiveness over existing treatments, but also had side effects (e.g., nausea, fever, diarrhea and cramping) that potentially interfered with employment. Thus, the model allows side effects along with health to interact with labor supply decisions. Key model parameters, including those governing health-work tradeoffs, can vary by education, capturing variation in the benefits of HAART. Finally, the model incorporates insurance and out-of-pocket treatment costs to capture how price can reduce medication use. Notice, the model frames non-use of effective medicine as reflecting a set of tradeoffs. This goes against a typical narrative whereby behaviors underlying health disparities are implicitly characterized as faulty decision-making, carelessness or recklessness among disadvantaged — and often marginalized — groups (Adimora and Schoenbach, 2002; Robinson and Moodie-Mills, 2012; Stafford and Wood, 2017).

We match the model to rich data on treatment choices and labor supply decisions of HIV+ men.[4] 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+ 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,

[2] An example from outside of economics that using HIV as an historical analogy to draw more general lessons Marcus and Snowden (2020).

[3] A further advantage to studying health disparities in this context is that the educational investments of individuals in our sample were completed prior to the (unexpected) onset of the AIDS epidemic so that we do not need to consider the impact of health on education.

[4] 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 US. We introduce the data set in Section 2.

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.

Using the model, we compute the welfare impacts of HAART, measured as difference in lifetime utility between the first year after HAART entered the market compared to a counterfactual scenario in which HAART is not invented. We find that, while HAART led to higher lifetime utility across education groups, the change is larger for those with more 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.

Since differences in health behaviors (and resulting health disparities) following an innovation are in part due to difficulties working while taking medication, policies affecting labor market structures may move the dial. To explore this possibility we analyze a counterfactual policy that increases non-labor income.[5] In particular, we raise non-employment income by $10,000 over a six-month period 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 69% percent. Given persistence of good health, 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 6% (since many would have gone onto HAART anyway) and of being healthy next period by 3.7%. There are no appreciable effects of the policy on health behaviors of other groups, e.g., those with more education. In short, we find that policies affecting labor supply can reduce incentives to engage in dangerous health behaviors and improve population health, and that these effects are 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

[5] 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.

(Adler and Rehkopf, 2008; Beer et al., 2011; Conti et al., 2010; Currie, 2009; Cutler et al., 2011; Goldman and Smith, 2011; Williams and Jackson, 2005). In this literature, barriers to access are frequently identified as the culprit (Lasser et al., 2006; Williams 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 judgement (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).[6] 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.

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 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 consistently 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).

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).

[6]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.

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). In general, these papers envision agents as engaging in risky health behaviors (either risky sex or medical non-compliance) as a function of preferences and prevailing market conditions (ranging from the sex market, the labor market, rates of infection and the process of innovation). We are closest to Papageorge (2016), who uses the same data set to examine the interaction between health, side effects and work. The key difference is that we modify the framework in Papageorge (2016) to examine differences in health-work tradeoffs by socio-demographic groups. This captures the idea that patients, especially less advantaged ones, may find it optimal to take health risks in order to work. Policy design needs to reflect this reality to be more effective.

The rest of the paper proceeds as follows. Section 2 describes the data used for estimation and presents key empirical patterns. Section 3 presents the structural model and describes the estimation. Section 4 discusses parameter estimates and the value of innovation, and section 5.3 discusses results of counterfactual simulations. Section 6 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.[7] 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.

[7]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/.

It also contains the individuals' highest completed level of education. We split individuals into a higher-education group containing those who 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 1,156 individuals comprising 10,830 observations across 13 years.[8] 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 (Papageorge, 2016). 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), mortality rates 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. Employment decisions are likewise binary: individuals work full-time or not.[9] Work experience accumulated prior to the beginning of the survey equals the individuals potential experience: the number of years since the graduation age given education status. After the beginning

[8]Specifically, we start with the full MACS sample of 139,288 observations for 7,175 individuals. After removing HIV negative individuals and people with missing HIV status, we are left with 59,308 observations comprising 3,761 individuals. After restricting the sample to survey in visits the time period 1991-2003, we are left with 20,019 observations for 2,264 individuals. Removing individuals outside of the age range 30-65 leaves 19,210 observations from 2,111 people. Dropping observations with missing data leaves 11,370 observations for 1,437 individuals. Finally, we drop 540 observations from 281 non-white individuals from a refresher sample to the panel due to the sampling methodology used to select these individuals.

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

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 64% 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 specially difficult to work with side effects. The structural model developed in the section after is based on these patterns and takes into account the various tradeoffs HIV+ individuals face.

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 8% to 2% for those with less than a college degree and from 5% to 1% for those with a college degree. Figure 2 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 for both education groups. Moreover, low-education individuals exhibit generally higher mortality rates.

Consistent with lower mortality rates, HAART introduction led to higher CD4 counts. Overall, the average sample CD4 count is 460, well above the threshold for transition from HIV to AIDS and reflecting survivor bias. For both education levels, CD4 counts are higher after HAART becomes available, increasing by 86 units for those with less education and 94 units for those with

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

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

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 once HAART is introduced: 66% to 79% in the lower- and 69% to 83% in the higher-education group. Figure 3 shows the probability of high CD4 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 2 presents coefficient estimates from logistic regressions for being above 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, 61% of those with less than a college degree and 69% of those with a college degree use it. These shifts are illustrated in Figure 4, which shows treatment choices over time. Prior to the introduction of HAART, a large portion of the sample (41% of the lower-education and 36% 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 mono-therapy, 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

[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 4.3 and appendix A.

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 59% to 77% for those with less than a college degree and from 64% to 87% 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 61% of the time, while those with more education use it 69% of the time. Figure 5 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 4 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, over 70% 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 3 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 treatmen t 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 5 shows that higher-education individuals are more likely to ever be observed using treatment compared to lower-education people (89% versus 84%). They also spend more time on medication: higher-education individuals use medication in 77% of survey visits compared to 69% 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 5 shows that those with less education are slower to adopt HAART when it becomes available. The average of first survey visit at which those with a college degree start HAART is 27.05 (roughly the first semester of 1997). The corresponding number for those with less than a college degree is 27.88, 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 more likely to have stopped HAART. Among those that ever stop HAART, 78% 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, 39% 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, 41% versus 39% respectively. The share of individuals suffering ailments does not differ significantly pre- and post-HAART. Papageorge (2016) argues that this is 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 6 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 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 due 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 67% 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 10 percentage points less likely to be employed. The transition matrix in Table 7 shows that unemployment is persistent, especially for those with less education. Among those who were not working in a given period, 90.3% of the higher-education individuals will not be working next period; the corresponding number for the lower-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 8 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 high CD4 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.

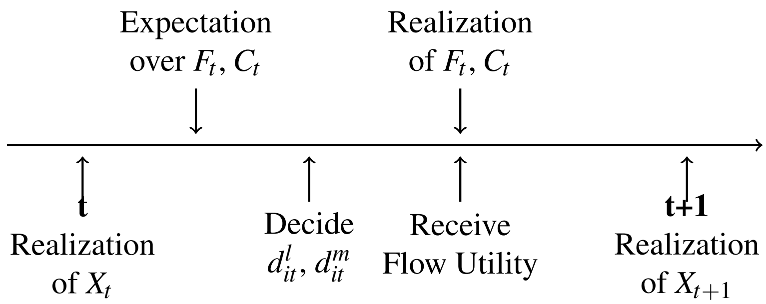
Several additional variables in the dataset can shed light on the patterns described above (Table 9). While individuals with less education are only slightly more likely to experience ailments, we hypothesize that ailments have different implications for the two education groups. Individuals with less education are significantly more likely to work in occupations that require manual labor, which likely makes work more difficult while experiencing side effects. Indeed, 15% of those with less than a college degree report stopping medications specifically because of side effects, compared to 11% 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.

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 in order 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 \$15,909-15,214 on average per six-months (pre- and post-HAART), while those with a college degree earn \$23,108-22,337 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 10 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 may be more difficult for those with less education.[14]

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

[14] In addition to the side effects, cost barriers could prevent individuals from accessing medications. However, the

FIGURE 1: Model Timing



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

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.

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).

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 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^l_{it} 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^m_{0it}), mono therapy (d^m_{1it}), and combo therapy (d^m_{2it}). In the second era ($t \geq \bar{t}$) an additional treatment alternative called HAART becomes available (d^m_{3it}). Treatments are mutually exclusive and individuals must choose one. Hence, the collection of treatment-specific indicators $d^m_{rit} \in \{0,1\}$ satisfies $\sum_{r=0}^{2+\mathbf{I}\{t\geq\bar{t}\}} d^m_{rit} = 1$. The treatment decision vector $d^m_{it} \in \{0,1\}^{3+\mathbf{I}\{t\geq\bar{t}\}}$ 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.

3.2 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} from a Bernoulli distribution with probability:

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

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

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 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]

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 $x_{it}^b \equiv [h_{it-1}, a_{it-1}, h_{it-1} \times a_{it-1}, s_i, \nu_t^b]$. 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}.

3.3 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:

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

[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.

where $x_{it}^{ailments} \equiv [h_{it-1}, d_{it}^{m}, a_{it-1}, a_{it-1}^{2}, s_i, \nu_t^{ailments}]$. The vector $x_{it}^{ailments}$ captures the side effects of treatment alternatives and it also controls for prior health, education and aging. The scalar $\nu_t^{ailments}$ 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 increments as a function of their labor market participation:

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

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

3.4 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:

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

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

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

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:

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

4 Estimation and Results

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.

4.1 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 logarithmic, i.e. $\tilde{u}(c_{it}) = \ln(c_{it})$.

4.2 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 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 contribution 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 chose 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.

Since our measures of health are based on an objective immune system measure, it likely contains a number of otherwise assumed unobservable factors. That said, we do not allow for unobserved heterogeneity. So we are at some risk of missing whether some patients fare systematically better on the new treatment HAART than others, or suffer more side effects, for unobservable reasons. In such a case we would be attributing lack of use to utility when, for some people, it might be due to individual-specific treatment characteristics. Papageorge (2016) allows for unobserved heterogeneity in a similar model and finds some evidence of unobserved differences but consistent basic patterns across types.

4.3 Parameter estimates

This section presents estimates of preference parameters and parameters governing outcomes and transitions. Table 11 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. Ailments are 40% more costly for those with less education, in line with hypotheses from the reduced form results. Regardless of educational attainment, individuals not suffering from ailments get utility from work (rows 4 and 5). This effect is stronger for those with more education. However, when agents suffer from ailments, working decreaes utility (rows 6 and 7). For those with less than a college degree, the disutility of working with ailments is -2.22 ($\theta^u_{2,f=0}$) while for those with more education the cost is less, -1.45 ($\theta^u_{2,f=0}$+$\theta^u_{2,f=0,s=1}$).

Given that individuals with less education have a stronger aversion to ailments, we would expect the tradeoff between health and ailments to differ across education groups. Figures 6 and 7 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. The cross-education differences are larger when agents are working, because the disutility of working with ailments is larger for those with less education. 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 is the most costly, followed by switching among treatments. For all three types of switches, 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.

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 A. Table 16 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 17 shows parameter estimates for the death process. Individuals with high CD4 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 18. 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 19. In addition, health is associated with higher incomes, and income grows over time. Age and experience are also associated with increases in income, though the increases slow over time. Table 20 shows parameter estimates for the insurance process. Employment is associated with a significant increase in the probability of insurance coverage, as is higher education. High CD4 is associated with a small 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 21). Unsurprisingly, bot medication usage and ailments are 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, .

4.4 Model Fit

Table 12 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 67% of the time. The results are similar for HAART use, with the model predicting HAART use in 36% of periods and the data showing HAART use in 38% 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 underpredicts medication use among those with high CD4 and overpredicts it among those with low CD4. However, the model predicts that these individuals are slightly less likely to use treatment. Both the model and the data show that individuals with less education are less likely to use treatment.

5 Results

5.1 The Value of HAART

HAART was an important innovation with major implications for HIV+ individuals. Figures 8 and 9 show total expected lifetime value for a 30 year old individual in each period by education status for those with high and low CD4 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 13 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, in percentage terms, for agents with low CD4, 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 low CD4, HAART's introduction is associated with a 94.9%-105.9% increase in expected lifetime value, compared to an increase of 59.6%-50.2% for those with high CD4. 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 slightly more for those with less education, because their expected lifetime value was lower to begin with.

5.2 Decomposing Differences in the Value of HAART

In order to understand why HAART was more important for those with more education, we decompose the differences in lifetime value in Table 14. Panel 1 replicates the results from Table 13, showing expected lifetime value pre- and post-HAART by education and health status. The following panels gradually cumulatively replace 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 only slightly. 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 about half of the gap between the education groups but also decreases the percent increase in value after HAART was invented. 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.

5.3 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 10–12 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 10). This change 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 19 and 26 percentage points less likely to work after the policy, compared with a 10 to 15 percentage point 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 from work. Second, the 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+ 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 11). 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, 84% of those without a college degree and 91% of those with a college degree will start using HAART without the policy change. The policy change increases that probability by 5.0 percentage points for the less educated group and by 1.5 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 69%, from 8% to 13%. For those with more education, HAART use increases by 22%, from 13% to 16%.

Finally, the increases in medication use lead to increases in the probability of having a CD4 count above AIDS levels (Figure 12). 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 3.7% for those with less than a college degree and by 1.0% 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, so it is easier to encourage them to leave work. Figures 13-15 replicate figures 10-12 but hold the income process constant across education groups, while Figures 16-18 replicate figures 10-12 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. In Figure 13, giving the lower-education group the income process of the higher-education group reduces the gap in the employment effect, though there are still significant gaps, especially when looking at percent change rather than percentage point change. This suggests that income differences account for part of the differential response, but not all of it. Similarly, Figures 14 and 15 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 changes to employment (Figure 16) are small, relative to the effect of changing the income process, but the effects on HAART use (Figure 17) and health (Figure 18) are comparable. 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 15 shows the effects of the simulations shown in Figures 10-12 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 (small differences from Figures 10-12 are due to simulation error). The following three rows show the effects in the following period, a year out from baseline. For individuals who start with high CD4, 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 high CD4 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 8.6 percentage points higher than it would be in the absence of the policy for those with less than a college degree and 4.0 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 99-100% probability at $t+1$ and a 98-99% probability at $t+2$. Given this, 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, 84% of those with less education and 91% of those with a college degree would have started HAART in $t+1$, while 95% and 98% would have started HAART by $t+2$, respectively. With the policy intervention, HAART take-up happens faster, with 89% of those with less education and 92% 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.

6 Conclusion

This paper develops a model for assessing variation in the value of medical innovation across socio-demographic groups. We focus on an innovation for the treatment of HIV, HAART, which was introduced in the mid-1990s. While HAART is far more effective than earlier treatments, it had harsh side effects, which interfered with employment, especially so for patients with less education. 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.

An important feature of our model is how we envision health disparities. They may arise from out-of-pockets costs, but could also reflect persistent differences in behavior, e.g., non-use of effective medication. Yet, we do not characterize such behavior differences as recklessness, carelessness, lack of information or some kind of decision-making bias concentrated among disadvantaged groups. Rather, agents in the model we posit face health-work tradeoffs and we find that these are starker for people with less education. 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.

While our focus is on HIV, we view the AIDS epidemic as a useful historical analogy that provides lessons for other worldwide health crises, including 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 is more difficult for people in cramped housing or who are unable to tele-work. In both cases, policies often amount to blaming and shaming behaviors that put health at risk. Then as now, a more useful approach, one that can contribute to risk mitigation, is to understand the circumstances and tradeoffs that people face and to design policy accordingly.

Tables and Figures

TABLE 1: Summary statistics by education and HAART-era

	All	Pre HAART	Post HAART	Pre HAART	Post HAART
		<College		College+	
College +	0.64	0.00	0.00	1.00	1.00
Age	44	40	45	42	47
Death	0.04	0.08	0.02	0.05	0.01
CD4 Count	460	401	487	413	507
High CD4 ($\geq$ 250)	0.76	0.66	0.79	0.69	0.83
Treatment	0.75	0.59	0.77	0.64	0.87
Monotherapy	0.20	0.36	0.06	0.35	0.09
Combotherapy	0.17	0.23	0.10	0.29	0.09
HAART	0.38	0.00	0.61	0.00	0.69
Ailments	0.39	0.41	0.41	0.38	0.39
Full Time Work	0.67	0.64	0.58	0.74	0.67
Income ($/half year)	20,524	15,909	15,214	23,108	22,377
Insurance	0.95	0.89	0.93	0.95	0.97
MOOP ($/half year)	543	316	425	433	748
N (t)	10,830	1,705	1,624	3,177	4,324

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 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. 10,830 person-visit observations for 1,156 individuals.

TABLE 2: Next Period High CD4, by Education

	All	<College	College+
<College	-0.197**		
	(0.077)		
Health (h_{it})	4.245***	4.487***	4.119***
	(0.074)	(0.136)	(0.088)
Age (a_{it})	0.093*	0.051	0.100
	(0.055)	(0.097)	(0.068)
Age^2 (a_{it}^2)	-0.001*	-0.000	-0.001*
	(0.001)	(0.001)	(0.001)
Pre-HAART v_t	-0.080***	-0.071***	-0.083***
	(0.015)	(0.027)	(0.018)
Post-HAART v_t	0.064***	0.045***	0.075***
	(0.009)	(0.017)	(0.011)
Constant	-3.485***	-3.382	-3.340**
	(1.227)	(2.121)	(1.546)
Observations	10,425	3,156	7,269

Notes: Standard errors in parentheses. Logit models for 1,156 individuals in the sample. Health is defined as CD4>250. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 3: Treatment Use, by Education

	All	<College	College+
<College	-0.449***		
	(0.053)		
Health (h_{it})	-2.026***	-1.743***	-2.271***
	(0.089)	(0.127)	(0.129)
Insurance ($y_{it}^{insurance}$)	1.040***	1.204***	0.878***
	(0.098)	(0.141)	(0.138)
Work (d_{it+1}^{l})	-0.558***	-0.646***	-0.500***
	(0.059)	(0.094)	(0.076)
Age (a_{it})	0.095**	0.069	0.117**
	(0.040)	(0.062)	(0.052)
Age^2 (a_{it}^2)	-0.001*	-0.001	-0.001*
	(0.000)	(0.001)	(0.001)
Pre-HAART v_t	-0.089***	-0.073***	-0.098***
	(0.011)	(0.018)	(0.013)
Post-HAART v_t	0.074***	0.065***	0.079***
	(0.006)	(0.011)	(0.008)
Constant	-0.401	-0.539	-0.576
	(0.887)	(1.366)	(1.159)
Observations	10,425	3,156	7,269

Notes: Standard errors in parentheses. Logit models for 1,156 in the sample. Treatment is an indicator for whether the individual is taking any medication. *** p<0.01, ** p<0.05, * p<0.1

TABLE 4: Period-by-period HIV treatment choice transitions from periods t to t+1

		Time t+1			
		None	Mono	Combo	HAART
		Pre-HAART, <College			
Time t	No Treatment	88.97	7.74	3.3	–
	Monotherapy	3.62	77.24	19.14	–
	Combotherapy	3.09	20.27	76.63	–
		Pre-HAART, College+			
Time t	No Treatment	89.45	7.98	2.57	–
	Monotherapy	2.82	72.7	24.48	–
	Combotherapy	0.97	21.53	77.5	–
		Post-HAART, <College			
Time t	No Treatment	85.68	1.02	4.09	9.21
	Monotherapy	3.6	58.56	10.81	27.03
	Combotherapy	2.63	3.16	63.16	31.05
	HAART	1.57	2.58	1.23	94.62
		Post-HAART, College+			
Time t	No Treatment	84.29	0.65	4.09	10.97
	Monotherapy	1.19	66.51	6.65	25.65
	Combotherapy	1.98	2.98	62.3	32.74
	HAART	1.06	3.08	0.95	94.91

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 5: Medication spell characteristics by education level for analysis sample

	<College	College +	p-value
Ever Use Treatment	0.84	0.89	0.012
Share of Survey Visits Using Treatment	0.69	0.77	0.002
Ever Use HAART	0.72	0.81	0.013
Share of Survey Visits Using HAART (when available)	0.52	0.60	0.012
First Used HAART	27.88	27.05	0.019
Treatment Transitions (per visit)	0.15	0.16	0.558
Ever Stopped HAART	0.19	0.26	0.045
Ever Started HAART After Stopping	0.15	0.19	0.199
Ever Started HAART After Stopping (conditional on stopping)	0.78	0.73	0.493

Notes: One observation per person for 1,156 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.

TABLE 6: No Ailments, by Education

	All	<College	College+
<College	-0.175***		
	(0.046)		
Health (h_{it})	0.802***	0.885***	0.763***
	(0.051)	(0.089)	(0.063)
Mono	-0.694***	-0.519***	-0.784***
	(0.066)	(0.111)	(0.083)
Combo	-0.748***	-0.657***	-0.810***
	(0.069)	(0.119)	(0.086)
HAART	-0.847***	-0.811***	-0.888***
	(0.067)	(0.120)	(0.083)
Age (a_{it})	-0.137***	-0.139**	-0.144***
	(0.033)	(0.055)	(0.042)
Age^2 (a_{it}^2)	0.001***	0.001**	0.001***
	(0.000)	(0.001)	(0.000)
Pre-HAART ν_t	-0.014	-0.020	-0.010
	(0.010)	(0.017)	(0.012)
Post-HAART ν_t	0.013**	0.024**	0.010
	(0.005)	(0.011)	(0.006)
Constant	3.723***	3.368***	4.008***
	(0.747)	(1.225)	(0.951)
Observations	10,425	3,156	7,269

Notes: Standard errors in parentheses. Logit models for 1,156 individuals in the sample. No ailments is an indicator for if the individual suffered no ailments in the period.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 7: Period-by-period employment choice transitions from periods t to t+1

		Time t+1	
		Not Working	Working
		<College	
Time t	Not Working	90.31	9.69
	Working	8.34	91.66
		College+	
Time t	Not Working	87.94	12.06
	Working	7.16	92.84

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

TABLE 8: Full Time Work, by Education

	All	<College	College+
<College	-1.185***		
	(0.059)		
Ailments ($y_{it}^{ailments}$)	-0.981***	-1.214***	-0.869***
	(0.047)	(0.086)	(0.057)
Health (h_{it+1})	0.822***	0.782***	0.835***
	(0.056)	(0.098)	(0.069)
Using Treatment	-0.258***	-0.326***	-0.225***
	(0.061)	(0.098)	(0.078)
Age (a_{it})	-0.112**	-0.424***	0.010
	(0.044)	(0.081)	(0.059)
Age^2 (a_{it}^2)	-0.001**	0.002**	-0.002***
	(0.000)	(0.001)	(0.001)
Experience (e_{it})	0.136***	0.138***	0.141***
	(0.011)	(0.024)	(0.014)
Experience^2 (e_{it}^2)	-0.001***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)
Pre-HAART v_t	0.006	-0.002	0.009
	(0.010)	(0.018)	(0.013)
Post-HAART v_t	0.031***	0.058***	0.023***
	(0.006)	(0.012)	(0.007)
Constant	4.387***	10.704***	1.375
	(0.926)	(1.650)	(1.236)
Observations	10,425	3,156	7,269

Notes: Standard errors in parentheses. Logit models for 1,156 individuals in the sample. *** p<0.01, ** p<0.05, * p<0.1

TABLE 9: Additional characteristics by education level

	<College	College +	p-value
Manual occupation	5.11	4.49	0.000
Stopped meds for side effects	0.15	0.11	0.000
Changed job due to HIV	0.06	0.05	0.010

Notes: These questions are not asked of all participants in all visits so 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.

TABLE 10: Income, by Education

	All	<College	College+
<College	-5.644***		
	(0.189)		
Experience (e_{it})	0.132***	0.061	0.144***
	(0.037)	(0.071)	(0.047)
Experience^2 (e_{it}^2)	-0.003***	-0.001	-0.003***
	(0.001)	(0.001)	(0.001)
Age (a_{it})	0.612***	0.632***	0.642***
	(0.140)	(0.239)	(0.187)
Age^2 (a_{it}^2)	-0.004***	-0.005**	-0.004**
	(0.002)	(0.003)	(0.002)
Health (h_{it})	0.942***	1.194***	0.826***
	(0.190)	(0.318)	(0.237)
Work (d_{it+1}^l)	9.378***	9.890***	9.102***
	(0.174)	(0.297)	(0.215)
Pre-HAART v_t	0.002	-0.020	0.013
	(0.034)	(0.058)	(0.042)
Post-HAART v_t	-0.096***	-0.087**	-0.099***
	(0.019)	(0.034)	(0.022)
Constant	-3.726	-8.233*	-4.758
	(2.962)	(4.945)	(3.919)
Observations	10,425	3,156	7,269

Notes: Standard errors in parentheses. Linear regression models for 1,156 individuals in the sample. Income is in thousands of year 2000 dollars per half year. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 11: Estimated Structural Utility Parameters

Definition	Parameter	Estimate	Standard Error
No Ailments	$\theta^u_{1,f=1}$	0	$--$
Ailments	$\theta^u_{1,f=0}$	-1.47	0.130
Ailments, College +	$\theta^u_{1,f=0,s=1}$	0.41	0.140
Work, No Ailments	$\theta^u_{2,f=1}$	1.18	0.056
Work, No Ailments, College +	$\theta^u_{2,f=1,s=1}$	0.36	0.068
Work, Ailments	$\theta^u_{2,f=0}$	-2.22	0.079
Work, Ailments, College+	$\theta^u_{2,f=0,s=1}$	0.77	0.099
Start Treatment, No Ailments	$\theta^u_{3,f=1}$	0.33	0.569
Start Treatment, Ailments	$\theta^u_{3,f=0}$	1.15	0.525
Change Treatment, No Ailments	$\theta^u_{4,f=1}$	-5.45	0.143
Change Treatment, Ailments	$\theta^u_{4,f=0}$	2.16	0.159
Stop Treatment, No Ailments	$\theta^u_{5,f=1}$	-9.13	0.533
Stop Treatment, Ailments	$\theta^u_{5,f=0}$	-2.09	0.944

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

TABLE 12: Model Fit

		Pr(Work)		Pr(HAART)	
Healthy	Coll. +	Data	Model	Data	Model
0	0	0.42	0.47	0.29	0.36
1	0	0.68	0.65	0.31	0.27
0	1	0.53	0.57	0.35	0.43
1	1	0.75	0.72	0.42	0.38
All		0.67	0.67	0.38	0.36

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

TABLE 13: Expected Total Lifetime Value

	<College		College+	
	*Low CD*4	*High CD*4	*Low CD*4	*High CD*4
Combotherapy (1995)	33.5	68.0	59.2	100.0
HAART (1996)	68.9	102.2	115.4	149.6
Absolute Gain	35.5	34.2	56.2	49.6
Percent Gain	105.9	50.2	94.9	49.6

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.

TABLE 14: Value Decomposition

	<College		College+	
	Low CD4	*High CD4*	*Low CD4*	*High CD4*
All education differences				
Combotherapy (1995)	33.5	68.0	59.2	100.0
HAART (1996)	68.9	102.2	115.4	149.6
Absolute Gain	35.5	34.2	56.2	49.6
Percent Gain	105.9	50.2	94.9	49.6
Same Income Process				
Combotherapy (1995)	37.5	74.9	59.2	100.0
HAART (1996)	77.1	112.5	115.4	149.6
Absolute Gain	39.6	37.7	56.2	49.6
Percent Gain	105.7	50.3	94.9	49.6
+Insurance & MOOP				
Combotherapy (1995)	37.4	74.8	59.2	100.0
HAART (1996)	76.9	112.3	115.4	149.6
Absolute Gain	39.5	37.6	56.2	49.6
Percent Gain	105.6	50.3	94.9	49.6
+Health				
Combotherapy (1995)	38.2	76.3	59.2	100.0
HAART (1996)	78.9	114.5	115.4	149.6
Absolute Gain	40.8	38.2	56.2	49.6
Percent Gain	106.8	50.0	94.9	49.6
+Ailments				
Combotherapy (1995)	39.2	78.3	59.2	100.0
HAART (1996)	81.4	117.5	115.4	149.6
Absolute Gain	42.1	39.2	56.2	49.6
Percent Gain	107.4	50.1	94.9	49.6
+Survival				
Combotherapy (1995)	52.4	89.3	59.2	100.0
HAART (1996)	101.6	133.3	115.4	149.6
Absolute Gain	49.2	43.9	56.2	49.6
Percent Gain	93.9	49.2	94.9	49.6
+Utility Parameters				
Combotherapy (1995)	59.2	100.0	59.2	100.0
HAART (1996)	115.4	149.6	115.4	149.6
Absolute Gain	56.2	49.6	56.2	49.6
Percent Gain	94.9	49.6	94.9	49.6

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. The first panel shows the results with all differences intact, as shown in table 13. Total expected lifetime value for a 30 year old male on best available treatment, 1995 (visit 23) versus 1996 (visit 26). Higher education, high CD4, combo-therapy normalized to 100.

TABLE 15: Non-Labor Income Simulation t+1 & t+2

		<College				College+			
		No Subs	Subsidy	PP Δ	% Δ	No Subs	Subsidy	PP Δ	% Δ
High CD4, on HAART									
t+1	Work	72.7	50.8	-21.9	-30.1	78.1	65.9	-12.2	-15.6
	HAART	95.6	96.5	0.9	0.9	97.6	97.8	0.2	0.2
	Health	94.1	94.1	0.0	0.0	94.4	94.4	0.0	0.0
t+2	Work	70.9	49.1	-21.7	-30.7	76.8	64.2	-12.6	-16.4
	HAART	92.0	93.7	1.6	1.8	95.5	96.0	0.4	0.5
	Health	90.2	90.3	0.1	0.1	90.7	90.7	0.0	0.0
High CD4, No Treatment									
t+1	Work	80.4	61.2	-19.2	-23.9	82.7	72.7	-10.1	-12.2
	HAART	7.0	12.4	5.4	76.7	12.5	15.3	2.7	21.9
	Health	91.9	92.1	0.1	0.2	92.4	92.5	0.1	0.1
t+2	Work	77.5	56.7	-20.8	-26.9	80.3	69.7	-10.6	-13.2
	HAART	18.8	27.5	8.6	45.8	27.3	31.2	4.0	14.5
	Health	86.8	87.2	0.4	0.4	87.8	88.0	0.2	0.2
Low CD4, on HAART									
t+1	Work	60.1	34.3	-25.8	-42.9	67.7	52.1	-15.6	-23.0
	HAART	99.0	99.3	0.2	0.2	99.6	99.7	0.1	0.1
	Health	26.0	26.0	0.0	0.1	27.1	27.1	0.0	0.1
t+2	Work	61.9	38.1	-23.9	-38.5	69.3	54.9	-14.4	-20.8
	HAART	98.0	98.5	0.5	0.5	99.1	99.2	0.1	0.1
	Health	43.8	43.9	0.1	0.2	45.4	45.4	0.0	0.0
Low CD4, No Treatment									
t+1	Work	61.2	35.6	-25.6	-41.8	68.2	52.8	-15.4	-22.6
	HAART	84.2	89.1	4.8	5.7	90.9	92.3	1.4	1.5
	Health	23.6	24.4	0.7	3.1	25.6	25.9	0.2	0.9
t+2	Work	62.0	38.0	-24.0	-38.7	69.1	54.8	-14.3	-20.7
	HAART	94.9	96.8	1.9	2.0	97.7	98.2	0.4	0.5
	Health	41.8	42.5	0.7	1.7	44.2	44.4	0.2	0.5

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 10-12 due to simulation error.

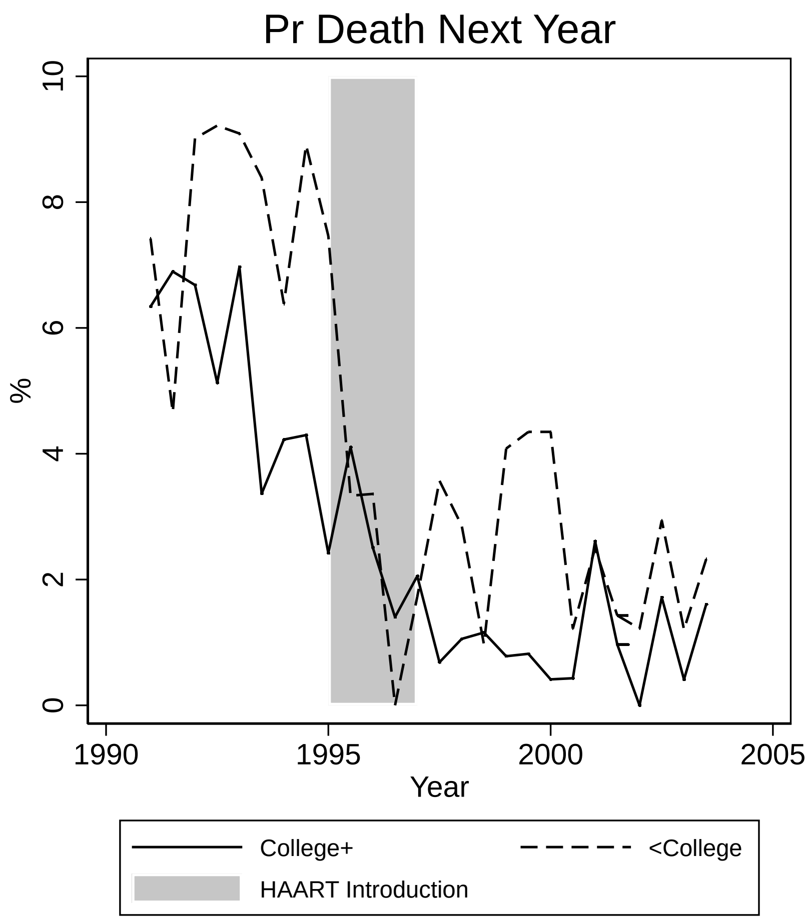


FIGURE 2: Death probability over time, by educational attainment

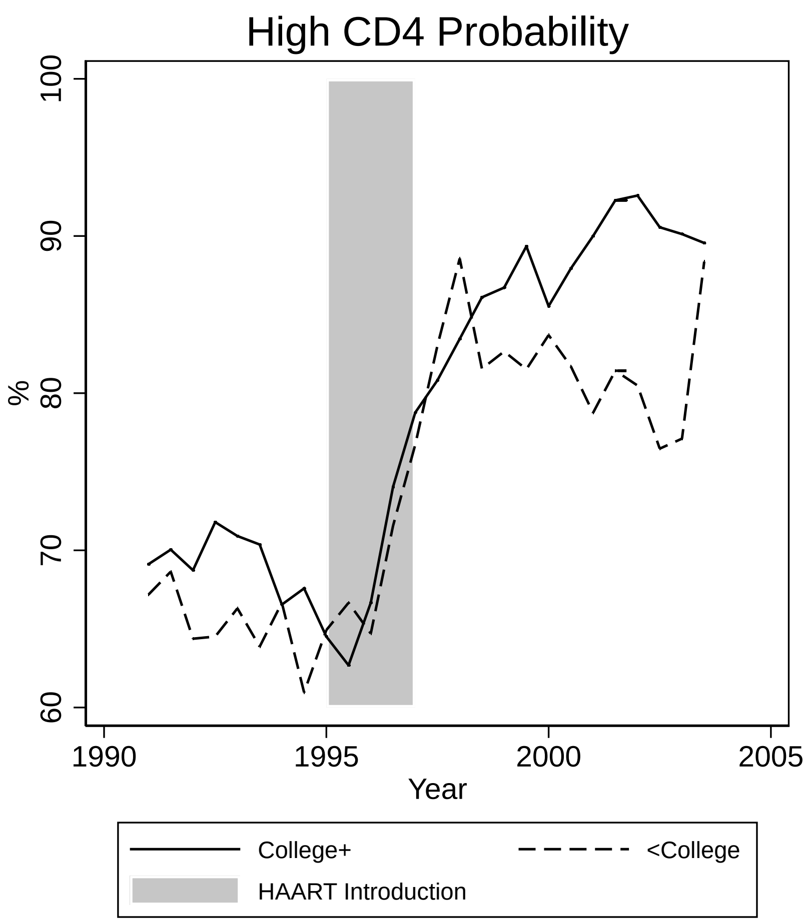


FIGURE 3: High CD4 count (>250) over time, by educational attainment

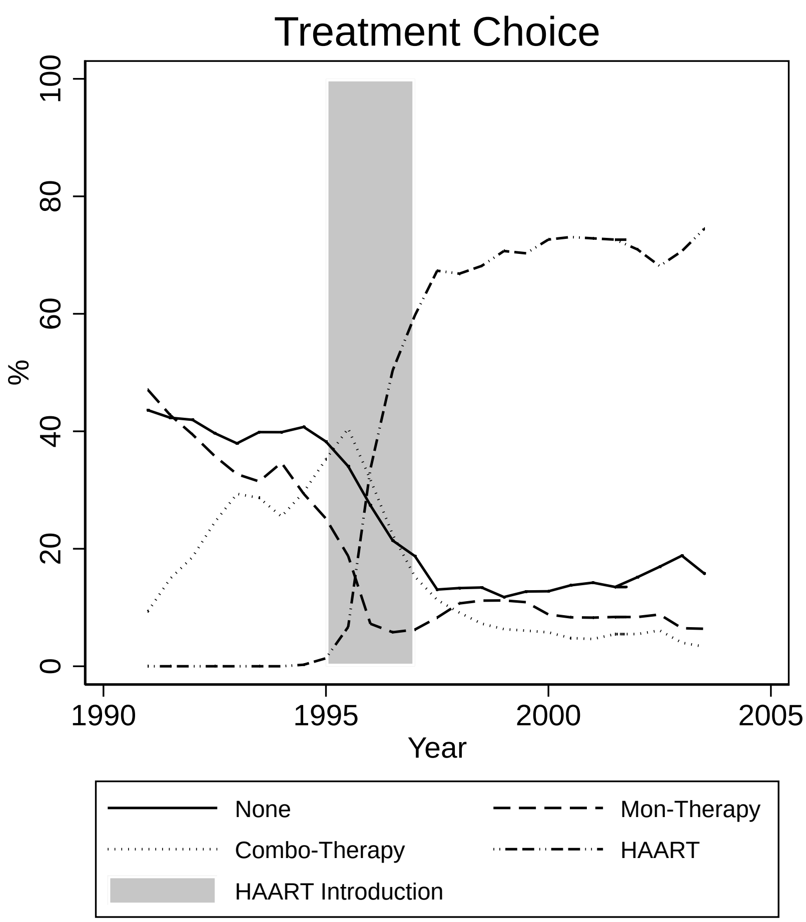


FIGURE 4: Treatment consumption over time

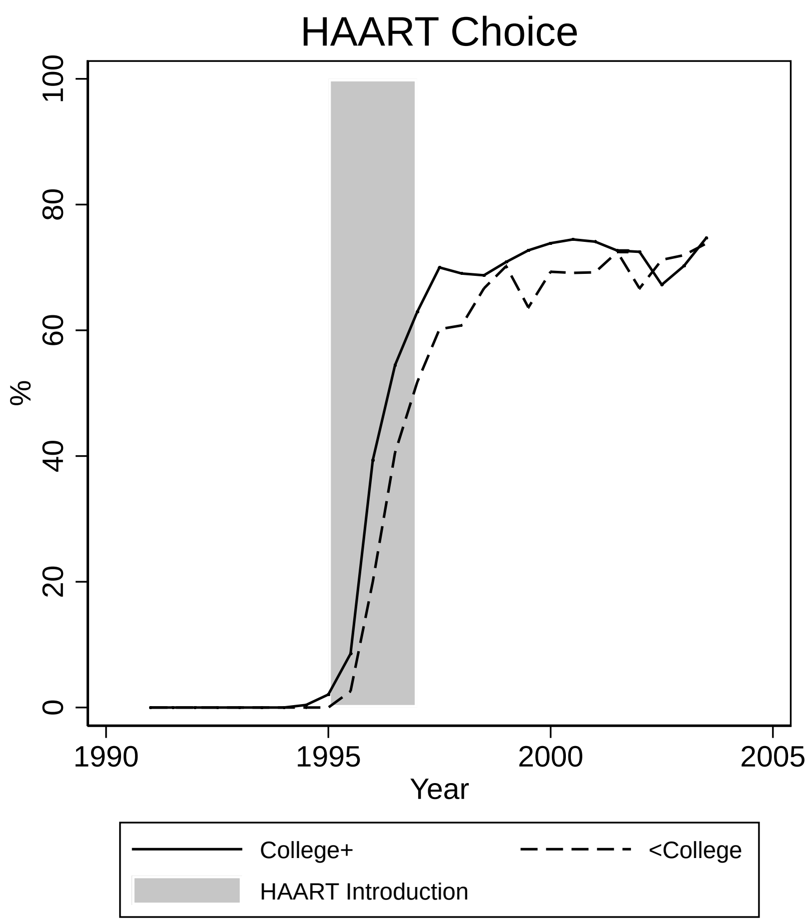


FIGURE 5: HAART consumption over time, by educational attainment

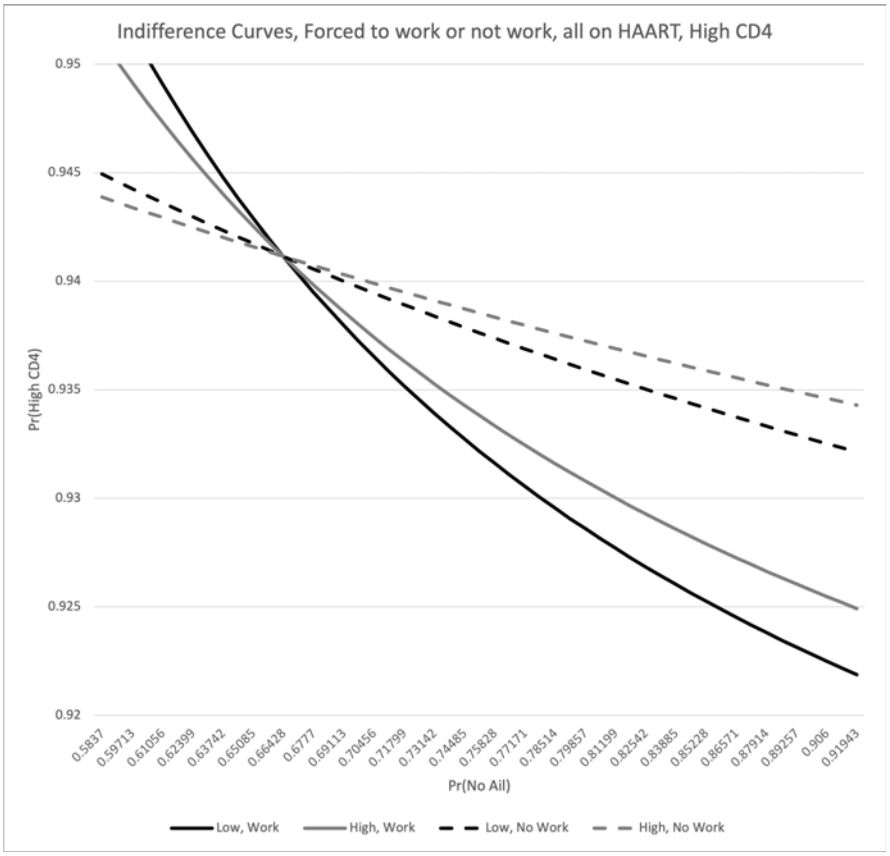


FIGURE 6: Indifference Curves: High CD4

Notes: This figure shows simulated indifference curves for medications that generate combinations of health and ailment probabilities. The point at which the indifference curves cross is the health and ailment probabilities from HAART for an agent with high CD4 and without a college degree. 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 larger for agents forced to work, because the disutility of working with ailments is higher for those with less education. The simulated agent had high CD4 last period, is 30 years old, has 10 years of work experiences, and is in visit 26 (1996)

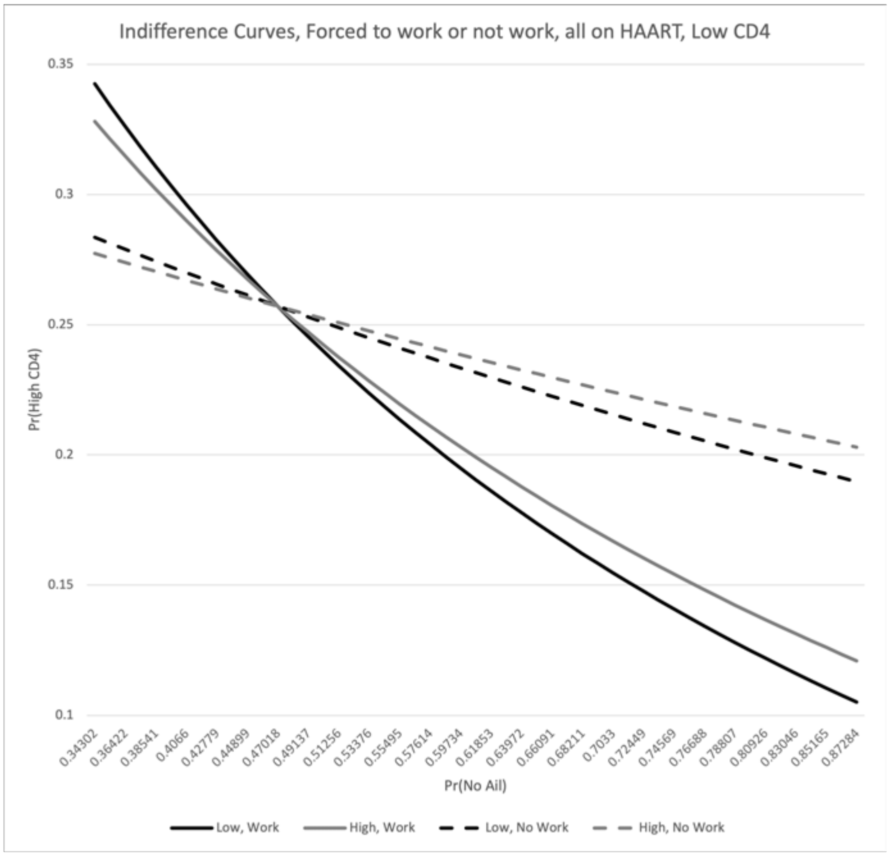


FIGURE 7: Indifference Curves: Low CD4

Notes: This figure shows simulated indifference curves for medications that generate combinations of health and ailment probabilities. The point at which the indifference curves cross is the health and ailment probabilities from HAART for an agent with low CD4 and without a college degree. The slope of the simulated indifference curve is slightly 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 larger for agents forced to work, because the disutility of working with ailments is higher for those with less education. The simulated agent had low CD4 last period, is 30 years old, has 10 years of work experiences, and is in visit 26 (1996)

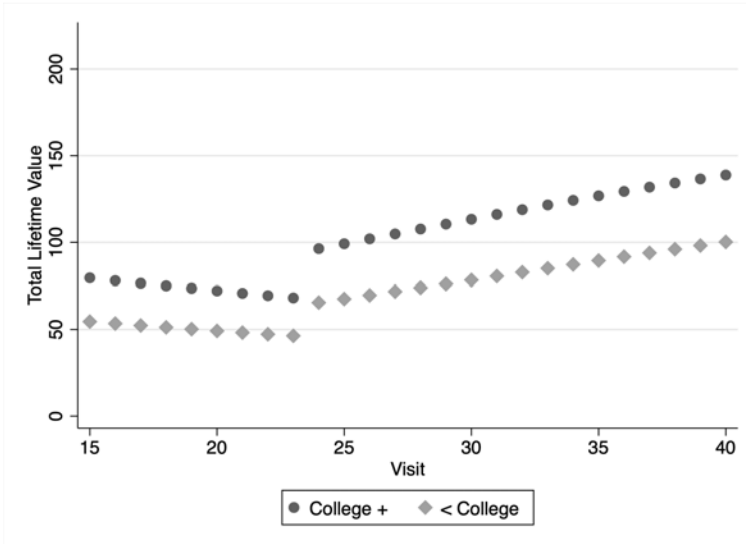


FIGURE 8: Total Lifetime Utility by Visit and Education, Healthy

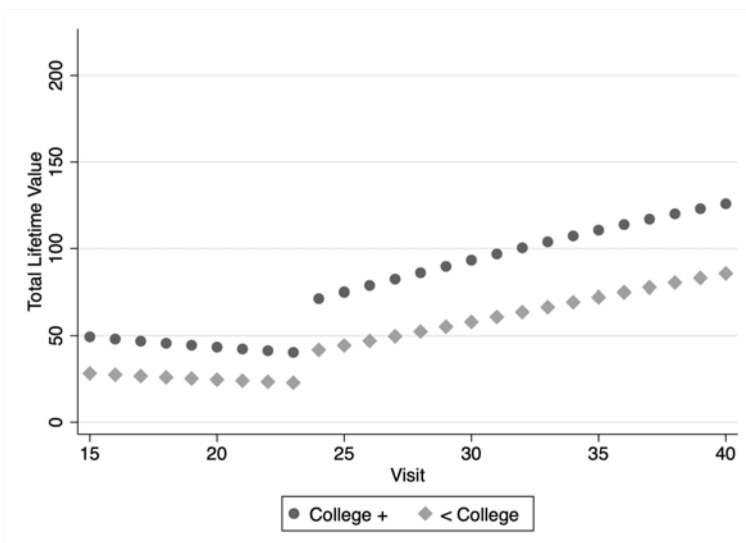


FIGURE 9: Total Lifetime Utility by Visit and Education, Unhealthy

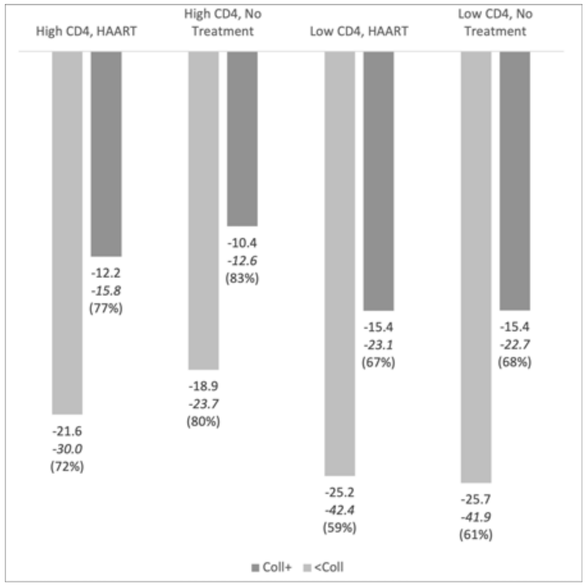


FIGURE 10: Non-Labor Income Simulation: Work Changes

Notes: This figure shows the change in the probability of working 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.

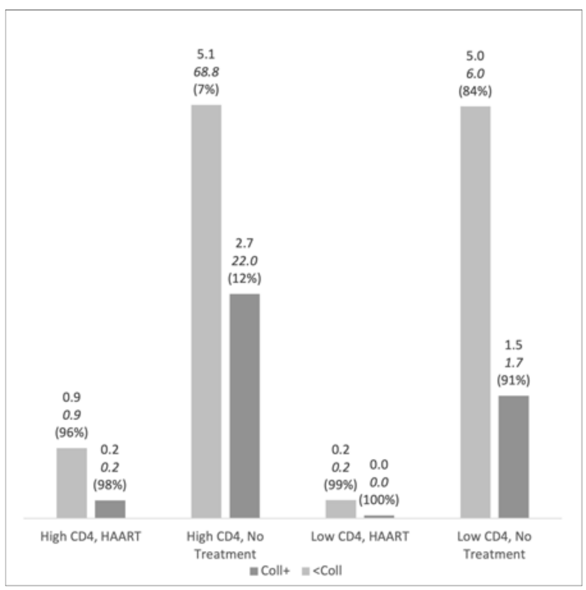


FIGURE 11: Non-Labor Income Simulation: HAART Changes

Notes: This figure shows the change in the probability of using HAART 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.

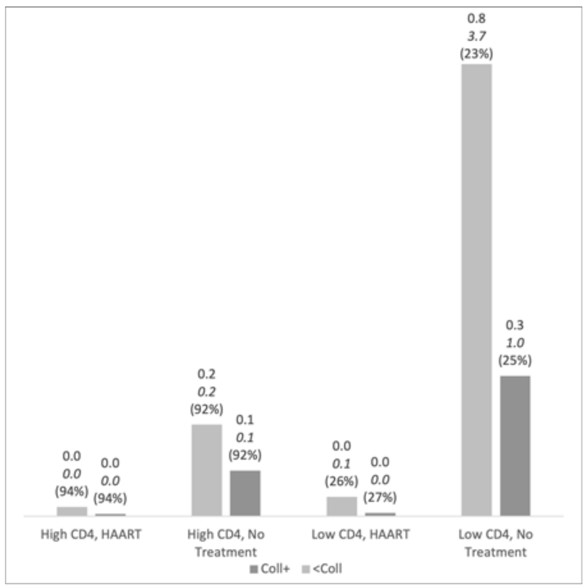


FIGURE 12: Non-Labor Income Simulation: Health Changes

Notes: This figure shows the change in the probability of having a high CD4 next period for HIV+ men across four possible current-period health-treatment states given $10,000-per-six-months increase in non-labor income for non-workers. Bars represent percentage point change. Percent change in italics, probability of high CD4 next period pre-policy-change in parentheses.

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A Appendix Tables and Figures

TABLE 16: Health Process

VARIABLES	(1) Δh_{it}
Health (h_{it-1})	-0.019
	(0.169)
Health X Mono $\left(h_{it-1} \cdot d^m_{1it}\right)$	0.141**
	(0.069)
Health X Combo $\left(h_{it-1} \cdot d^m_{2it}\right)$	0.329***
	(0.074)
Health X HAART $\left(h_{it-1} \cdot d^m_{3it}\right)$	0.542***
	(0.064)
Low Health X Mono $\left((1-h_{it-1}) \cdot d^m_{1it}\right)$	0.045
	(0.182)
Low Health X Combo $\left((1-h_{it-1}) \cdot d^m_{2it}\right)$	0.088
	(0.183)
Low Health X HAART $\left((1-h_{it-1}) \cdot d^m_{3it}\right)$	1.213***
	(0.184)
Age (a_{it-1})	0.103***
	(0.032)
Age^2 (a^2_{it-1})	-0.001***
	(0.000)
Pre-HAART ν_t	-0.040***
	(0.010)
Post-HAART ν_t	0.002
	(0.005)
<College	-0.062
	(0.045)
Constant	-2.662***
	(0.730)
Observations	10,425

VARIABLES	(1) Health h_{it}
Health (h_{it-1})	5.119***
	(0.332)
Health Booster X Low Health $\left(\hat{\Delta} h_{it} \cdot (1-h_{it-1})\right)$	4.314***
	(0.362)
Health Booster X Health $\left(\hat{\Delta} h_{it-1} \cdot h_{it}\right)$	3.125***
	(0.583)
Constant	-3.815***
	(0.208)
Observations	10,425

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

TABLE 17: Death Process

VARIABLES	(1) Death b_{it+1}
Health (h_{it})	-5.484***
	(0.885)
Age (a_{it})	0.012
	(0.009)
Age X Health ($a_{it} \cdot h_{it}$)	0.062***
	(0.019)
<College	0.421***
	(0.109)
Pre-HAART ν_t	0.013
	(0.021)
Post-HAART ν_t	-0.095***
	(0.017)
Constant	-2.443***
	(0.394)
Observations	10,830

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 models.

TABLE 18: No Ailment Process

	(1)
VARIABLES	No Ailments $\left(1-y_{it}^{ailments}\right)$
Health (h_{it-1})	0.802***
	(0.051)
Mono	-0.694***
	(0.066)
Combo	-0.748***
	(0.069)
HAART	-0.847***
	(0.067)
Age (a_{it-1})	-0.137***
	(0.033)
Age^2 (a_{it-1}^2)	0.001***
	(0.000)
Pre-HAART ν_t	-0.014
	(0.010)
Post-HAART ν_t	0.013**
	(0.005)
<College	-0.175***
	(0.046)
Constant	3.723***
	(0.747)
Observations	10,425

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

TABLE 19: Income Process

VARIABLES	(1) Income y_{it}^{income}
Experience (e_{it-1})	0.132***
	(0.037)
Experience^2 (e_{it-1}^2)	-0.003***
	(0.001)
Age (a_{it-1})	0.612***
	(0.140)
Age^2 (a_{it-1}^2)	-0.004***
	(0.002)
Health (h_{it-1})	0.942***
	(0.190)
Work (d_{it}^l)	9.378***
	(0.174)
<College	-5.644***
	(0.189)
Pre-HAART ν_t	0.002
	(0.034)
Post-HAART ν_t	-0.096***
	(0.019)
Constant	-3.726
	(2.962)
Observations	10,425
R-squared	0.342

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

TABLE 20: Insurance Process

	(1)
VARIABLES	Insurance $y_{it}^{insurance}$
Health (h_{it-1})	-0.823***
	(0.122)
Age (a_{it-1})	-0.278***
	(0.089)
Age^2 (a_{it-1}^2)	0.003***
	(0.001)
Experience (e_{it-1})	0.053**
	(0.021)
Experience^2 (e_{it-1}^2)	-0.001
	(0.000)
Work (d_{it}^l)	0.861***
	(0.096)
<College	-0.973***
	(0.107)
Pre-HAART ν_t	-0.029
	(0.018)
Post-HAART ν_t	0.058***
	(0.013)
Constant	8.327***
	(1.840)
Observations	10,425

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

TABLE 21: Medical Out of Pocket Process

VARIABLES	(1) Medical OOP Expenses $y_{it}^{expenses}$
Income $\left(y_{it}^{income}\right)$	0.011***
	(0.001)
Insurance $\left(y_{it}^{insurance}\right)$	-0.244***
	(0.079)
Insurance X Mono $\left(y_{it}^{insurance} \cdot d_{1it}^{m}\right)$	0.309***
	(0.038)
Insurance X Combo $\left(y_{it}^{insurance} \cdot d_{2it}^{m}\right)$	0.365***
	(0.041)
Insurance X HAART $\left(y_{it}^{insurance} \cdot d_{3it}^{m}\right)$	0.425***
	(0.038)
No Insurance X Mono $\left((1-y_{it}^{insurance}) \cdot d_{1it}^{m}\right)$	0.691***
	(0.154)
No Insurance X Combo $\left((1-y_{it}^{insurance}) \cdot d_{3it}^{m}\right)$	0.173
	(0.151)
No Insurance X HAART $\left((1-y_{it}^{insurance}) \cdot d_{3it}^{m}\right)$	-0.061
	(0.140)
Health (h_{it})	-0.025
	(0.042)
No Ailments $(1-y_{it}^{ailments})$	-0.147***
	(0.051)
Health X Ailments $\left(h_{it} \cdot y_{it}^{ailments}\right)$	-0.073
	(0.058)
Age (a_{it})	-0.019
	(0.019)
Age^2 (a_{it}^2)	0.000
	(0.000)
<College	-0.127***
	(0.028)
Pre-HAART ν_t	-0.001
	(0.006)
Post-HAART ν_t	0.018***
	(0.003)
Constant	0.710
	(0.434)
Observations	10,425
R-squared	0.054

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.

B Non Labor Income Simulations, Removing Key Differences Between Education Groups

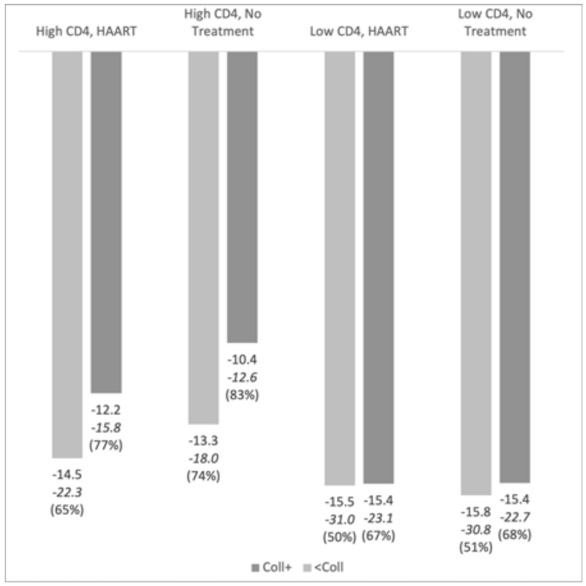

FIGURE 13: This figure shows the change in the probability of working in the next period for HIV+ men across four possible current-period health-treatment states given a \$10,000-per-six-months increase in non-labor income for non-workers, removing education differences in the income process. Bars represent percentage point changes. Percent changes are in italics and baseline probabilities (absent the policy) are in parentheses.

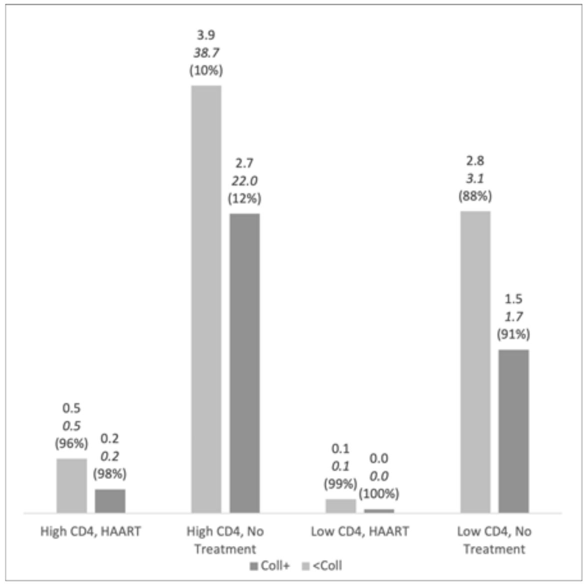

FIGURE 14: This figure shows the change in the probability of using HAART in the next period for HIV+ men across four possible current-period health-treatment states given a \$10,000-per-six-months increase in non-labor income for non-workers, removing education differences in the income process. Bars represent percentage point changes. Percent changes are in italics and baseline probabilities (absent the policy) are in parentheses.

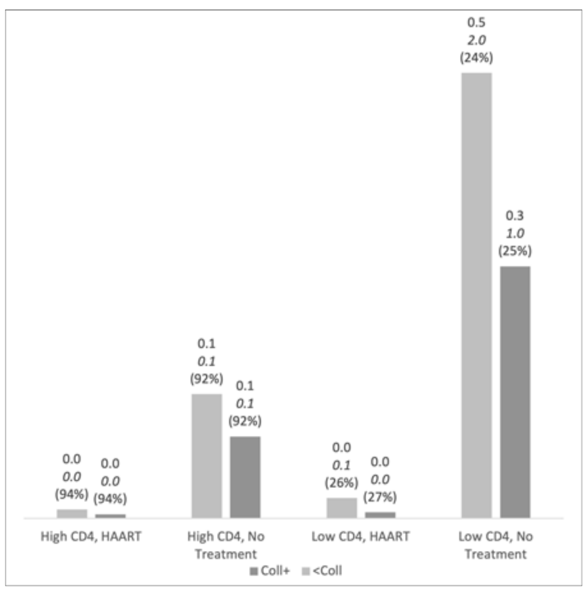

FIGURE 15: This figure shows the change in the probability of having a high CD4 next period for HIV+ men across four possible current-period health-treatment states given \$10,000-per-six-months increase in non-labor income for non-workers, removing education differences in the income process. Bars represent percentage point change. Percent change in italics, probability of high CD4 next period pre-policy-change in parentheses.

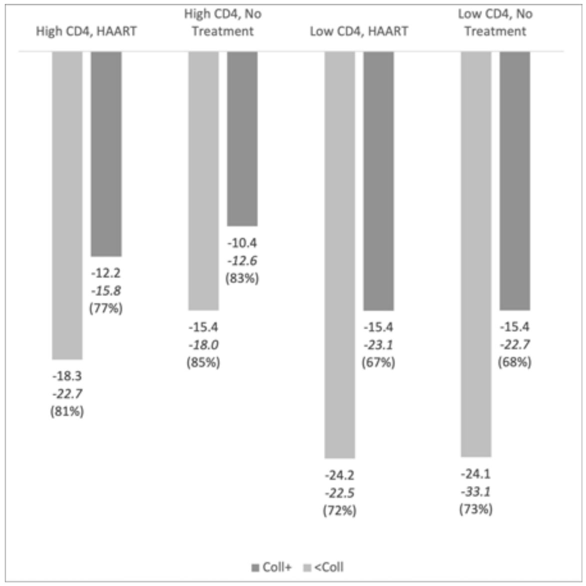

FIGURE 16: This figure shows the change in the probability of working in the next period for HIV+ men across four possible current-period health-treatment states given a $10,000-per-six-months increase in non-labor income for non-workers, removing education differences in the utility of work and ailments. Bars represent percentage point changes. Percent changes are in italics and baseline probabilities (absent the policy) are in parentheses.

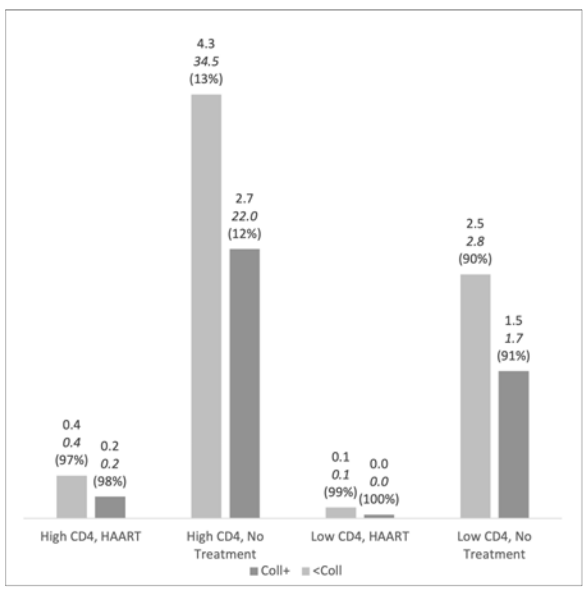

FIGURE 17: This figure shows the change in the probability of using HAART in the next period for HIV+ men across four possible current-period health-treatment states given a $10,000-per-six-months increase in non-labor income for non-workers, removing education differences in the utility of work and ailments. Bars represent percentage point changes. Percent changes are in italics and baseline probabilities (absent the policy) are in parentheses.

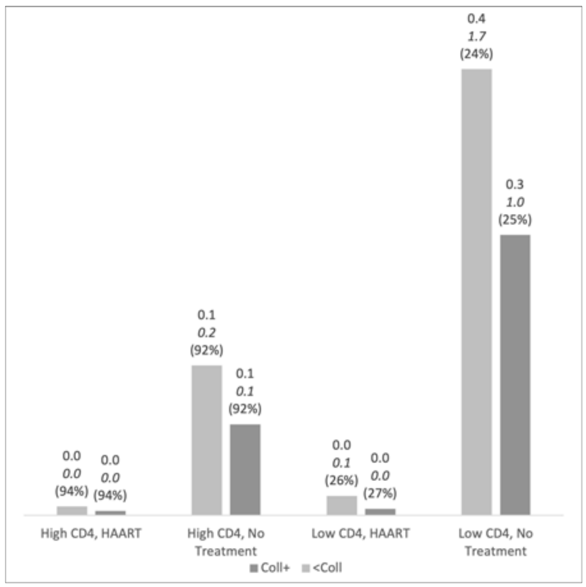

FIGURE 18: This figure shows the change in the probability of having a high CD4 next period for HIV+ men across four possible current-period health-treatment states given \$10,000-per-six-months increase in non-labor income for non-workers, removing education differences in the utility of work and ailments. Bars represent percentage point change. Percent change in italics, probability of high CD4 next period pre-policy-change in parentheses.