Innovation and Diffusion of Medical Treatment*

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Abstract: We develop and estimate a dynamic structural model of demand for a product line whose characteristics evolve over time as a consequence of consumer choices. We provide a new approach to the econometric challenge of estimating demand under uncertain innovation that includes sporadic breakthroughs and frequent, incremental changes. We use our framework to analyze consumer choice and the realized path of innovations over a long time horizon in a maturing product market: HIV drugs. In our model product quality is multidimensional since medications differ by their efficacy and their propensity to cause side effects. We allow for the possibility that new, more effective medicines can sometimes have harsher side effects. Atomistic consumers do not account for the role of aggregate demand on the speed and direction of innovation, leading to possible externalities. Using our estimated model we find that a planner that internalizes the externalities can increase welfare by at least 2% by increasing experimentation. Our results also indicate that providing monetary incentives for trial participation can be welfare improving.

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1 Introduction

In many product markets, innovation leads to substantial changes in product quality from one point in time to the next. Research relating innovation to consumer demand tends to emphasize the impact of new products on individuals' choices, behavior and welfare. Going back to Hicks (1932), economists have recognized that consumer behavior can also drive innovation. The idea is that innovation is not a random scientific process. Rather, profit-seeking firms direct their inventive activity (e.g., R&D investments) in an effort to develop new products that meet potential demand. This type of demand-driven innovation (sometimes referred to as "demand pull" (Schmookler, 1966; Scherer, 1982)) implies a possible externality since atomistic consumers do not account for the impact of aggregate behavior on the innovation process when making decisions (Jovanovic and MacDonald, 1994; Waldfogel, 2003; Finkelstein, 2004; Goettler and Gordon, 2011). A potential implication is that pricing the externality could improve consumer welfare by accelerating the introduction of new products.

Several features of the market for pharmaceuticals make it an interesting context to study demand-driven innovation. First, medical products have two dimensions of quality: efficacy and side effects and consumer preferences are heterogeneous. Thus, it is not generally meaningful to see one product as strictly better than another and many differentiated products can coexist in a given market. Innovations can also be better on one dimension and worse along another, a leading example being effective new medicines with harsh side effects. Second, in medical markets product quality is often uncertain, especially when products are new. Experimentation is therefore common among consumers and helps to drive innovation (Bolton and Harris, 1999; Dranove et al., 2014). Patients often resort to experimenting when they are sick and lack access to better options. It is thus often the most desperate among consumers who drive medical innovation, which benefits healthier patients along with generations of potential future patients.[1] Correctly pricing the externality could thus not only improve efficiency, but also equity. The reasoning is that incentivizing experimentation among all consumers (rather than relying solely upon the sickest patients) could accelerate innovation as in other markets, but also distributes the burden of innovating more evenly across patients.

In this paper, we specify and estimate a structural model of demand-driven innovation. In the model, individual consumers maximize their lifetime utility by choosing from a menu of medical treatments, which includes the option to experiment with new products. Consumers

[1]This point is linked to the model of endogenous growth in Romer (1986) where producer innovations may generate profits for potential future producers.

experiment by choosing products they have never tried before and become fully aware of their qualities only after they have used a product at least once. Alternatively, they can use new technologies that are not yet on the market. In software, this is known as beta-testing; in medicine, this is done through participation in clinical trials. Experimental products may be superior to products already on the market, but they may also be of dangerously low quality.

A key feature of the model is that innovation is endogenous to aggregate demand. In particular, we estimate a stochastic process of product innovation that is conditioned on shifting market shares, including rates of trial participation. Since products are multi-dimensional, market shares affect can affect both the speed of innovation and also its direction, i.e., the relative magnitude of shifts in efficacy versus side effects given the current state of medical technology. When making choices, consumers use this innovation process to form beliefs about future innovations and resulting evolving choice sets. Thus, consumers are neither fully aware of how the product market will evolve, nor fully unaware, in which case technology shifts would be treated as unexpected regime changes. Consumers also account for the impact of aggregate behavior on future products when making choices. To fix ideas, consumers in relatively good health may face incentives to avoid new or experimental medical treatments if they expect large numbers of other consumers to participate in clinical trials and thus generate better drugs in the future.

We match our model to data on the realized path of innovations, product quality and consumer choices over a long time horizon in a maturing product market: HIV drugs.[2] HIV is a medical condition that reduces the ability of the immune system to fight off routine infections (a condition known as AIDS).[3] It reached epidemic proportions in several countries starting in 1984 leading to just over 613,000 deaths in the U.S. by 2008.[4] The benefit of observing a long panel in the market for HIV drugs is that we can see how the path of innovation unfolded over time. In developed countries, where access to medication is widespread and subsidized, technological advancement means that HIV is currently a manageable condition and the side effects of medications are fairly mild. This was not always the case. In the early years of the epidemic, available treatments were not only largely ineffective, but also had uncomfortable, painful and even deadly side effects. Each year brought innovations, most of which were small. Some new medications were worse than existing technology since

[2]HIV stands for human immunodeficiency virus.

[3]AIDS stands for acquired immunodeficiency syndrome.

[4]For comparison, over the same period in the U.S., there were 508,000 homicides and U.S. deaths in World War II were just under 420,000. Currently, there are roughly 50,000 new infections and 13,000 deaths per year in the U.S. that are attributed to HIV/AIDS. Globally, the number of deaths due to HIV/AIDS stands at roughly 35,000,000.

since they were more toxic without being more effective. In the mid-nineties, a new set of treatments (collectively known as HAART) was introduced, which transformed HIV from a virtual death sentence to a chronic condition.[5] Within two years, mortality rates fell by over 80% among HIV+ men (Bhaskaran et al., 2008). HAART therefore marked a clear departure from existing products in the market for HIV treatments. However, HAART also involved drugs that were highly toxic, leading to side effects that were often intolerable and drove some people to avoid using them. Strikingly, innovations occurring after HAART had fewer side effects, but were generally not more effective than earlier versions of HAART. To explain this pattern, we examine the possibility that, once a level of efficacy was achieved that insured patient survival, patient demand for drugs with fewer side effects helped to drive innovation towards treatments with fewer side effects.

Our results reveal that individuals' preferences tilt the path of innovation towards treatments with fewer side effects, away from the invention of more effective treatments. Moreover, individuals have a strong distaste for experimentation that can slow the diffusion of new, superior products as well as the development of future treatments in clinical trials. Because individuals are atomistic and they do not incorporate the consequences of their actions in the path of technology, a social planner could improve welfare by fostering experimentation. As a measure of the externality, we compute the marginal increase in aggregate welfare generated by a planner who sends the marginal person to clinical trials at the atomistic equilibrium. Since the marginal person does not want to join a trial, he loses a little more than \$600 when he is forced to participate. However, because trial participation spurs innovation by pushing up the expected quality and the expected number of new products, the net social gain is about \$2,000 per individual. Finally, we find that a more realistic policy that relies on a flat subsidy to induce a marginal increase in trial participation also generates net social gains. Therefore, our results indicate that providing monetary incentives for trial participation can be welfare improving by accelerating the progress of innovation.

This study contributes to a literature on dynamic demand under uncertainty. Following Petrin (2002), each product in our model is a bundle of characteristics, in our case, efficacy and side effects.[6] Moreover, similar to (Gowrisankaran and Rysman, 2012), we allow product characteristics to have dynamic impacts on consumers. An important feature of our model is that we allow rational consumers to experiment with new products. In our context, there

[5]HAART stands for highly active anti-retroviral treatment. There is no vaccine or cure for HIV or AIDS, but HAART is the current standard treatment. In general, 1996 is marked as the year when two crucial clinical guidelines that comprise HAART came to be commonly acknowledged. First, protease inhibitors (made widely available towards the end of 1995) would be an effective HIV treatment. Second, several anti-retroviral drugs taken simultaneously could indefinitely delay the onset of AIDS.

[6]Studies pioneering the 'characteristics approach' include Stigler (1945), Lancaster (1966) and Rosen (1974).

are two motivations. First, following Erdem and Keane (1996) and Crawford and Shum (2005), we allow consumers to gain by experimenting with unfamiliar products, which they can continue to use in the future.[7] Second, we allow dynamically optimizing consumers to participate in clinical trials to use products that are otherwise unavailable, may be worse than the state of the art, but may provide early access to lifesaving new technologies. Modeling trial participation as a rational choice relates our work to Chan and Hamilton (2006), who model the decision to remain in a clinical to maintain access to good HIV medicine.

A key departure from literature on dynamic demand with experimentation is that we explicitly model how these decisions driven innovation and thus future products, which consumers forecast when making their current decisions. Several papers have demonstrated that market size affects the speed of innovation. For example, Finkelstein (2004) shows that policies promoting vaccine use accelerate the development of vaccines. Also in the medical context, Dranove et al. (2014) identify a "social value" of pharmaceutical innovation, showing that Medicare Part D spurred the development of some drugs. A common idea in this literature is that if consumer behavior drives innovation, which benefits other consumers, it follows that a demand externality arises. Waldfogel (2003) uses the term "preference externalities" to describe the mechanism through which market shares can influence products, thus benefitting consumers with similar tastes.[8] More closely related to us, Bolton and Harris (1999) argue that a free-riding problem emerges if experimentation accelerates innovation. In our context, if clinical trials provide social benefits by spurring innovation, individually rational consumers may choose to participate less than is socially optimal.

We also contribute to research on structural estimation by providing a simulation-based econometric method to estimate models of endogenous innovation. Methodologically, our approach builds on Hotz and Miller (1993) and Hotz et al. (1994) in using conditional choice probabilities (henceforth, *CCPs*) and forward simulation techniques to incorporate how individuals form expectations about future innovations.[9] In our context, the choice set that individuals face evolves stochastically over time, which means the problem is non-stationary. To make our model tractable, we summarize the current state of technology using a non-stationary reference point (or *centroid*) that emerges endogenously from consumer

[7]Empirical models of learning and experimentation also include Miller (1984) and Hincapié (2017).

[8]He also highlights the individuals with different tastes benefit less. Demand externalities have been discussed in a variety of scenarios, including sorting into neighborhoods (Bayer and McMillan, 2012) and the emergence of food deserts (Allcott et al., 2015). In the context of obesity, Bhattacharya and Packalen (2012) provide evidence that individual efforts to prevent obesity can shrink the market size for obesity treatments, which slows technological progress. If so, individuals may over-invest in preventative care compared to the social optimum.

[9]We also build on Altuğ and Miller (1998) in providing an empirical dynamic model with aggregate shocks.

demand. We then define a non-parametric, stationary distribution of innovations identified from the distance between the centroid and new products in the following period. We model consumer beliefs about future choice as technology paths simulated using this innovation distribution.

Our approach to handling non-stationarity in modeling innovation is similar to the approach in Goettler and Gordon (2011), who develop a model relating market structure to innovation in the market for microprocessors. They find that, in contrast to a monopoly, the presence of a second firm can slow innovation (since firms do not expect to capture all profits), but that consumer surplus falls in the absence of a competing firm due to monopolistic prices. To handle non-stationarity, in each period, the state of the art becomes the starting point for future innovations, which is analogous to the the role the centroid plays in our model. Despite these similarities, there are some important differences in their setting and thus their modeling choices. In their setting, product quality is one-dimensional and the innovation distribution is effectively binary (either improving by a fixed amount or not). They also assume consumers are homogeneous, which means that the choice set in their context is also effectively limited to upgrading to the best technology or staying with the current one. In contrast, in our case, product quality is multi-dimensional, which means that product quality can evolve in many different directions on a two-dimensional plane. Also, as we show, the empirical distribution of innovations for HIV drugs is not well-approximated as movements with a fixed distance. Finally, we must account for a larger choice set since multiple dimensions of product quality coupled with consumer preference heterogeneity imply that many products can co-exist in a single market. A weakness in our approach in comparison to Goettler and Gordon (2011) is that we are unable to explicitly model firm interaction, which limits counterfactuals we can perform. A benefit of our approach, however, is that we are able to examine welfare implications of counterfactual policies in a setting where consumer behavior not only affects the speed of innovation, but also the direction it takes by tilting the path of technology towards more favorable products, in our case, those with lower efficacy and fewer side effects.[10]

The remainder of this paper is organized as follows. Section 2 describes the data set we use. In Section 3, we specify the structural model and in Section 4 we discuss estimation. In Section 5, we present parameter estimates and describe model implications for the distribution of innovations. In Section 6, we study counterfactual technology paths and the link between consumer choice and innovation. In Section 7, we examine the choice externality

[10]In particular, we are unable to conduct policy analysis related to market structure using our framework. An interesting extension of the current paper would be to merge the two approaches by integrating firm decision-making into a model where products have multiple qualities.

and consumer welfare. Section 8 concludes.

2 Data

In this section we introduce the data set used in this paper and describe some of the key empirical patterns we use to identify structural parameters. We use the public data set from the Multi-Center AIDS cohort Study (MACS). The MACS is an ongoing longitudinal investigation (beginning in 1984) of HIV infection in men who have sex with men (MSM) conducted at four sites: Baltimore, Chicago, Pittsburgh and Los Angeles.[11] At each semi-annual visit, survey data are collected on HIV+ men's treatment decisions, out-of-pocket treatment expenditures, physical ailments, which can reflect drug side effects, along with sociodemographic information, such as labor supply, income, race, and education.

In addition, blood tests are administered at each visit to objectively measure health status. Our main objective measure of immune system health is *CD4 count*, defined as the number of white blood cells per cubic millimeter of blood. Absent HIV infection, a normal range is between 500 and 1500. For HIV+ individuals, a count below 500 indicates that the immune system has begun to deteriorate due to HIV, but can still fight off infections such that the individual is not symptomatic. When CD4 count drops below about 300, a patient is said to suffer from AIDS.[12] AIDS means that the immune system becomes unable to fight off routine infections and survival probability drops.

2.1 Summary Statistics

The full MACS data set contains information on 6,972 subjects at 49 possible semi-annual visits for a total of 111,271 observations in the form of subject-visit dyads. We limit our attention to HIV+ individuals, leaving us with 47,753 observations. Due to lack of data on gross income and out-of-pocket treatment costs at earlier visits, we drop observations prior to visit 14 (roughly, late 1990) and for robustness in the reporting of survival we also drop

[11] Data in this manuscript were collected by the Multi-Center AIDS Cohort Study (MACS) with centers (Principal Investigators) at The Johns Hopkins Bloomberg School of Public Health (Joseph B. Margolick, Lisa P. Jacobson), Howard Brown Health Center, Feinberg School of Medicine, Northwestern University, and Cook County Bureau of Health Services (John P. Phair, Steven M. Wolinsky), University of California, Los Angeles (Roger Detels), and University of Pittsburgh (Charles R. Rinaldo). The MACS is funded by the National Institute of Allergy and Infectious Diseases, with additional supplemental funding from the National Cancer Institute. UO1-AI-35042, 5-MO1-RR-00052 (GCRC), UO1-AI-35043, UO1-AI-35039, UO1-AI-35040, UO1-AI-35041. Website located at http://www.statepi.jhsph.edu/macs/macs.html.

[12] AIDS stands for acquired immunodeficiency syndrome. The CD4 cutoff below which AIDS occurs varies between 200 and 350.

observations after visit 47 (about 2008). These sample period restrictions leave us with 29,523 observations and 2,420 individuals. Next, we drop observations where data are missing on at least one of the variables used in subsequent analysis (though we conduct various robustness checks to insure that our results are not driven by these exclusions). After these exclusions, the remaining analytic sample consists of 1,719 unique individuals and 16,851 observations.

Summary statistics by individual are reported in Table 1. The first column presents statistics for the analytic sample.[13] 68% of sample subjects are white, 22% are black and about 9% are hispanic. Race variation in our sample is important since previous research has emphasized difficulties in recruiting blacks into clinical trials, which may reflect different costs associated with treatments or variation in expected health outcomes (Harris et al., 1996). About 86% of the sample received some secondary education or more and nearly a quarter (23%) attended graduate school. Consistent with previous research studying medication choice using the MACS data set, there is evidence of substantial variation in labor supply (Papageorge, 2016). 74% of the sample is observed working at least once and 68% of the sample is observed not working at least once.

Underscoring the seriousness of HIV infection, about 40% of the HIV+ subjects we observe at least once over the sample period die prior to the end of the sample period. However, product market innovation led to drastic changes for HIV+ men. The most striking example is the introduction of HAART in the mid-1990s, which was much more effective at improving underlying health compared to the treatments that preceded it. Conditional on surviving until the invention of HAART, 20% of subjects are observed dying. This understates the impact of HAART since the sample under study is an aging cohort, i.e., observed survival rates are much higher even when the cohort is older after HAART becomes available. Further, according to Table 1, about 83% of subjects are observed using a market product at least once. Moreover, nearly a quarter (24%) opt for early access by participating in a clinical trial at least once during the sample period, suggesting that patients are willing to try experimental products where quality is uncertain.

2.2 Consumer Demand

In this section, we study consumer demand in the maturing market for HIV drugs. We emphasize two key patterns in the data. First, consumers are willing to use drugs with side effects when drugs are also effective. Otherwise, they often avoid drugs altogether. Second, consumers participate in clinical trials when they are very sick and when existing

[13]For comparison, the third column reports statistics for a larger sample of 2,420 individuals, where we have not dropped observations due to missing data on any particular variable.

technologies are of low quality. Once good technology comes available, willingness to experiment plunges. Together, these patterns in the data support two ideas that underlie our theoretical model developed in Section 3. First, product quality in the medical context is multi-dimensional. Second, experimentation is a rational choice to gain access to unavailable and possibly superior technology.

In conducting our preliminary analysis of consumer demand, we pay close attention to comparisons of behavior before and after the introduction of HAART. Since HAART marked a large innovation on earlier treatments, it induced strong and observable consumer responses that help to identify consumer preferences over medications. Summary statistics for subject-visit dyads are found in Table 2 for the full analytic sample (column [1]) and then separately for the pre and the post-HAART eras (columns [2] and [3], respectively). We split the sample by HAART era to illustrate substantial changes to choices and outcomes after HAART was introduced.

Perhaps the most striking example of the impact of HAART on consumers is through its effect on survival. In Figure 1, we plot the probability of dying between periods t and $t+1$ conditional on survival until t. Death rates are much higher prior to HAART introduction and despite a multitude of new treatments coming available. After HAART, death rates plunge, and continue to fall until 2007, as smaller innovations occur that make drugs incrementally more effective and less toxic. HAART introduction also affected immune system health, as measured by CD4 count. According to Table 2, average CD4 count among HIV+ men in our sample is 407 in the pre-HAART era, rising to 524 in the post-HAART era. In Figure 2(a), we plot average CD4 count over time for people on market drugs and no treatment for HIV. Over time, health for people taking no drugs remains fairly constant while health for individuals in a market drug rises.[14]

Given the impact of HAART on health, it is important to understand why many consumers did not use it. In Figure 3(a), we plot the proportion of HIV+ consumers using an HIV treatment. Notice that treatment consumption is about 50% in 1990 and actually falls prior to HAART introduction. This reflects that products available on the market are of fairly low quality. Still, if quality were uni-dimensional, even a low quality drug would be better than no drug at all. Moreover, even after HAART is invented, though there is a considerable rise in market product usage, there is a substantial proportion of HIV+ men not using treatment.

Treatment costs are one possible explanation. In Table 2, we see that treatment costs rise after HAART introduction, from about \$179 to \$327 for six months of treatment. In

[14]Notice that average age rises and labor supply and income decline after HAART, consistent with the fact that we observe an aging cohort, which is more likely to retire and report lower gross income over time.

other words, even in the post-HAART era, costs are fairly low given that individual earnings average about $37,000 per year. It is worth mentioning, moreover, that non-users of market drugs pay non-zero costs for drugs, perhaps spending more money on medication to fight opportunistic infections. In other words, the incremental out-of-pocket cost of effective HIV treatments does not appear sufficient to explain why some people avoid HIV treatments.

Another possibility is that drug quality is multi-dimensional in which case demand reflects a distaste for another feature of HIV drugs. Given data on physical ailments, we explore the possibility that consumer demand reveals a distaste for side effects. Interestingly, after HAART introduction, the proportion of individuals reporting physical ailments declines only slightly (45% to 41%). The small change reflects the net effect of two countervailing dynamics (Papageorge, 2016). HAART improved health on average, which lowered reported ailments attributable to symptoms of HIV. However, HAART also led to side effects among users, thereby increasing reports of ailments. The increase in side effects also reflects how use of HIV treatment rose with the introduction of HAART, from 45% to 76%. We also plot physical ailments over time in Figure 2(b). For non-users of HIV medications, ailments remain fairly steady. For users of HIV medications, ailments drop prior to HAART introduction and then rise after HAART, which is consistent with HAART being a highly effective drug with side effects. However, after 2001, ailments decline for individuals using HIV drugs. This reflects later improvements to medications, which lowered their side effects.

Further evidence in support of the idea that there are two important dimensions of quality that influence demand comes from market consumption by CD4 count, plotted in Figure 3(a). Sicker people are far more willing to take low effective medications despite side effects in the years before HAART. After HAART, notice a striking convergence in the proportion of men using medications, driven largely by healthy individuals going onto medication. Thus, the rise in consumption of HIV treatments after HAART was introduced suggests that patients are more likely to use drugs despite side effects if the utility cost of suffering ailments is offset by expected improvements to health. HAART was more effective than earlier drugs, which encouraged people to use it despite its side effects. This would explain the rapid rise in use of HIV treatments after HAART is introduced since individuals would be more willing to use drugs with side effects as long as drugs are effective at improving underlying health.

Another option for individuals in the product market we study is to join a clinical trial to gain early access to new products. Studying how individuals experiment with new drugs by joining a clinical trial further highlights how consumers respond to innovations in the market for HIV drugs. Trial participation over time and by health status is plotted in Figure 3(b). The figure reveals several dynamics. First, early trial participation is driven largely by individuals with low CD4 counts. This suggests that, as individuals become ill, they also

become more willing to experiment with new products of uncertain qualities. Second, in the years just prior to HAART introduction, the drugs that comprise HAART, including protease inhibitors, marked a substantial improvement over drugs available on the market. In those years, trial participation gave individuals early access to much better products. This relates to the idea of *beta testing* in markets where some consumers are willing to experiment with new products with high potential quality.

After HAART trial participation plunges and there is a marked convergence by health status in the proportion of patients in trials. These patterns suggest that, once effective drugs are available, trial participation is no longer driven by sick people willing to face uncertainty in exchange for early access to a possibly high-quality product. The reason is that, once HAART is available on the market, individuals no longer need to participate in a trial to access good drugs. Shifts in trial participation over time suggest that this form of experimentation is a rational choice to gain access to new technology, especially in a maturing market where existing technology is not particularly good. Patients, especially sick ones whose survival is at risk, are willing to experiment to gain access to something better, but are less willing to do so when good treatment is available on the market.

2.3 Market-Level Innovation

The previous section examined consumer demand patterns in light of shifting product quality over time, highlighting that side effects seem to play a larger role in demand after survival is more or less assured. In this section, we consider market-level innovation. To start, we illustrate innovation and diffusion of new products over time in the market for HIV treatment using a "heat map" displayed in Figure 4. For the approximately 90 drugs that were most used, we compute market share over our sample period.[15] Dark blue corresponds to low (or zero) market share and warmer colors indicate higher market shares. Several patterns emerge from this heat map. In earlier years, there are fewer treatments with high market shares. Over time, as many treatments are introduced, market shares drop, which suggests there is heterogeneity in preferences. In fact, low market shares are common in the years following HAART introduction, when many new treatments were introduced, most of which were effective, but with strong side effects. After HAART, moreover, many drugs became obsolete, suggesting that new drugs are improvements on old ones.[16] As the market matured,

[15] Appendix A is a data appendix that contains additional information on individual drugs and treatment combinations. Table S1 discusses which drugs or combinations are taken in clinical trials. Table S2 lists the chemical compositions of each drug. Table S3 shows how drugs are combined into treatments. Table S4 discusses "core treatments", which are the main sets of treatments we observe, including the individual drugs they are composed of, whether or not they count as HAART and their entry and exit visits.

[16] An exception is AZT, which remained a standard component of HAART.

some treatments were developed that were effective and offered fewer side effects, yielding a concentrated market once again.

2.4 Relating Innovation to Demand

Finally, we discuss evidence for the idea that the observed innovation path is a response to consumer preferences. In Figure 5, we plot drug qualities (effectiveness and side effects) for different periods of time. The figure illustrates the path of technology over time. After HAART's large innovation in efficacy in the mid-1990's, new drugs were less likely to be improvements on the efficacy dimension. Indeed, after the mid-1990's, average CD4 count rises to healthy levels, but stays below 600 (relative to 1000, which is roughly the average for HIV− people). This means that once products were developed that allowed patients to recover healthy (but not uninfected-level) CD4 counts, there is instead a rightward shift as innovations lead to reductions in side effects without noticeable improvements in efficacy. Consumer demand patterns suggest a preference for drugs with fewer side effects — especially when survival is less of a concern. The path of innovation seems to have followed this pattern. This is not surprising given that profit maximizing firms would presumably direct their inventive activities towards products where potential demand is high. In the following section, we formalize this idea, specifying a model where innovation is endogenous to aggregate consumer demand.

3 Model

This section describes a model of innovation in the market for HIV treatments. Each treatment is multidimensional: it can improve health, but can also have side effects that lead to physical ailments. Health and side effects can have both short-run and long-run consequences, affecting utility, labor market outcomes, future health and survival. New products are developed in clinical trials and both the entry of new products along with the exit of incumbent products are governed by stochastic processes that are endogenous to aggregate consumer demand. The entry and exit processes we specify capture, in reduced form, how firms and government institutions (e.g., the FDA) interact to develop and introduce new medical treatments.

The data set we use provides rich information on consumers and so we model demand in greater detail than supply. Agents in the model maximize lifetime utility by choosing an HIV medical treatment. They can choose a product that is available on the market, access an experimental treatment by participating in a clinical trial, or opt for no treatment at

all. Conditional on consumer characteristics, all treatments on the market cost the same. When making treatment decisions, consumers face several sources of uncertainty. They are uncertain about current-period outcomes, including their income and realized treatment side effects. They are also uncertain about the evolution of other individual-specific state variables, including their health, which affects future ailments and survival. Finally, consumers face uncertainty over the evolution of the product market resulting from entry and exit of products.

We highlight two features of the model. First, innovation is explicitly tied to consumer behavior. New products are drawn from a distribution that is a function of the share of patients in clinical trials along with endogenous market shares, both of which aggregate dynamically optimal individual choices. Second, when making treatment choices, consumers form beliefs over evolving choice sets arising from innovation and the exit of older products. In modeling consumer beliefs over future innovations, we avoid two simplifying assumptions. We do not assume that consumers have perfect foresight over future products. Nor do we assume that they are fully unaware of the innovation process, in which case changes to the choice set would amount to regime shifts. Rather, we model consumers as forming beliefs using the same stochastic processes governing entry and exit that we specify to capture supply. To understand these model features, consider the following example. A relatively healthy consumer may avoid choosing effective drugs with strong side effects in the current period if he believes that the introduction of effective drugs with fewer side effects is imminent. In contrast, a sick consumer may not want to avoid medication despite side effects if he fears that he may not survive until better drugs are introduced. Moreover, if sicker patients' choices accelerate innovation, this can further incentive healthier patients to delay using treatments.

Section 3.1 discusses the supply of treatment, including entry of new products and exit of incumbent products from the market. Section 3.2 specifies consumer demand for treatment, including choice sets, utility and individual state-to-state transitions.

3.1 Supply

We specify a reduced-form model of supply that captures the evolution of product characteristics. We do not model firm behavior, strategic pricing, R&D decisions or the role of government institutions.[17] Entry and exit occur at the end of the period immediately before

[17]Modeling supply in this way limits the sorts of counterfactuals we can perform. For example, our model would be ill-equipped to evaluate policies affecting market structure. We return to this point when discussing the counterfactual policy simulations we perform with the estimated structural model.

the next period begins. We start by describing the aggregate state at the beginning of period t, followed by specifications for product entry and exit.

3.1.1 The Aggregate State

The aggregate state is denoted Ξ_t and summarizes market-level quantities at period t. It contains current and lagged product qualities $\mathbb{P}_t$, market shares $\mathbb{S}_t$, and the distribution of consumer characteristics $\mathcal{F}_t$, each described below. The aggregate state is given by:

$$\Xi_t = \{\mathbb{P}_t, \mathbb{S}_t, \mathcal{F}_t\}$$

Product Characteristics: Let $\mathcal{P}_t$ be the characteristics of products available at t. $\mathbb{P}_t$ denotes the set of characteristics for treatments available on the market in periods t, $t-1$ and $t-2$:

$$\mathbb{P}_t = \{\mathcal{P}_t, \mathcal{P}_{t-1}, \mathcal{P}_{t-2}\}$$

Market Shares: Let s_{t-1} denote a set containing the shares of products available at $t-1$. $\mathbb{S}_t$ is a set of product market shares for periods $t-1$ and $t-2$.

$$\mathbb{S}_t = \{s_{t-1}, s_{t-2}\}$$

Consumer Characteristics: $\mathcal{F}_t$ is the current distribution of consumer characteristics.[18]

3.1.2 Entry

We now explain product entry for new products that are available starting at the beginning of period $t+1$. The entry process is conditional on information that is in the state space at the start of period t. Entry of new products is modeled as a two-dimensional conditional distribution of new product characteristics $F_{\theta|\omega_t}$ conditioned on an endogenous reference point for innovation or *centroid*, denoted ω_t along with a distribution of number of new products F_N. Each of these objects is described in greater detail below.

Centroid: At any period t, the centroid for innovation ω_t is a two-dimensional weighted average of product characteristics for treatments available on the market in period $t-1$,

[18] The initial distribution of consumer characteristics is denoted $\mathcal{F}_0$.

where the weights are endogenous market shares:

$$\begin{aligned} \omega_t &= f_1^S(\mathbb{S}_t, \mathbb{P}_t) \\ &= \sum_{k \in \mathcal{P}_{t-1}} s_{kt-1}\theta_k. \end{aligned} \tag{1}$$

Each HIV treatment has two characteristics: its effectiveness at raising CD4 count, which we denote θ_k^h, and its propensity to cause side effects, denoted θ_k^x. The characteristics of product k are collected into a vector denoted $\theta_k \in \mathbb{R}^2$. Market share for product k is denoted s_{kt-1}, defined as the ratio of individuals who consume treatment k relative to the number of individuals who consume any treatment. The centroid essentially summarizes the evolving state of the product characteristics, serving as a baseline around which new products emerge.[19]

Characteristics of New Products: Every new product k introduced at $t+1$, characterized by θ_{kt+t}, is an innovation around the previous period centroid as follows:

$$\theta_{kt+1} = \omega_t + \nu_{kt}^* \tag{2}$$

The magnitude and the direction of the innovation depend on the previous level of experimentation in clinical trials:

$$\nu_{kt}^* = \Theta_0^\nu + \Theta_1^\nu \cdot TrialsShare_{t-1} + \nu_k \tag{3}$$

In equation (3), Θ_0^ν and Θ_1^ν are two-dimensional vectors of parameters. Θ_1^ν captures how participation in clinical trials can shift the magnitude and the direction of innovation.[20] The share of individuals who consumed a trial product in the prior period is denoted $TrialsShare_{t-1}$, which is an endogenous object derived from the consumer's decision problem. To express this point, we write it as a function of product and consumer characteristics as follows:

$$TrialsShare_t = f_2^S(\mathbb{P}_t, \mathcal{F}_t). \tag{4}$$

The size of the innovation also depends on ν_k, a two-dimensional vector of mean-zero exogenous disturbances in technology drawn from a two-dimensional stationary distribution,

[19] If nobody uses a treatment the base for innovation remains the same, i.e. $\omega_t = \omega_{t-1}$.

[20] For instance, larger parameter values imply that increased trial participation leads to larger innovations on average. Alternatively, parameter values could also imply that higher levels of trial participation lead to larger effectiveness versus side effects innovations if the parameter mapping $Trialshare_{t-1}$ to effectiveness is larger than the parameter mapping it to side effects.

denoted F_ν. We do not specify a parametric form for F_ν. As will be explained in Section 4, when we discuss estimation, F_ν is a non-parametric distribution estimated using the full history of observed innovations around the centroid.

Using equations (1)-(3), we are now able to define the distribution of new product characteristics θ_{k1+1}, denoted $F_{\theta|\omega_t}$. The distribution is a translation of F_ν so that it is centered around $(\omega_t + \Theta_0^\nu + \Theta_1^\nu \cdot TrialsShare_{t-1})$.

Number of New Products: We now specify the process governing the number of new products drawn from $F_{\theta|\omega_t}$ and which enter the market at $t+1$. The number of new products is denoted New_{t+1} and is distributed according to F_N. We specify F_N as a negative binomial that permits dispersion in the mean:

$$\begin{aligned} New_{t+1} &\sim Poisson\left(\mu_t^*\right) \\ \mu_t^* &\sim Gamma\left(1/\alpha^N, \alpha^N \mu_t\right) \\ \mu_t &= \exp(\beta_0^N + \beta_1^N Q_t + \beta_2^N TrialsShare_{t-1}) \\ \ln \alpha_t^N &= \alpha_0^N + \alpha_1^N Q_t \end{aligned} \tag{5}$$

The binomial model is conditioned on the magnitude of innovations introduced at time t, denoted Q_t, along with trial participation during period $t-1$. The inclusion of $TrialsShare_t$ is motivated by empirical evidence showing that more experimentation can be conducted if larger proportions of consumers participate in clinical trials. We include Q_t to capture the fact that large breakthroughs tend to be followed by a relatively large number of new products. This may occur if breakthrough spur innovative activity as firms attempt to capture market share. The magnitude of previous innovations measures the distance (in characteristics space) between products at time t and the previous period centroid around which they were drawn:[21]

$$\begin{aligned} Q_t &= f_3^S(\mathbb{S}_t, \mathbb{P}_t) \\ &= \sum_{r \in \{h,x\}} \frac{\max_{\theta^r \text{ new at } t} \left\{\theta^r - \omega_{t-1}^r\right\}}{\max_{\theta^r \text{new at } \tau, \forall \tau} \left\{\theta^r - \omega_{\tau-1}^r\right\}} \end{aligned} \tag{6}$$

In summary, ω_t, $F_{\theta|\omega_t}$, and F_N imply that the path of innovation is endogenous to consumer demand. Individual choices, aggregated into market shares, affect the centroid in

[21] The relative change is computed for each of the two dimensions of product characteristics (health and lack of ailments) and is scaled by the maximum change observed over the sample period. In order to compute Q_t we need the scaling quantities $\max_{\theta^r \text{ new at } \tau, \forall \tau} \left\{\theta^r - \omega_{\tau-1}^r\right\}$ for $r \in \{h, x\}$ which are estimated consistently by their data counterparts.

equation (1). By affecting ω_t, market shares affect the characteristics of each new product θ_{kt} according to equation (2). Intuitively, treatments that keep patients alive and those associated with fewer ailments capture larger shares of the market. These more popular treatments hold greater weight in the centroid around which innovations are drawn. Additionally, aggregate participation in clinical trials affects both the speed and the direction of innovation, captured by equation (3). Finally, both trial participation and the magnitude of previous innovations affect the expected number of new products introduced into the market.

3.1.3 Exit

Exit of incumbent treatments happens at two different levels: *exit for switchers* and *overall exit*. *Exit for switchers* happens when the product is no longer available for individuals who have yet to use it, but is still available for those who were consuming the product in the prior period. *Overall exit* happens when the product is no longer available to any consumer. Exit happens according to the following rules that aim to reconcile empirical observations and theory.[22]

1. If the ratio of people switching to product k relative to the total number of individuals switching onto a new product falls bellow $\tilde{\sigma}_1$ during three consecutive periods, the product is withdrawn from the market. $\tilde{\sigma}_1$ is chosen as the minimum conditional share observed in the data and the number of consecutive periods (three) is chosen so that a single period of low demand does not lead to a premature exit.

2. If the ratio of people consuming product k (either by staying or by switching onto it) relative to the total number of people consuming any market product falls below $\tilde{\sigma}_2$ during two consecutive periods, the product is withdrawn from the market. $\tilde{\sigma}_2$ is chosen as the minimum conditional share observed in the data.

The exit criteria can be written in terms of the aggregate state of the problem as follows:

$$ProductsWithdrawn_{t+1} = f_4^S(\mathbb{S}_t, \mathbb{P}_t, \mathcal{F}_t)$$

3.1.4 The Evolution of the Aggregate State

Given the current aggregate state Ξ_t and the exogenous distribution of innovations F_ν, aggregate choices induce a new distribution of consumer characteristics $\mathcal{F}_{t+1}$. Through the

[22]Expected shares must be positive due to model assumptions on the taste shocks of consumers. Distributional assumptions on taste shocks are stated below, when we discuss the demand portion of the model.

entry and exit mechanisms, a new set of available products comes available and is denoted $\mathcal{P}_{t+1}$, which is used to form $\mathbb{P}_{t+1}$. Finally, consumer choices can be summarized into market shares $\mathcal{S}_t$, which are used to form $\mathbb{S}_{t+1}$. Thus, we have all the components of the one-period-ahead aggregate state Ξ_{t+1}, which captures the supply of medical treatment. We now turn to consumer demand.

3.2 Demand

The individual chooses medical treatment to maximize expected discounted lifetime utility. In making decisions, he observes his current state which includes individual-specific variables, such as health, along with market-level variables, such as the current state of medical technology. Individuals use market-level variables to form expectations over the future path of innovation. In specifying the individual's problem, we discuss state variables, the choice set, flow utility and stochastic processes governing outcomes and state-to-state transition probabilities. Next, we discuss consumer information and aggregate state forecasts. We conclude this section by specifying the value function.

3.2.1 State Variables

The state for individual i at period t is denoted $\mathcal{Z}_{it}$, where

$$\mathcal{Z}_{it} \equiv \langle z_{it}, \varepsilon_{it} \rangle \tag{7}$$

z_{it} is a set of state variables that is further sub-divided into a set of individual-specific variables, denoted $z_{it}^{\mathcal{I}}$, and a set of aggregate variables denoted $z_t^{\mathcal{M}}$:

$$z_{it} \equiv \left\langle z_{it}^{\mathcal{I}}, z_t^{\mathcal{M}} \right\rangle \tag{8}$$

The individual-specific state variables, $z_{it}^{\mathcal{I}}$, are

$$\begin{aligned}
b_i &: \text{a set of race indicators} \\
edu_i &: \text{a set of time invariant education indicators} \\
h_{it-1} \in \mathbb{R}_+ &: \text{health at the start of period } t \\
a_{it-1} \in \{25, 25.5, \ldots\} &: \text{age at the start of period } t \\
l_{it-1} \in \{0, 1\} &: \text{worked during the prior period } t-1 \\
q_{it-1} = \left\{q_{it-1}^x, q_{it-1}^h\right\} \in \mathbb{R}^2 &: \text{characteristics of product consumed last period} \\
\eta_i &: \text{person-specific income characteristic}
\end{aligned}$$

The individual is either white, black or Hispanic and has one of four mutually exclusive educational categories: high school, some college, college or more than college. His health, measured by CD4 count, is a continuous positive number.[23] His age is measured in half-year increments, corresponding to the frequency of MACS data collection. l_{it-1} indicates whether the individual worked last period. If the individual consumed a market product in the prior period, the characteristics of that product, denoted q_{it-1}, are part of his current state space. q^x_{it-1} measures lack of side effects of the treatment and q^h_{it-1} measures treatment effectiveness. η_i is an exogenous person-specific characteristic that affects his income generating potential. Besides individual-specific variables, z_{it} contains aggregate level components, collected in $z^{\mathcal{M}}_t$, which individuals use to forecast the evolution of the market. $z^{\mathcal{M}}_t$ will be described further in Section 3.2.5. Individuals also receive a vector of choice-specific additive utility disturbances ε_{it} which are assumed independent across time, individuals and choices.[24]

3.2.2 Choices

At each period t the individual chooses whether or not to use medication. If he opts for medication, he may choose the same product he consumed in the previous period or he may choose from the set of other treatments currently available on the market. Alternatively, he may choose a trial treatment. The individual faces uncertainty about the quality of both market and trial treatments.

Market Products: We begin by describing how consumers choose market products. The individual learns about the quality of a product immediately after using it. Hence, if he chooses the same market treatment he consumed last period, he faces no uncertainty regarding its characteristics.[25] Alternatively, if he decides to try a different market drug, his alternative is to choose one among several groups or *clusters*, which contain drugs with similar qualities. The agent is then randomly assigned a drug within the cluster he selected.

Formally, at every period t there is a set of market products $\mathcal{P}_t$ clustered in several groups collected in $\mathcal{G}_t$ with typical element g_t. $\mathcal{G}_t$ denotes both the collection of clusters available at t and the cardinality of the collection (i.e., the total number of clusters). When individual i decides to consume a market treatment that is different from the one he consumed last period, he must choose a cluster $g_t \in \mathcal{G}_t$. By selecting g_t, he chooses random assignment to one of all products in g_t. Our clustering process is a device to make the model tractable

[23] CD4 ranges from 0 to 2915 in our analytic sample with a median of 448. Healthy CD4 counts are those above 500 units per mm^3 and typically range between 500 and 1,500.

[24] In estimation, η_i and ε_{it} will be unobserved to the econometrician.

[25] As discussed above, his state space includes the characteristics of the drug consumed in the prior period q_{it-1}.

and estimation feasible by substantially reducing the state space while still allowing individuals to choose among numerous medical treatments. This approach also captures the idea that consumers often choose drugs after observing product labels without knowing specific drug characteristics beyond the fact that certain labels are associated to a particular mean and variance of characteristics. Product clusters at t yield from a k-means algorithm (see Appendix B). At any given period we set the maximum value of $\mathcal{G}_t$ at $\mathcal{G}^{\max} = 3$ so that the individual knows how many groups will be available every period. Our choice of $\mathcal{G}^{\max}$ guaranties that there is a non-negligible number of consumers choosing each cluster.

Conditional on choosing a cluster, the probability of being assigned one of the products within the cluster is given by weights that depend on the treatment characteristics and the number of products in the cluster. The weight of product k in cluster g_t is given by the following equations

$$\tilde{s}_{k|g_t} = \frac{\mathbb{E}\left[s_{k|g_t}|X^w_{k,t}\right]}{\sum_{r\in g_t}\mathbb{E}\left[s_{r|g_t}|X^w_{k,t}\right]} \tag{9}$$

$$\mathbb{E}\left[s_{k|g_t}|X^w_{k,t}\right] = \exp\left(X^w_{k,t}\beta^w\right) \tag{10}$$

where $X^w_{k,t}$ includes a constant term, the ranking (within its cluster) of the characteristics of the product, the number of members in the cluster, whether the product is new, and several interactions. We assume that agents do not observe the characteristics of each individual product. Rather, consumers at t observe the first two moments of the cluster distribution implied by the weights. These cluster-level characteristics observed by the consumer are denoted

$$W_t = f^D_1(\mathcal{P}_t). \tag{11}$$

Trial Products: If the individual chooses neither a cluster nor to stay in his previous treatment, he may instead join a clinical trial to get an experimental treatment. Trial product characteristics are unknown, but are draws around the centroid ω_{t-1} according to equation (2).[26] Thus, consumers are aware that product characteristics of trial treatments are distributed according to $F_{\theta|\omega_t}$, which is equivalent to the distribution of new product characteristics. A key difference between choosing a cluster of products g_t and the trial treatment is that, after choosing group g_t and once the quality of the assigned product is learned, the consumer has the chance of choosing the same treatment with certainty the next period. In the case of a trial, the consumer must always take a new draw from the innovation distribution.

[26] One way to think about this point is that consumers entering a trial see ω_{t-1} as the quality of a placebo drug administered in a trial. This makes sense in the context of HIV since new drugs are not tested against no drug at all, but are instead tested against "current best practices" (see Ickovics and Meisler (1997)).

Having described each option, we now formally specify the choice set. Let d_{jit} be the choice indicator that takes the value of one if agent i in period t chooses medical treatment j in the choice set $\mathcal{C}_{it}$. The choice set is time-specific because the characteristics of available products evolve with entry and exit of products. The choice set is also individual specific since individuals who chose a market treatment in the prior period may choose that treatment again. If the individual did not choose a market treatment in the prior period his choice set is:

$$\mathcal{C}_{it} = \begin{cases} 0 & \text{No Treatment} \\ 1 & \text{Cluster } g_t = 1 \\ 2 & \text{Cluster } g_t = 2 \\ \vdots & \vdots \\ \mathcal{G}^{max} & \text{Cluster } g_t = \mathcal{G}^{max} \\ \mathcal{G}^{max} + 1 & \text{Trial} \end{cases} \tag{12}$$

If the individual chose a market treatment in the prior period, his choice set $\mathcal{C}_{it}$ is augmented by one alternative to include the possibility of consuming his previous period treatment with full knowledge of its characteristics.[27]

3.2.3 Utility

For choice $j \in \mathcal{C}_{it}$ and state z_{it}, the utility at period t for individual i is a function of his health, ailments and net income, given by

$$y_{jit} + \varepsilon_{jit} = \alpha_m(m_{jit} - o_{jit}) + \alpha_{jit}\left(z_{it}\right) + \alpha_{xp} x_{jit} d_{0it} + \varepsilon_{jit} \tag{13}$$

The first expression on the right-hand-side of equation (13) is gross income m_{jit} minus out-of-pocket payments for medical treatment o_{jit}, so that α_m captures consumption utility. The second expression captures choice-specific utility. $\alpha_{jit}\left(z_{it}\right)$ is the sum of choice-specific preference parameters that depend on race, age and health and is defined as follows:

$$\alpha_{jit}\left(z_{it}\right) \equiv \alpha'_{jb} b_i + \alpha_{ja} a_{it-1} + \alpha_{jh} h_{it-1} \tag{14}$$

For clusters, market treatment demand is modeled using a characteristics approach, which means that we omit cluster-specific dummy variables in the utility function and instead assume that variation in cluster choices is fully captured by cluster characteristics (effective-

[27] To clarify, if a consumer chooses a cluster in period t, in period $t+1$ he may choose the treatment he was randomly assigned to in period t. Alternatively, he may choose the same cluster, which means he is randomly assigned once again to a treatment in the cluster.

ness and side effects). This implies that parameters α'_{jb}, α_{ja}, and α_{jh} are constant across clusters. The utility function also includes separate sets of parameters for clinical trials participation and for staying on a current treatment in the next period. This captures how experimentation in treatment choices can imply additional costs or benefits. In the case of clinical trials, utility parameters capture, for example, the fear of trying an experimental drug or preferences for altruism since trial participation may help future patients. In the case of continuing to use the same product, utility parameters may capture a preference for certainty, which could help to explain consumer reluctance to switch even when better products enter the market.

Health affects lifetime utility through its impact on future health and survival. It also affects the probability of suffering physical ailments, which affect utility directly and through earnings. These processes are described in Section 3.2.4. In addition, we allow health to directly affect flow utility by interacting it with the indicator variable for trial participation. This captures the possibility that the time and psychic costs of finding a trial slot can vary by health if, for example, doctors are more willing to encourage experimentation or if trial slots are more readily available for sicker patients. Similarly, we interact lagged health with choosing a cluster to capture how individuals may be more willing (or encouraged by doctors) to choose random assignment to a cluster treatment when in poor health. We normalize α_{jh} to zero for those who continue using the same product. Therefore, α_{jh} captures the additional effect that health has on the utility of experimenting with a new treatment, either through cluster use or trial participation.

The third expression in equation (13) captures the utility cost of physical ailments. $x_{jit} = 1$ indicates that the individual does not suffer from physical ailments and d_{0it} is an indicator for not consuming a medical treatment. The interaction captures how distaste for ailments can vary depending on whether or not a treatment is being consumed. For example, distaste for physical ailments may be less strong for individuals using a treatment, in which case ailments are a sign of effectiveness. We normalize the utility cost of ailments while using a treatment to zero. Hence, α_{xp} represents the differential distaste for ailments for individuals who are not taking a treatment.

The fourth expression in (13) is ε_{jit}, which are unobserved choice-specific taste shocks. They are Extreme Value Type I distributed and are assumed independent across choices, individuals and time. Finally, for identification purposes, we normalize the non pecuniary benefits from not consuming a treatment to zero (Magnac and Thesmar, 2002; Arcidiacono and Miller, 2015)

3.2.4 Outcomes and Transitions

In this section, we specify the stochastic processes governing the evolution of state variables in z_{it} as well as the outcome variables: income, out-of-pocket payments, ailments, and survival.

Income: Gross income is a function of today's state, z_{it}, and ailments, x_{jit}. It is given by

$$m_{jit} = X^m_{jit}\Gamma^m + \eta_i + \epsilon^m_{it} \tag{15}$$

where $X^m_{jit} = [1, h_{it-1}, \ldots, h^7_{it-1}, a_{it-1}, a^2_{it-1}, b_i, edu_i, l_{it}, x_{jit}]$ and η_i is the individual-specific income generating potential. Gross income does not include product cost, which is accounted for in the payments equation below. Individuals observe the income iid shocks ϵ^m_{it} before making their treatment choice.

Payments: Out-of-pocket payments are censored at zero. They are given by the following tobit specification

$$o_{jit} = o\left(X^o_{jit}, \epsilon^o_{it}; \Gamma^o\right) \tag{16}$$

where $X^o_{jit} = [1, h_{it-1}, \ldots, h^6_{it-1}, a_{it-1}, a^2_{it-1}, b_i, edu_i, \{d_{jit}\}^5_{j=0}, l_{it}, x_{jit}]$ and ϵ^o_{it} is the error term in the underlying equation. Since we do not directly observe prices, and in order to simplify the problem, we assume a constant cost of participating in a trial as well as a constant cost of consuming a market product.[28]

Labor Supply: We do not model labor supply explicitly as a choice as it is not the main purpose of this paper. However, labor supply may be affected by treatment choices, e.g., through health status and physical aliments. Moreover, labor supply affects income and therefore utility. To capture this, we treat labor supply as a state variable that individuals know at the beginning of the period before making their treatment decision. Individuals draw their labor market participation from the distribution characterized by

$$\Pr[l_{it} = 1 | X^l_{it}] = \frac{1}{1 + \exp(X^l_{it}\Gamma^l)} \tag{17}$$

where $X^l_{it} = [1, l_{it-1}, h_{it-1}, \ldots, h^4_{it-1}, a_{it-1}, a^2_{it-1}, b_i, edu_i]$.

Physical Ailments: First, define a mapping from the choice to the characteristics of the treatment

$$\theta(d_{jit}) = \{\theta^x(d_{jit}), \theta^h(d_{jit})\} \tag{18}$$

where $\theta(d_{jit}) = q_{it-1}$ if the individual consumes his prior-period market treatment. $\theta(d_{jit})$ is

[28] End-users customarily pay a standardized deductible that is a fraction of the brochure price of the drug paid by the insurance company. Median out-of-pocket drug costs are about \$300 every six months for a regime of drugs that would cost the insurance company between \$5,000 and \$15,000.

a stochastic variable if the individual chooses a cluster or if he joins a trial. A production function transforms drug characteristics and health into aliments. Let x_{jit} be an indicator that takes the value of 1 if the individual does not suffer ailments in t after choosing alternative $j \in \mathcal{C}_{it}$. The probability of not having physical ailments for individual i is modeled as:

$$\Pr\left[x_{jit} = 1|\cdot\right] = \frac{\exp\left(\sum_{m=0}^{5} \gamma_m^x h_{it-1}^m + \theta^x\left(d_{jit}\right)\right)}{1 + \exp\left(\cdot\right)} \tag{19}$$

Health: CD4 count is our objective measure of health. Like ailments, health at the beginning of period t is a function of previous health and drug characteristics. The production function of health is specified as:

$$h_{jit} = \sum_{m=0}^{5} \gamma_m^h h_{it-1}^m + \theta^h\left(d_{jit}\right) + \epsilon_{it}^h \tag{20}$$

We assume that $\mathbb{E}[\epsilon_{it}^h|\cdot] = 0$, where the expectation is conditional on the vector of regressors of the health production function.[29]

Survival: At the end of any period t individuals may survive into the next, denoted by $S_{it+1} = 1$, with the following probability

$$D_{it+1}\left(z_{it+1}\right) \equiv \Pr[S_{it+1} = 1|z_{it+1}] = \frac{1}{1 + \exp(X_{it}^d \Gamma^d)} \tag{21}$$

where $X_{it}^d = [1, h_{jit}, \ldots, h_{jit}^5, a_{it}, a_{it}^2, b_i, edu_i, x_{jit}]$.

3.2.5 Consumer Information and Aggregate State Forecasts

We assume that consumers have rational expectations, but they do not observe the entire aggregate state Ξ_t. Instead, they observe the reduced aggregate state $z_t^{\mathcal{M}}$, which is a mapping from Ξ_t, and integrate over the treatment characteristics that they do not observe. The aggregate portion of the individual's state is given by

$$z_t^{\mathcal{M}} \equiv \langle \omega_t, W_t, \mathcal{F}_t \rangle \tag{22}$$

The individual observes the centroid for innovation ω_t, described in Section 3.1, which determines the expected characteristics of trial products. His information set also contains the characteristics W_t of the clusters of products he observes, described in Section 3.2. Finally, he observes the current distribution of consumer characteristics $\mathcal{F}_t$. When agents form expectations over future innovations, they are likewise assumed to observe cluster characteristics

[29] We do not make parametric assumptions on the health disturbance. It is estimated non-parametrically using the residuals of the health production function.

rather than the characteristics of each treatment. A timeline of the model can be found in Appendix B.

3.2.6 The Value Function

We define the value function conditional on choice $j \in \mathcal{C}_{it}$, net of taste shocks, for individual i at time t as follows:

$$v_{jit}(z_{it}) = \mathbb{E}_y[y_{jit}|z_{it}] + \beta \mathbb{E}_z \left[D_{it+1}\left(z_{it+1}\right) \mathbb{E}_\epsilon \left[\max_{c \in \mathcal{C}_{it+1}} \left\{ v_{cit+1}(z_{it+1}) + \varepsilon_{cit+1} \right\} \right] \middle| z_{it}, j \right] \tag{23}$$

Expectations are taken over product characteristics affecting the flow utility and the evolution of both observed and unobserved state variables. The first expectations operator, $\mathbb{E}_y$, denotes expectations over outcomes that affect flow utility, including income and physical ailments. The second operator, $\mathbb{E}_z$, denotes expectations over the evolution of observed state variables z_{it}. The third operator, $\mathbb{E}_\epsilon$, denotes expectations taken over the joint distribution of future unobserved choice-specific taste shifters. The value function is fairly standard except for the time and individual subscripts on the choice set $\mathcal{C}_{it+1}$. These subscripts capture the evolving choice set due to product innovation, which makes the problem non-stationary and therefore not estimable using standard methods typically used to evaluate conditional value functions. We now turn to a discussion of how we estimate the structural model.

4 Estimation

We estimate model parameters using a GMM estimator. In Section 4.1, we provide an overview of the estimation procedure, summarizing the algorithm, which includes 10 steps. The first nine steps constitute the "first stage," used to obtain quantities that do not change with utility parameters, including simulation of future choice and technology paths. We compute these quantities a single time and use them in the "second stage" to construct moments used in GMM estimation of utility parameters. In Section 4.2, we provide further details on the GMM estimator. We first describe the theoretical moment conditions and their sample analogs. We also discuss our forward simulation procedure, which is designed to incorporate non-stationarity along with endogenous innovation. Finally, we discuss estimation of the non-parametric distribution of innovations. A more extensive treatment of the estimation procedure is found in Appendix C.

4.1 Overview

Our estimation procedure can be summarized in the following steps:

1. *Products as treatments.* We start by defining a product as a combination of single-product components. AZT or the combination of AZT+3TC+Saquinavir are both examples of products in our framework.

2. *Outcome equations.* We estimate processes for income, out-of-pocket payment, labor supply and survival (see equations (15), (16), (17), and (21)).

3. *Product characteristics.* Given products defined in step 1, we estimate the health and no-ailment processes in equations (19) and (20) as well as product characteristics, using equations (30) and (31) in Appendix C.[30]

4. *Clusters.* Using the estimated product characteristics in step 3, we use a k-means algorithm to obtain clusters of products for every period (see equation (27) in Appendix B). Then, using the characteristics of the products in each cluster, we obtain within cluster weights for each product in each cluster (see equations (10) and (9)). Finally, using within cluster weights we compute cluster characteristics—mean and variance matrix.

5. *Centroid.* Using product characteristics from step 3, we back out centroids for innovation for each period (see equation (1)).

6. *Distribution of innovations.* Every new product is modeled as a draw around the centroid (see equation (2)). Hence, for every new product at a given period we compute the realized innovation as the residual from subtracting the centroid (step 5) from the product characteristic (step 3). Using the realized innovations we estimate the parameters of the innovations equation (3). Finally, we non-parametrically estimate the stationary distribution of innovations F_v using the residuals ν_{rt-1} from estimating equation (3).

7. *Distribution of number of draws.* Using data for the amount of new products per period we estimate the distribution of number of new products (see equations (5) and (6)).

8. *Conditional choice probabilities (CCPs).* Using cluster characteristic from step 4, centroids from step 5 and other aggregate and individual-specific state variables we estimate flexible parametric CCPs (see Appendix C).

[30] Product characteristics are obtained using product indicators in the estimating equations (31) and (30) in Appendix C.

9. *Simulation.* We follow Hotz et al. (1994) and use forward simulation to generate choice and technology paths as well as future individual states that serve as inputs to the simulated continuation value. In our forward simulation we use the CCPs estimated in step 8, as well as all estimated results from steps 2 through 7.

10. *Structural utility parameters.* Finally, we implement a GMM estimator using a moment condition which is a function of the forward simulated data in step 9, CCPs, and utility parameters.

4.2 Moment Condition

We use GMM to estimate utility parameters. Our moment conditions rely on differences between alternative representations of the difference in conditional value functions $v_{jit}(z_{it}) - v_{oit}(z_{it})$.[31] The first represesntation is the log odds ratio formed with current-period conditional choice probabilities. The second representation relies on the results in Proposition 1, which yields the conditional value function as a mapping of future conditional choice probabilities and utility parameters.

Proposition 1. *Let $V(z_{it}, \varepsilon_{it})$ be the value function for individual i at period t who has a state given by z_{it} and ε_{it}. Let $p_{jit}(z_{it})$ be the probability that individual i chooses option j at time t conditional on his state z_{it}. Define $\mathbb{E}[\,|\, j, d_i^o]$ as the expectation conditional on decision j at t and optimal behavior, denoted d_i^o, up to some period $T^* > t$.[32] Define $\psi_{kit}(z_{it}) \equiv \mathbb{E}_\varepsilon[\varepsilon_{kit} | d_{it}^o = k, z_{it}]$ as the expected value of the kth taste shock conditional on alternative k being optimal. Finally, let γ be the Euler constant. Then, the conditional value function can be written as*

$$\begin{aligned} v_{jit}(z_{it}) &= \mathbb{E}_y[y_{jit}|z_{it}] \\ &+ \sum_{s=1}^{T^*} \beta^s \mathbb{E}\left[\left(\prod_{r=1}^{s} D_{it+r}(z_{it+r}) \right) \sum_{k \in C_{t+1}} p_{ikt+s}(z_{it+s}) \left[y_{ikt+s}(z_{it+s}) + \psi_{ikt+s}(z_{it+s}) \right] \middle| z_{it}, j, d_i^o \right] \\ &+ \beta^{T^*+1} \mathbb{E}\left[\left(\prod_{r=1}^{T^*} D_{it+r}(z_{it+r}) \right) V(z_{it+T^*+1}, \varepsilon_{it+T^*+1}) \middle| z_{it}, j, d_i^o \right] \end{aligned} \tag{24}$$

and

$$\psi_{kit}(z_{it}) = \gamma - \ln(p_{kit}(z_{it})) \tag{25}$$

Proof: see Appendix E

Let $J = 6$ be the maximum possible cardinality of the individual's choice set and let $w(z_{it})$

[31] These moment conditions appeal to well-known results following from our assumption that the taste shocks ε_{jit} are iid Extreme Value Type I distributed (Hotz and Miller (1993)).

[32] Recall that D_{it+s} is the one-period-ahead probability of survival, defined in Section 3.2

be a vector of instruments orthogonal to the difference between alternative representations. Using equation (24) we can form the following moment conditions:

$$\mathbb{E}\left\{ w\left(z_{it}\right) \otimes \begin{bmatrix} \ln\left(\frac{p_{oit}(z_{it})}{p_{1it}(z_{it})}\right) + v_{1it}(z_{it}) - v_{oit}(z_{it}) \\ \vdots \\ \ln\left(\frac{p_{oit}(z_{it})}{p_{J-1it}(z_{it})}\right) + v_{J-1it}(z_{it}) - v_{oit}(z_{it}) \end{bmatrix} \right\} = 0. \tag{26}$$

4.2.1 Sample Analog and Forward Simulation

To form sample analogs of the moments in equation (26), we first substitute the theoretical log odds ratio using the estimated CCPs. Second, we use Proposition 1 to obtain differences in conditional value functions using forward simulation (Hotz et al., 1994). In our forward simulation procedure, for every individual i at time t facing choice set $\mathcal{C}_{it}$, we fix choice j and use the estimated stochastic processes governing outcomes and transitions to simulate his state variables at $t+1$. We then use the estimated parameters of the CCPs to simulate $t+1$ choices conditional on the new simulated state. We continue the same process until T^*, the value of which is set high enough so that the product $\beta^{T^*+1}\prod_{r=1}^{T^*} D_{it+r}\left(z_{it+r}\right)$ approaches zero, eliminating further differences in conditional value functions beyond T^*.

Forward simulation is used in a variety of settings to compute conditional valuation functions. The procedure we use is designed to capture how individuals making decisions form beliefs are aware of the stochastic processes linking aggregate behavior to the evolution of choice sets. In particular, we first simulate aggregate behavior forward, which allows us to construct paths of technological innovation. We construct one such artificial path for each observation in the data. In other words, for every individual i at period t we forward simulate the choices of all individuals in the sample at period t, and gather the technological path generated by their collective choices. Then, because individuals are atomistic, for each observation we can generate several sequences of future choices and payoffs taking as given a random subset of artificial technological paths.[33] This serves two purposes. It maintains the assumption, needed for consistency of the estimator, that the sample draws from the moment conditions—the contributions from each observation—are independent from each other. Additionally, using a random selection of artificial technological paths for every observation prevents simulation errors in technology paths from propagating across all observations.

The CCPs used in the forward simulation procedure condition on $z_t^{\mathcal{M}}$, which is the market-level information we assume consumers observe, rather than the full aggregate state

[33] We generate twenty sequences of choices and payoffs per observation.

Ξ_t. This captures how agents in the model make decisions using limited information about the aggregate state. In particular, we obtain individuals' expectations by simulating future paths of the full aggregate state Ξ_t using choices generated by individuals who make decisions with limited information $z_t^{\mathcal{M}}$.[34]

4.2.2 Estimating the Non-Parametric Distribution of Innovations F_ν

The forward simulation of future choice sets relies on the distribution of innovations. According to equations (2) and (3), the characteristics of new products entering the market today are determined by last period's centroid, previous trial participation and a draw from the distribution of innovations F_ν.[35] After computing centroids for innovation ω_t given by equation (1), for each new product at t, characterized by θ_{kt}, we compute a realized innovation vector as

$$\nu_{kt}^{\theta*} = \theta_{kt} - \omega_{t-1}$$

We do not impose that innovation vectors cannot be strictly negative. In other words, relative to the centroid, inferior products with lower quality in both dimensions (health and ailments) may be introduced.[36] We use the realized innovations vector to estimate parameters Θ_0^ν and Θ_1^ν in equation (3). Using the residuals from this exercise, we estimate F_ν non-parametrically.

5 Parameter Estimates and Choice Dynamics

This section discusses parameter estimates. Section 5.1 describes estimates that affect innovation. Section 5.2 provides utility parameters. Section 5.3 discusses parameters governing state-to-state transitions and outcomes. Section 5.4 assesses model fit.

5.1 Innovation

The innovation process is described in equations (2) and (3). Estimates of Θ_0^ν and Θ_1^ν from equation (3) are found in the first two panels of Table 3. Recall, both parameters are two-dimensional vectors that map trial participation to the characteristics of new treatments.

[34] Because we simulate the future path of Ξ_t, we can also obtain the simulated future path of the subset $z_t^{\mathcal{M}}$.

[35] To estimate the innovation equation (3) and the distribution of innovations we use all periods in the MACS data with relevant information on treatment consumed, health and ailments (1986 to 2008). Over the time span in our data we observe 76 realized innovations.

[36] This is not at odds with what we observe in the data, and theoretical reasons why this may happen have been provided in the literature (Miller, 1988).

The first and second panels of Table 3 contain parameters relating trial participation to new treatment effectiveness and to new treatment side effects, respectively. According to the estimates of Θ_1^ν, higher rates of consumer participation in clinical trials lead to improvements in new drugs on both dimensions of quality. However, the magnitude of this effect varies across quality dimensions. To see this, consider the differences in constants (Θ_0^ν), both of which are negative, suggesting that new drugs would on average be worse (relative to the centroid) if no consumers participated in trials. While expected health innovations are positive for lagged trial shares above 5.6%, the same is true for expected innovations on the ailments dimension when trial participation is 7.7%. As average trial participation in our sample is 7% (Table 2), if we ignored the role of the centroid, on average the quality of products would appear to improve over time in terms of health quality but would remain largely unchanged in terms the ailments they cause through side effects. However, new products are drawn around the centroid, which is time-varying and a function of market shares. Therefore, if individuals prefer treatments with fewer side effects, the centroid will move in that direction of the characteristics space, which means more innovations will be drawn from that part of the space. In this sense, future products tend to be similar to products with larger market shares.

The stochastic component of an innovation is a draw from the non-parametric distribution F_ν (see equation (3).) Figure 6 plots the distribution, showing that it is unimodal and concentrated around $(0, 0)$.[37] This means that, conditional on trial participation, the stochastic component of experimentation can result in treatments that are either better or worse relative to the centroid, with an average of no change. Because products are multi-dimensional, it is possible for the stochastic component to generate products that are more efficacious, but which cause worse ailments via side effects, or vice versa. However, according to the bottom panel of Table 3, which shows the covariance matrix of the distribution of innovations, there is a positive correlation of about 0.24 between the two quality dimensions of an innovation. Therefore, improvements to effectiveness tend to have fewer side effects than existing technologies once we have conditioned on trial participation rates.

Estimates of parameters of the distribution of the number of new products drawn from innovation distribution are shown in Table 4. Estimates suggest that large positive innovations in previous periods lead to larger numbers of new products. The magnitude of previous innovations also reduces the dispersion around the number of new products that enter. Both

[37] In a separate exercise, we estimate the non-parametric distribution of innovations using directly the realized innovations from equation (2), ignoring equation in (3). This yields a bimodal distribution of innovations with one of the modes located approximately at the status quo point $(0, 0)$, and a second mode located north of the first one along the health axis. As shown in Figure 6, F_ν is no longer bimodal once we control for previous aggregate experimentation in clinical trials.

patterns are consistent with firms vying for market share following breakthroughs by producing similar products. The share of consumers opting to participate in a clinical trial in the prior period also increases the likelihood of more products entering the market. Our interpretation is that as more consumers select trial products firms increase their experimental activity. This leads to an increase in the quantity of viable new treatments that can be introduced into the market. The estimated distribution of the number of new products fits the data very well, according to Figure 7, which plots empirical distribution along with the average (over time periods) of the predicted probabilities generated by the model.

5.2 Utility Parameter Estimates

Utility parameters are reported in Table 5. Individuals gain positive utility from income net of out-of-pocket treatment costs, which captures consumption utility. Moreover, a lack of physical ailments enters positively into flow utility. Prior literature has shown that even in the context of a deadly infection (HIV) individual treatment choices reflect a distaste for side effects (Chan and Hamilton, 2006; Papageorge, 2016). Recall, we have normalized to zero the impact of ailments for those consumers using a treatment. Therefore, the positive utility parameter for not suffering ailments while not consuming a treatment is relatively large. In other words, the cost of ailments is larger when consumers are not consuming a treatment. This finding is consistent with the idea that the utility cost of ailments from side effects of medical treatment may be less than the cost of ailments due to illness. One possible reason why is that consumers perceive ailments due to product side effects as an indicator of that effective treatments are working. Alternatively, ailments due to sickness may be more frightening than those due to medication that treats sickness.

Utility parameters for treatment choices are interacted with race and age. Since the non-pecuniary flow utility from no treatment is normalized to zero across groups, the non-pecuniary flow utility for different groups is relative to what they gain from not taking a treatment. According to parameter estimates, once we have accounted for dynamic payoffs, using treatments is costly for all consumers, with higher costs accruing to non-white consumers. Black men face a particularly high penalty of trial participation, a finding that is consistent with a broad literature investigating historical reasons why African Americans are reluctant to enter trials to use experimental drugs (Harris et al., 1996; Alsan and Wanamaker, 2016). However, age helps to mitigate the utility costs of treatment, reflecting how older agents are more accustomed to taking medications or have more contact with the medical community.

Recall that health is interacted with treatment choices that involve experimentation

(either participation in a clinical trial or choosing a new drug through a cluster). We find that better health leads to larger utility costs of experimentation. This is consistent with more frequent contact with doctors among less healthy patients, who may thus face lower costs of switching to new or experimental treatments. In the case of trials, there may be more slots available for sicker patients if a goal is to test drugs on patients who most need them.

Finally, the utility of remaining on a treatment is positive, which means that it is preferable to taking no treatment at all assuming the individual is suffering from ailments (which is normalized to zero) and to choosing a cluster or trial treatment. This underscores the idea that individuals are reluctant to experiment with new drugs. Taken together, utility estimates imply that the highest flow utility accrues to individuals who are not suffering ailments and who are not taking any treatment.

5.3 Transitions and Outcomes

Next, we discuss the processes describing how state variables produce outcomes or transition to other states. Processes for health and ailments are estimated condition on product using equations (19) and (20). Given the large number of treatments, to conserve on space, we present the coefficient estimates in Tables S5 and S6 in Appendix F (see Column 5 in both tables). Apart from specific treatments, current health also affects current physical ailments along with future health. To capture non-linearities in these relationships, we condition on a fifth-order polynomial in health. The estimated relationships are plotted in the top panels of Figure 8. While the slight concavity of the production function for health could be well approximated by a linear function, the production function for ailments is very non-linear. The figures suggest that in the region of CD4 counts below 250 units, changes in health generate much larger larger shifts in the log odds ratio of suffering ailments. The reason is that HIV infection has a gradual negative impact on immune system health, as measured by CD4 count. However, the impact of CD4 count on ailments is not gradual. It is virtually non-existent until CD4 count has dropped below about 250 and AIDS-related symptoms emerge.

We next consider processes governing income, out-of-pocket payments, labor supply and survival. As before, rather than interpret parameters on a high-order polynomial in health, we simply plot the non-linear relationships in the remaining panels of Figure 8. According to the figure, health exhibits strongly non-linear relationships with other outcomes, which helps to explain sharp differences in optimal choices for individuals with fairly similar CD4 counts. Again, this is due to large changes in physical health once the AIDS threshold is reached.

These relationships also also underscore the importance of modeling the relationship between health and outcomes in a non-linear fashion for HIV-positive individuals.

Estimates for processes governing income, out-of-pocket payments, labor supply and survival are found in Tables 6, 7, 8 and Table 9, respectively. Beyond the relationships with health discussed above, several key patterns emerge. Individuals who do not suffer ailments have higher income as their productivity is likely to be higher. Income is concave in age and it increases with employment and education, though racial minorities earn less on average. Conditional on positive out-of-pocket medical expenditures, these payments increase with age. Minorities spend less and more educated people spend more. Similarly, individuals that suffer ailments face higher expenditures, perhaps because they are managing other health conditions. Employment increases expected payments, which may reflect different pricing schemes for public versus private insurance. Labor force participation is stochastic in our model and it is revealed to individuals at the beginning of the period. Estimates show that the log odds ratio of working versus not working increases with age until about age 40, after which point it decreases. The odds of working increase with education. Moreover, there is strong persistence in employment, reflected by a large increase in employment odds for individuals who worked in the previous period. At the end of every period individuals face the possibility of death. Estimates in imply that the log odds ratio of death versus survival decreases with age until about age 35 and then increases. The likelihood of death is smaller for black individuals and for individuals who are not suffering ailments.

5.4 Simulated Choice Dynamics and Model Fit

In Figure 9, we plot observed treatment choices over time along with those generated by the model given the state at every point in time.[38] The estimated model captures key trends remarkably well, including the rise in treatment usage as drugs improve through innovation, and trial participation dynamics. We cannot fully reproduce the spike in trial participation shortly before HAART introduction. The reason for this may be that, although our model accounts for changes in the demand for trials, there was also a shift in the supply of trials as a number of new drugs were tested that would eventually comprise the breakthrough. Hence, the spike in trial participation would not be fully captured by our model as it focuses on patient demand.

[38]The fit of our parametric ccps is discussed in Appendix C.

6 The Evolution of Technology

Through the lens of our model, the observed path of technological innovation is a draw from an underlying stochastic process that relates the supply of new treatments to consumer behavior. Because we have estimated this stochastic process, conditional on an aggregate set of state variables, we can simulate counterfactual technological paths and compare them to the realized path we observe. In Section 6.1), we assess the probability of the observed path by comparing it to a distribution of simulated paths using the estimated parameters of the innovation process. In Section 6.2, we examine how consumer behavior affects the distribution. In particular, we show that demand can slow the progress of innovation due to consumer reluctance to use new drugs, which affects the position of the centroid. Moreover, consumer distaste for side effects can tilt the path of innovation towards new products with fewer side effects, but lower efficacy.

6.1 The Distribution of Technology Paths

We first assess the likelihood of the observed innovation path compared to what would have been predicted by the estimated innovation process. As the innovation process is used to model consumer beliefs about future innovations, this exercise also amounts to comparing the realized path of innovations to what a rational consumer would have expected starting at different points in time as the market for HIV drugs mature. To simulate technology paths, we use estimated parameters of the innovation process and draw from the non-parametric distribution F_ν. We simulate 100 innovation paths until we have reached the end of the realized path of innovations in 2008. We use two different observed periods as initial states: the first semester of 1991 and the second semester of 1996. 1991 captures the state of the market prior to the introduction of breakthroughs and health among HIV+ men was in decline. By 1996, HAART had been introduced, which led to upward shifts in average health of HIV+ men. Technology paths are plotted in Figures 10 and 11, where the solid line is the realized average and the light grey lines are the 100 simulates.

In Figure 10, we compare realized and simulated average health, ailments and survival probabilities. The panels on the left use 1991 market characteristics as starting values and the right panels start in 1996. Figure 11 shows centroid quantities and market shares over time. The upper-left panel of Figure 10 CD4 counts using 1991 as the starting point. In the first few years, simulated average health tracks realized average health quite closely, though is on average a bit worse. A larger difference emerges after 1996, however, once HAART in introduced. The reason is that HAART marks a departure from the expected

path of innovations and thus average health, which the simulations show. In other words, the estimated stochastic process treats the introduction as a low probability even, though by no means treats it as a zero-probability event. Indeed, though most of the simulated paths starting in 1991 underperform relative to HAART in the health dimension, there is a small number of paths that outperform HAART. Thus, with some probability, innovations might have emerged with even higher efficacy than HAART. In we instead use 1996 as the starting point (see the panel on the top right), the market generally underperforms relative to the simulations. Innovations did not raise average health after about 2000 even though the innovation process would have predicted steady improvements to efficacy and thus higher average health by 2005.

In the second row and third rows of Figure 10, we repeat the exercise with physical ailments and average probability of survival, respectively. The observed share of individuals suffering physical ailments is somewhat higher than the simulated paths starting in 1991. The introduction of HAART led more individuals to use medication than expected, which increased average ailments over time. If the starting point is 1996, however, the observe path of ailments is similar to the average from the simulations, which means rational agents forming expectations in 1996 would have expected population averages to evolve as they did. Simulated survival in the population is consistent with HAART being a surprise. Rational consumers forming beliefs in 1991 on average would expect lower survival than occurred due to the introduction of HAART. Starting in 1996, however, the same consumers would have expected slightly higher survival rates arising from continued innovations, which the market did not deliver, again due to the lack of subsequent innovations that improved efficacy.

Turning to market aggregates, Figure reffig:drawanddistributionCentroids simulates two quantities that determine the position of the centroid, the first capturing the weighted average of efficacy and the second capturing market average of side effects technology. Beginning in 1996, simulated paths of technology in the efficacy dimension show a trend similar to the realized path. However, HAART is a tail event and after it is introduced, the market outperforms most simulated distributions. Beginning in 1996, however, the market underperforms relative to expectations as the centroid is expected to continue moving towards higher efficacy drugs, which is not observed. For side effects innovations, the market underperforms if we simulate beginning in 1991 and 1996. An exception is that around 2001, when side effects innovation begin to occur, which means that by about 2005, the market outperforms relative to rational expectations formed in 1996. Finally, we consider market shares. Simulated market shares starting in 1991 track observed usage fairly well until about 1996. However, even without HAART, market shares rise in the years after 1997, likely because individual health would have been expected to continue its decline, which would have driven patients

onto market drugs even if they were not very effective. This is in line with earlier research showing that individuals avoid effective drugs with side effects when in good health, but will use less effective drugs in spite of side effects when in poor health (Papageorge, 2016).

6.2 Demand Pull: How Consumer Choices Affect Innovation

In the structural model, the distribution of innovations is a function of aggregate consumer behavior. To illustrate this feature of the model, we consider two policies. First, we study the evolution of product quality when the process of innovation is independent of demand. Second, we assess product quality when demand is allowed to affect innovation, but consumers are randomly assigned to products. Both policies exogenously separate consumer dynamic optimization from the process of innovation.

We start by studying innovation that is independent of consumer demand. To achieve this we redefine the centroid to be a simple average of products in the market and reestimate the process of innovation in Section 5.1.[39] Thus, product entry is no longer dependent on product demand. We also separate product exit from demand by adopting new exit rules designed to resemble the actions of a scientific authority tasked with keeping only the best products on the market. We consider two ways in which products of inferior quality are exogenously removed from the market. The first method, denoted *frontier*, removes all products from the market that are not on the technological frontier. This policy provides an upper bound for how quickly innovation can proceed according to model estimates. The second method, which captures expert intervention in a more realistic fashion, is denoted *thick frontier*. In this regime, the number of products leaving the market is given by the exit rate which we set at the baseline average, and the worst products are dropped independent of demand.[40]

Results in Figure 12 indicate that exogenous product removal from the market can lead to rapid improvements in product quality. However, more realistic exogenous interventions have limited gains in quality over demand-driven selection. The figure presents simple averages of health (right) and ailments (left) qualities of the products in the market. In the figure, the solid black line is the simulated path of innovation using model estimates, where innovation is endogenous to aggregate demand. The frontier regime paths are shown using dashed lines. According to the lines, exogenously removing all but the best products speeds innovation, leading to much much better products on both dimensions of quality, which is reflected in

[39]For simulation, we still need a path of trial participation to feed into the distribution of the number of new products and the innovation process in equation (3). We use the average path from the baseline simulations.

[40]The selection of which are the worst products in the thick frontier regime is explained in Appendix D.

higher average health and fewer average suffering of ailments. In contrast, under the thick frontier policy, where only the worst products are exogenously removed from the market in each period, the path of product quality evolution is not very different from the path delivered by consumer dynamic optimization, i.e., the baseline. The reason is that consumers rarely use the worst products, so removing them exogenously has relatively little impact on the position of the centroid and, therefore, on subsequent innovations. Still, the thick frontier policy does lead to health improvements. The reason is that the worst products that are removed from the market tend to be of especially low efficacy, but are still chosen by a subset of consumers since they have few side effects.

The second policy we consider assumes that consumers are randomly assigned to products, but otherwise does not change the innovation process, i.e., the definition of the centroid, and the distributions of innovations and number of new products. We fix the distribution for random choices to match the unconditional shares in the first year so that consumers do not respond to shifting technology or state variables. Results are shown in Figure 13 which presents average paths, computed over 500 simulations, for consumer characteristics and the status of technology captured by the centroid. The baseline solid lines in Figure 13 are the average of the grey lines in Figures 10 and 11.

One key result from this exercise is that random assignment improves health an d survival, but also leads to more physical ailments. The reason is that individuals prefer medical treatments with fewer side effects despite the detrimental impact on their health. This tilts the path of innovation towards new products with fewer side effects, but lower efficacy. In contrast, random assignment decouples consumer preferences from innovation, tilting innovation towards higher efficacy drugs, which improves health and raises survival rates. This can be seen by looking at average health, the position of the centroid or the likelihood of survival.

In general, results in this section underscore the importance of preferences in driving not only the speed, but also the direction of technological innovation. Consumers' distaste for side effects means they are willing to sacrifice efficacy for treatments with fewer side effects even if doing so increases the likelihood of poor health in the future. This behavior reveals that consumers do not make medical decisions to maximize longevity, but instead maximize lifetime utility, which includes quality of life and a lack of physical ailments. If the innovation process were independent of consumer demand, it would be difficult to argue that there is a role for a social planner to improve consumer welfare. However, as this section has shown, private choices affect public health through innovation by slowing the development of more efficacious treatments. In the next section we ask whether individual welfare can be improved by targeting the externalities with an array of interventions.

7 Demand Externalities

Our estimates show that individuals prefer to avoid experimentation. They dislike both using new products from clusters and participating in clinical trials. These preferences determine their behavior which affects the evolution of technology. Moreover, because they are atomistic, consumers do not internalize the marginal effects of their treatment choices on the centroid that guides innovation, or on the share of trial participation, which partly determines the expected direction of innovations and the expected number of products that appear on the market. As a result, a social planner could improve welfare by shifting choices.

In this section we study interventions that capture this idea in a tractable fashion. Given the size of the individual's state space, numerically solving the problem of an unrestricted planner quickly becomes intractable. We simplify the analysis by exploring the nature of the externalities using a one-period planner that is constrained to act on a subset of the individuals' information or who has a reduced set of alternatives to choose from.[41] Because the planner is constrained, the magnitude of the welfare improvement, if any, is a lower bound to what an unconstrained planner could achieve.

The first constrained one-period planner we consider assigns individuals to choices on the basis of their health and their previous treatment. In particular, when assigning individuals to choices, the planner considers two levels of health (high and low) and two categories of previous treatment choices (market treatment and no treatment/trial treatment). Compared to the amount of information in the individual's state $\mathcal{Z}_{it}$, the amount of information available to the constrained planner is minimal. Nevertheless, adding more dimensions of information increases very rapidly the number of assignment rules that we would need to evaluate. For every individual in a $\langle health,\ previous\ treatment \rangle$ category, the planner assigns one of the six choices available or lets the individual act freely.[42] Since the constrained planner has less information than the individual, it may be optimal for her to let some groups act freely even though those groups will not internalize the full costs or benefits of their behavior on the evolution of the technology. This setup is attractive because it allows the planner to choose the same solution as atomistic individuals. We solve the problem of the one-period planner in the first semester of 1991.

Results from this exercise, in Table 10, suggest that the constrained planner can deliver a

[41] An additional reason behind our choice of one-period planner policies is that they are unexpected shocks to consumers. Hence, we can still compute lifetime utility using the CCPs estimated in Section 4. Otherwise, individuals would adjust their choices anticipating planner policies, rendering our estimated CCPs invalid for assessment of lifetime utility under counterfactual policies.

[42] Given the structure of the model, the planner can impose that a consumer stay on treatment only if the consumer chose a market treatment in the prior period. Hence, the constrained planner can choose one of $7^2 * 6^2 = 1,764$ possible assignment rules.

small welfare improvement of about 2% over atomistic agents who make individually rational choices. This is a lower bound for the size of the externality. In her best assignment rules in Table 10, the constrained planner sends healthy individuals with no treatment information (group "highH, nop/trial," who are also the majority) to the no treatment alternative, which is consistent with the low quality of products in the early nineties. In most cases the planner does the same with sick individuals. Additionally, she relies on the treatment information of healthy consumers who got a market treatment last period, either by setting them free to choose or by making them stay in their current treatment. In this way, the information gained by consumers who used a treatment benefits all individuals in the market. A couple of her best rules also involve experimentation, with the planner sending sick individuals who do not have treatment information to clusters or to clinical trials. At the bottom, her worst assignment rules share one common trait: forced experimentation. The planner imposes a high experimentation cost on the healthy, who dislike experimentation the most, and discards the information of individuals who consumed a treatment last period.

In our second exercise we focus on the externality that arises from atomistic individuals who do not incorporate the marginal effects of their clinical experimentation on the evolution of technology, and who are then likely to participate in clinical trials in levels that do not maximize average welfare. We consider a one-time, constrained planner who observes the individuals' states but whose only tool is to send individuals to clinical trials or to let them choose freely among the other alternatives. Effectively, the planner creates a ranking based on how much individuals like clinical trials relative to their best alternative, and uses this ranking to send individuals to trials. Therefore, her problem nests the atomistic solution when she sends to trials all of those who were already joining trials optimally. We solve her problem in the first semester of 1991 and the second semester of 1996.

Results from this constrained, one-period planner, in Table 11, suggest that in 1991 the planner's optimal share of participation in clinical trials was virtually identical to the atomistic share, yielding an average welfare of about $345,000. More interestingly, in 1996 the planner's optimal share is twice as large as the atomistic share and provides an average welfare of about $360,000, about 2% higher than the atomistic average welfare (see Figure 14). As a measure of the externality, we compute the net social benefit from sending the marginal person to trials at the atomistic equilibrium. Because the marginal person does not want to join a trial, he loses a little more than $600 when he has to participate. However, because trial participation spurs innovation by pushing up the expected quality and the expected number of new products, the net social gain is more than $1,000,000 ($2,000 per individual).

Although the results above are suggestive, we hope that no government agency ever

attains the type of authority or information needed to unilaterally send people to clinical trials. As history has shown, who is sent to experimentation depends heavily on the weights allocated to individuals of a given group in the social welfare function (Harris et al., 1996). Instead, a more realistic and ethical solution would be to provide economic incentives for individuals to participate in clinical trials. The last row of Table 11 shows that the cost of attaining a marginal increase in trial participation from the atomistic share using a flat subsidy is a little over \$26,000, substantially below the net social gain.[43] Therefore, our results suggests that providing monetary incentives for trial participation can be welfare improving.

8 Conclusion

We build a structural model to assess how consumer choices affect the evolution of technology in the market for HIV drugs. We capture several mechanisms through which consumer demand affects innovation, including experimentation with new drugs by participating in clinical trials, which accelerates innovation. By joining a trial, individuals gain access to experimental products that may be high-quality breakthroughs, but may also be less efficacious or painfully toxic. Additionally, consumer decisions can bend the technological path if firms avoid innovating around unpopular products. Because individuals are atomistic, an externality arises.

Our results show that consumer behavior can slow the process of innovation and bend it towards less efficacious products that hamper survival probabilities. They also show that atomistic individuals sometimes engage in levels of experimentation that are not welfare maximizing. We explored these issues by considering constrained planner problems, which provides lower bound measures for the size of the externality. We find that a constrained planner can increase average welfare by around two percent (approximately \$6,000 per individual). Additionally, we show that welfare-enhancing levels of trial participation can be achieved using a flat subsidy. In other words, our results suggest that providing monetary incentives for trial participation can be welfare improving.

Given our data, we have focused on how demand and consumer heterogeneity affect the path of technological progress. Other studies have placed more emphasis on the supply side (Carranza, 2010; Goettler and Gordon, 2011; Gowrisankaran and Rysman, 2012). A natural step forward, although by no means a simple one, is to model competition among firms and

[43]For a given target trial share, the flat subsidy pays every participant in clinical trials the loss of the marginal person. Hence, for a marginal increase from the atomistic share, the flat subsidy pays \$628 to every clinical trials participant (see Table 11).

firm decisions to innovate by investing in R&D, while also maintaining an acceptable level of consumer heterogeneity and a role for demand pull. This approach would allow for a richer set of counterfactual policies that incorporate the interaction between consumer demand and firm strategic behavior.

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9 Figures and Tables

Table 1: Summary Statistics: Subjects. Visit 14-47 (1990-2007)

	Restricted Sample	
Subjects	1719	
	mean	std dev
Black	0.22	
Hispanic	0.09	
White	0.68	
High School	0.14	
Some College	0.29	
College	0.34	
More than College	0.23	
Died	0.40	
Died Conditional	0.20	
Ever Take Market Product	0.83	
Ever Take Trial Product	0.24	
Ever Work	0.74	
Ever Not Work	0.68	
Age in 1991	36.04	8.72

Notes: Standard deviation in square brackets. Data for unique individuals. *Ever Market Product* stands for ever consumed a market product during the period from visit 14 to visit 47. Similar definition holds for *Ever Trial Product*. *Died Conditional* is the proportion of individuals who died conditional on surviving until year 1995.

Table 2: Summary Statistics: Subjects-Visits. Visits 14-47 (1990-2007)

	Analytic Sample	Pre Haart	Post Haart
Obs	16851	6972	9879
Ailments	0.43	0.45	0.41
Market Product	0.65	0.49	0.76
Trial Product	0.07	0.09	0.05
Work	0.63	0.70	0.58
Age	44.48	40.89	47.01
	[8.03]	[6.99]	[7.75]
CD4	475	407	524
	[297]	[298]	[287]
Gross Income	17567	19036	16531
	[8787]	[8733]	[8677]
Out-of-pocket Pay	266	179	327
	[706]	[598]	[767]

Notes: Standard deviation in square brackets. Income and Out-of-pocket are semestral and measured in real dollars of 2000. Pre HAART era corresponds to visit <= 24 or (roughly) year <= 1995.

Table 3: Innovation Components

Health Innovation ν_{rt}^{*h}

	coef.	se
$TrialsShare_{t-1}$	433.11	53.26
$Constant$	-24.14	4.73

Ailments Innovation ν_{rt}^{*x}

	coef.	se
$TrialsShare_{t-1}$	1.93	1.01
$Constant$	-0.15	0.09

Distribution of Innovations F_ν

Covariance Matrix

	$Health$	$NoAilments$
$Health$	396.07	1.77
$NoAilments$	1.77	0.14

Notes: Top two panels correspond to estimates from equation (3). The bottom panel shows the covariance matrix of the distribution of innovations.

Table 4: Distribution of Number of New Products, F_N

	coef.	se
μ		
Q_t	0.432	0.246
$TrialsShare_{t-1}$	6.177	2.462
$\ln \alpha$		
$Constant$	-0.206	0.451
Q_t	-1.019	0.626

Notes: Model specified in (5). The variable Q_t measures the distance between the previous period's new products and the previous period's centroid. It captures the relatively higher number of new products that follow the appearance of better innovations. The variable $TrialsShare_{t-1}$ is the share of individuals going into a trial the previous period. According to the model in (5), $E[New_{t+1}] = \mu_t$ and $Var[New_{t+1}] = \mu_t(1 + \alpha\mu_t)$.

Table 5: Utility Parameters, y_{it}

parameter	variable	coef.	se
α_{4w}	$Cluster_{it} \cdot White$	-3.546	0.179
α_{4b}	$Cluster_{it} \cdot Black$	-4.190	0.190
α_{4l}	$Cluster_{it} \cdot Hispanic$	-3.967	0.647
α_{4a}	$Cluster_{it} \cdot Age_{it-1}$	0.043	0.004
α_{4h}	$Cluster_{it} \cdot Health_{it-1}/10^3$	-2.021	0.104
α_{5w}	$Trial_{it} \cdot White$	-1.468	0.136
α_{5b}	$Trial_{it} \cdot Black$	-2.553	0.142
α_{5l}	$Trial_{it} \cdot Hispanic$	-1.585	0.300
α_{5a}	$Trial_{it} \cdot Age_{it-1}$	0.032	0.003
α_{5h}	$Trial_{it} \cdot Health_{it-1}/10^3$	-2.461	0.078
α_{6w}	$Stay_{it} \cdot White$	0.502	0.130
α_{6b}	$Stay_{it} \cdot Black$	0.276	0.145
α_{6l}	$Stay_{it} \cdot Hispanic$	0.707	0.354
α_{6a}	$Stay_{it} \cdot Age_{it-1}$	0.009	0.002
α_{xp}	$NoAilments_{it} \cdot NoProduct_{it}$	1.019	0.260
α_m	$GrossIncome_{it} - OutPocketPay_{it}$	0.057	0.010

Notes: Estimation of equation (13). Discount factor $\beta = .95$. $Cluster_{it}$ indicates whether the individual chose one of the three clusters of products available. $Trial_{it}$ indicates whether he chose a trial treatment. $Stay_{it}$ indicates whether he decided to continue using the same treatment he used last period. $NoProduct_{it}$ indicates whether he did not consume a product. $Health_{it-1}$ is defined as the number of white blood cells per cubic millimeter of blood.

Table 6: Gross Income, m_{it}

variable	coef.	se
$Health_{it-1}$	0.018	0.004
$Health^2_{it-1}/10^3$	-0.064	0.019
$Health^3_{it-1}/10^7$	1.138	0.381
$Health^4_{it-1}/10^{10}$	-1.030	0.381
$Health^5_{it-1}/10^{14}$	4.854	1.950
$Health^6_{it-1}/10^{18}$	-11.270	4.850
$Health^7_{it-1}/10^{20}$	0.101	0.046
Age_{it-1}	0.482	0.114
Age^2_{it-1}	-0.006	0.001
$Black$	-5.534	0.366
$Hispanic$	-4.167	0.570
$Some\ College$	2.497	0.442
$College$	5.812	0.457
$More\ than\ College$	8.203	0.500
$LaborParticipation_{it}$	5.738	0.220
$NoAilments_{it}$	0.207	0.084
$Constant$	-2.095	2.620

Notes: Estimation of equation (15). Random effects regression of gross-income on covariates. m_{it} is measured in thousands of real dollars of 2000. Health is given by the CD4 count measured in hundreds of cells per microliter.

Table 7: Tobit Model for Out-of-pocket Payments, o_{it}

variable	coef.	se
$Health_{it-1}$	-0.002	0.000
$Health^2_{it-1}/10^3$	0.009	0.002
$Health^3_{it-1}/10^7$	-0.133	0.029
$Health^4_{it-1}/10^{10}$	0.090	0.022
$Health^5_{it-1}/10^{14}$	-0.266	0.071
$Health^6_{it-1}/10^{18}$	0.279	0.083
Age_{it-1}	0.037	0.007
Age^2_{it-1}	0.000	0.000
$Black$	-0.240	0.021
$Hispanic$	-0.119	0.025
$Some\ College$	0.169	0.026
$College$	0.318	0.033
$More\ than\ College$	0.336	0.030
$MarketProduct_{it}$	0.429	0.026
$TrialProduct_{it}$	0.313	0.043
$LaborParticipation_{it}$	0.105	0.016
$NoAilments_{it}$	-0.122	0.017
$Constant$	-1.459	0.182
σ^o	0.862	0.066

Notes: Estimation of equation (16). $MarketProduct_{it} = \sum_{k=1}^{4} d_{kit}$. Out-of-pocket Payments o_{it} are measured on thousands of real dollars of 2000. Health is given by the CD4 count measured in hundreds of cells per microliter.

Table 8: Logit Model for Labor Supply, l_{it}

variable	coef.	se
$Health_{it-1}$	0.009	0.001
$Health^2_{it-1}/10^3$	-0.013	0.002
$Health^3_{it-1}/10^7$	0.075	0.023
$Health^4_{it-1}/10^{10}$	-0.013	0.007
Age_{it-1}	0.102	0.032
Age^2_{it-1}	-0.001	0.000
$Black$	-0.168	0.073
$Hispanic$	-0.040	0.125
$Some\ College$	0.312	0.105
$College$	0.537	0.103
$More\ than\ College$	0.613	0.108
$LaborParticipation_{it-1}$	4.458	0.056
$Constant$	-5.914	0.742

Notes: Estimation of equation (17). Health is given by the CD4 count measured in hundreds of cells per microliter.

Table 9: Logit model for Death, $1 - S_{it+1}$

variable	coef.	se
$Health_{it-1}$	-0.028	0.003
$Health^2_{it-1}/10^3$	0.079	0.015
$Health^3_{it-1}/10^7$	-1.104	0.292
$Health^4_{it-1}/10^{10}$	0.704	0.220
$Health^5_{it-1}/10^{14}$	-1.610	0.561
Age_{it-1}	-0.116	0.058
Age^2_{it-1}	0.002	0.001
$Black$	-0.509	0.199
$Hispanic$	0.034	0.235
$Some\ College$	0.060	0.185
$College$	-0.353	0.185
$More\ than\ College$	-0.512	0.207
$NoAilments_{it}$	-1.140	0.159
$Constant$	1.682	1.358

Notes: Estimation of equation (21). Health is given by the CD4 count measured in hundreds of cells per microliter.

Table 10: Constrained Planner: Assignment Rules

		Groups			
	Group Share	0.50	0.26	0.05	0.19
	Average Welfare ($1000)	highH, nop/trial	highH, mk	lowH, nop/trial	lowH, mk
Top ten rules	351.99	6	7	7	6
	351.41	6	7	6	6
	350.89	6	4	7	6
	350.88	6	4	6	6
	349.42	6	7	6	7
	349.31	6	7	3	6
	349.11	6	7	1	6
	348.92	6	4	5	6
	348.79	7	4	5	7
	348.65	6	7	6	4
	⋮				
Atomistic	346.11	7	7	7	7
	⋮				
Bottom ten rules	169.72	1	5	5	5
	169.32	3	5	6	5
	169.17	3	5	7	5
	168.96	3	5	1	5
	168.11	1	5	6	5
	167.56	1	5	2	5
	167.55	3	5	5	5
	167.37	1	5	1	6
	167.19	1	5	3	6
	166.23	1	5	3	5

Notes: Best and worst assignment rules of a one-time constrained planner that solves her assignment problem in 1991. Groups are determined by health status (high or low) and previous treatment status (consumed a market treatment or not). The population shares of each of the groups are shown on top of their labels. Numbers 1 to 3 correspond to the three clusters available in 1991. Number 4 corresponds to staying in previous market treatment. Number 5 stands for trial and 6 stands for no treatment. Finally, number 7 stands for individually optimal choice; in other words, the planner renounces to her right to impose a choice and lets the individual in the group decide based on their richer information set.

Table 11: Constrained Planner: Optimal Experimentation

	1991 S1	1996 S2
Planner optimal trial share	0.100	0.185
Atomistic trial share	0.102	0.092
Average value at planner solution	345	360
Average value at atomistic equilibrium	345	354
Individual loss for marginal person sent to trials at atomistic equilibrium	-0.178	-0.628
Social gain from sending marginal person to trials at atomistic equilibrium	-1133	1051
Average gain from sending marginal person to trials at atomistic equilibrium	-1.32	2.36
Marginal increment in trial share	0.001	0.002
Cost to attain marginal increment (at atomistic solution) using flat subsidy	-	26.384

Notes: Constrained planner's problem solved at the first semester of 1991 and the second semester of 1996. Monetary values in $1,000s.

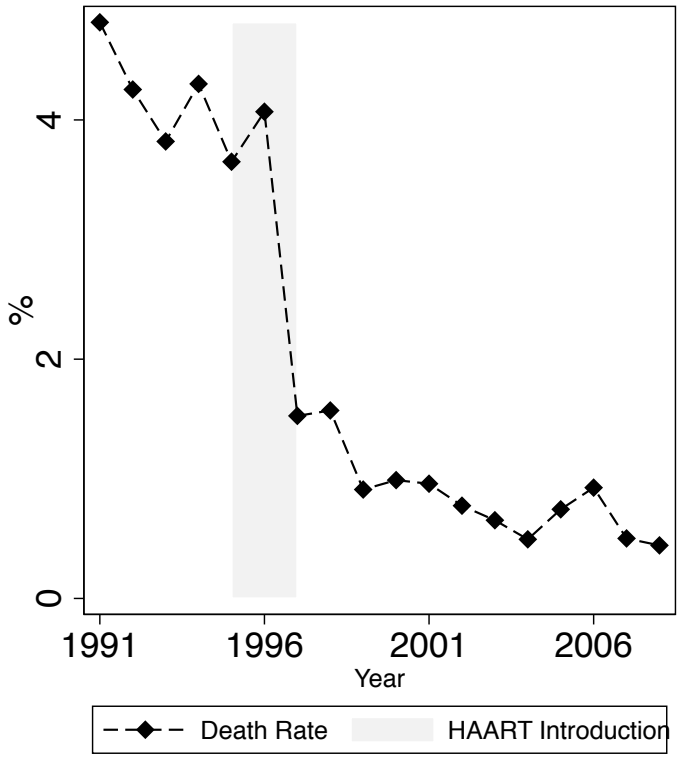
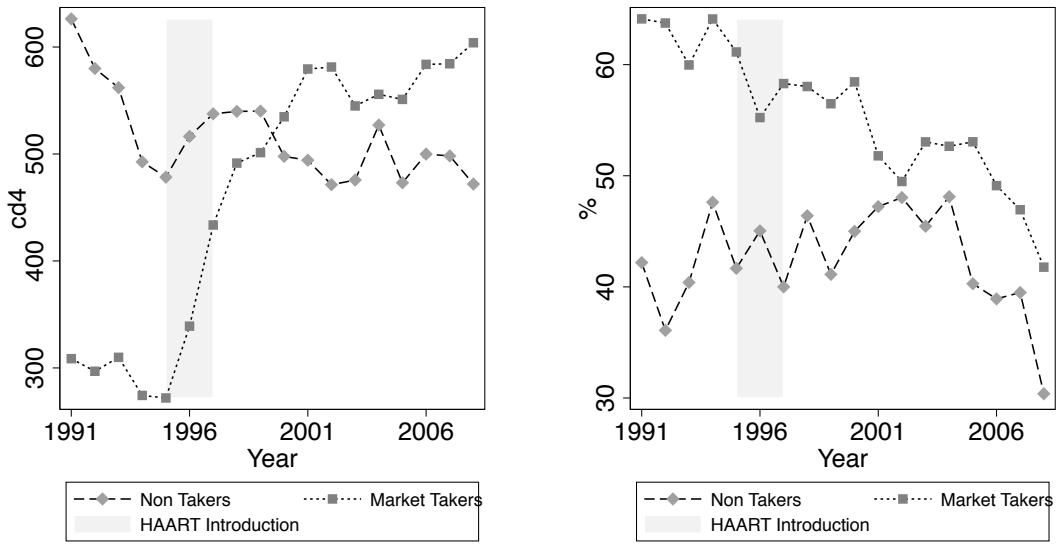
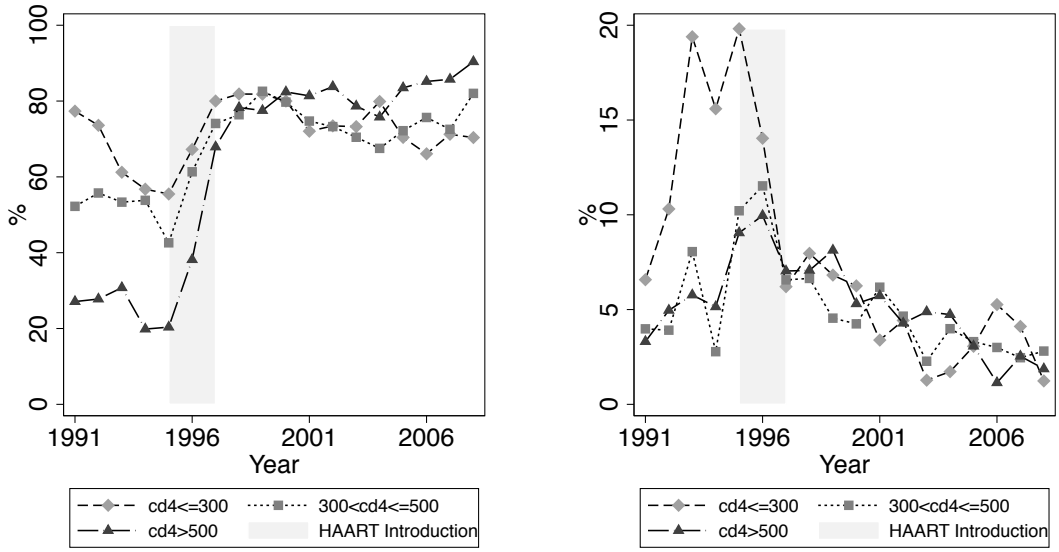


Figure 1: Death rate in the sample. More than 1500 surveyed individuals died for AIDS-related causes during our analysis period.



(a) (b)

Figure 2: Health and side effects summary trends over time. Panel 2(a) shows the mean CD4 over time by consumption status. Panel 2(b) contains mean ailments over time by consumption status.



(a) (b)

Figure 3: Consumer demand over time. Panel 3(a) shows treatment consumption over time by health status. Panel 3(b) shows trial participation over time by health status.

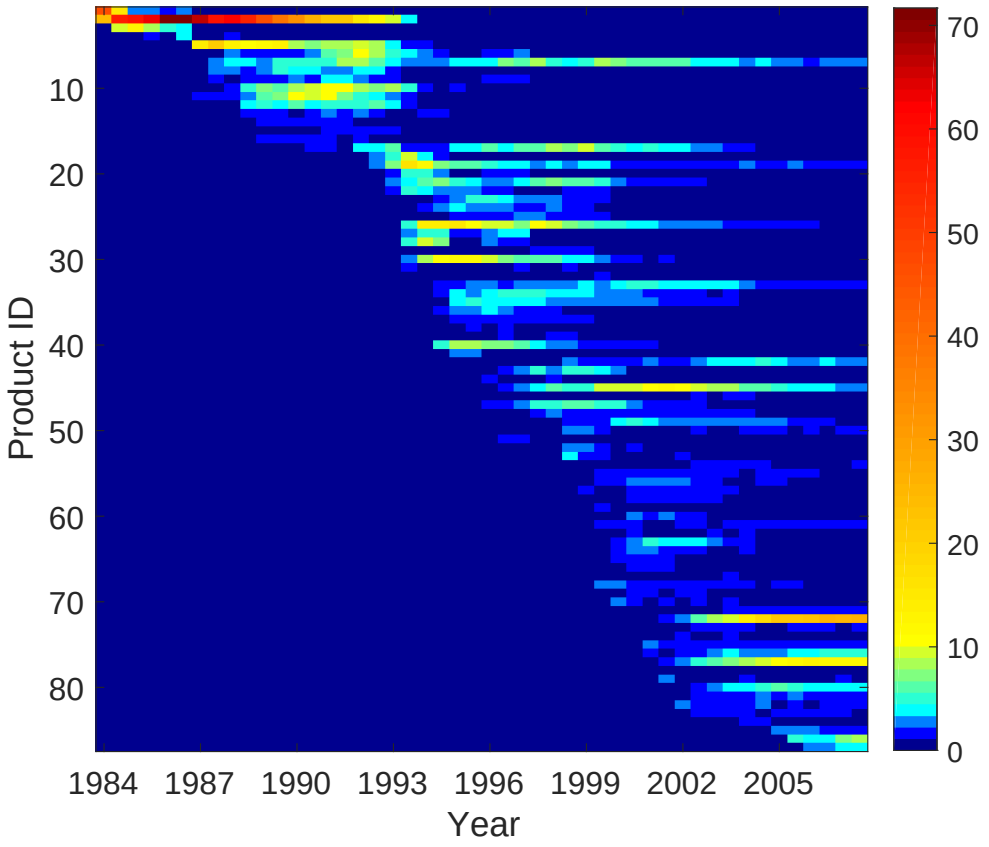


Figure 4: Diffusion of Products Over Time

Notes: HIV treatments from 1984 to 2008. Each id—or row—represents a product. Color indicates the share of the market that the product captures. Shares are conditional on consuming a product. Early on there are few products with high shares, as time passes new products strip market share from incumbents and less popular products exit.

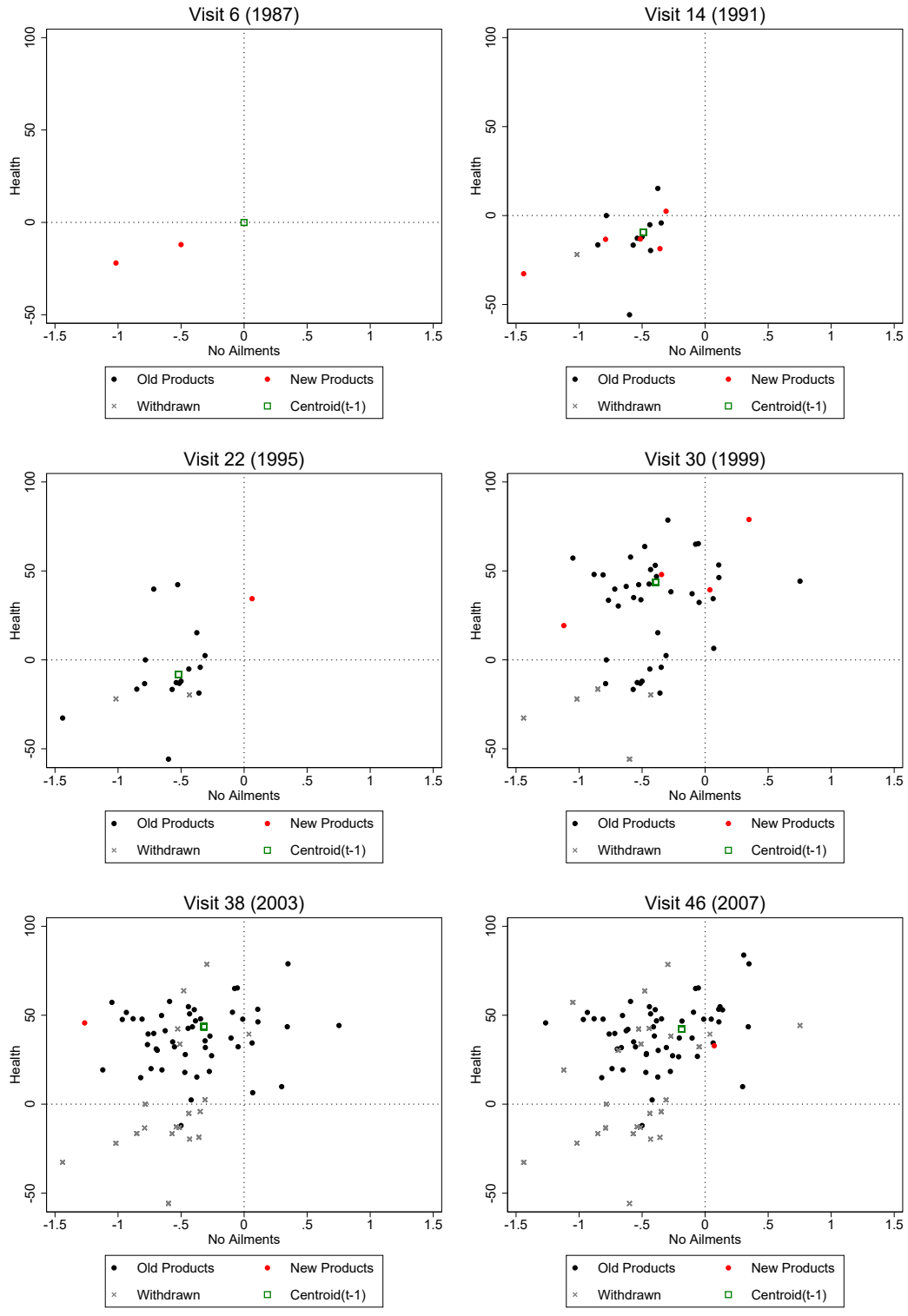


Figure 5: Treatment Evolution

Notes: Figure shows snapshots of the evolution of the state of the product market at the different stages. Products are two-dimensional. On the x-axis is a measure of a treatments ability to not cause side effects. On the y-axis is a measure of its contribution to underlying health. Dimensions are measured in different scales. Incumbent products are shown in black. New products are shown in red. Withdrawn products are shown as x. The green square is a measure of the prevalent technology in the previous period.

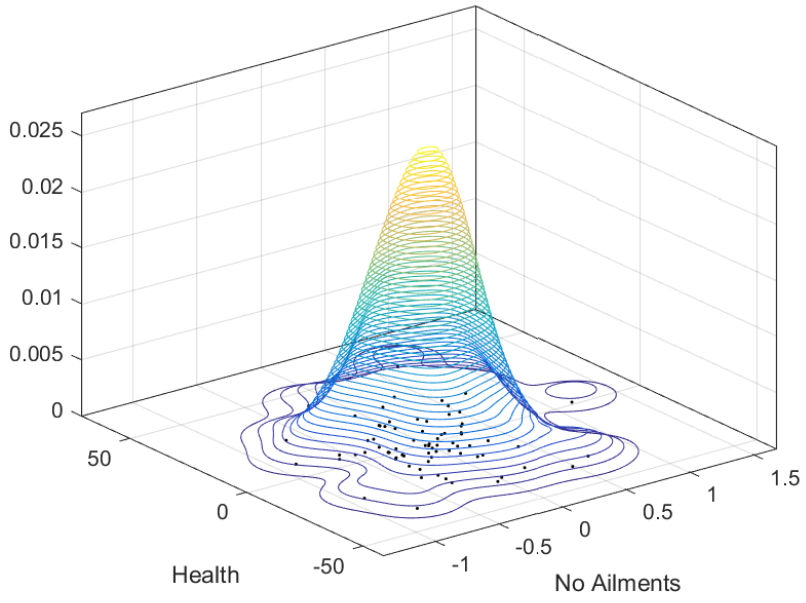


Figure 6: The Distribution of Innovations, F_ν.

Notes: F_ν is estimated non-parametrically from the realized innovation vectors ν_k implied by equations (2) and (3).

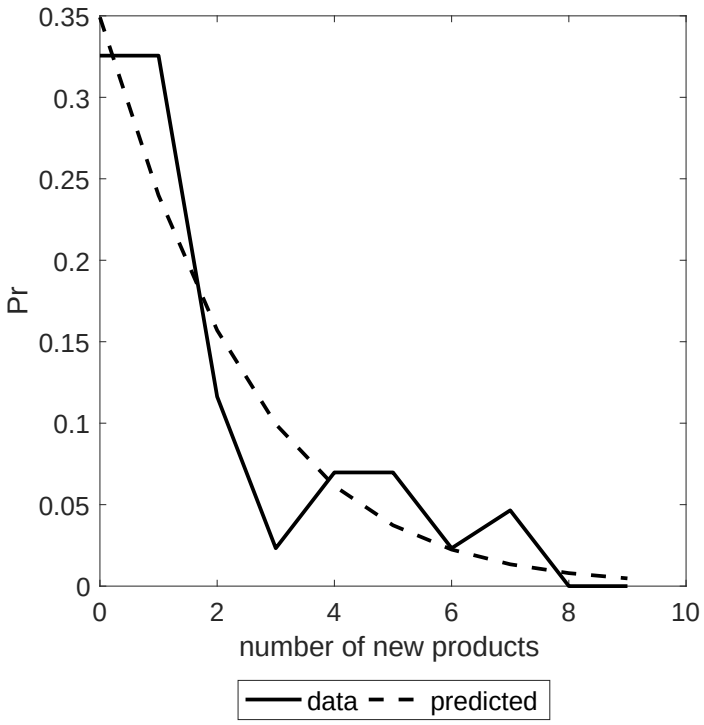


Figure 7: Distribution of Number of New Products

Notes: Model specified in (5). Figure shows the empirical distribution of new products and the average over time of the predicted probabilities using the estimated parameters in Table 4.

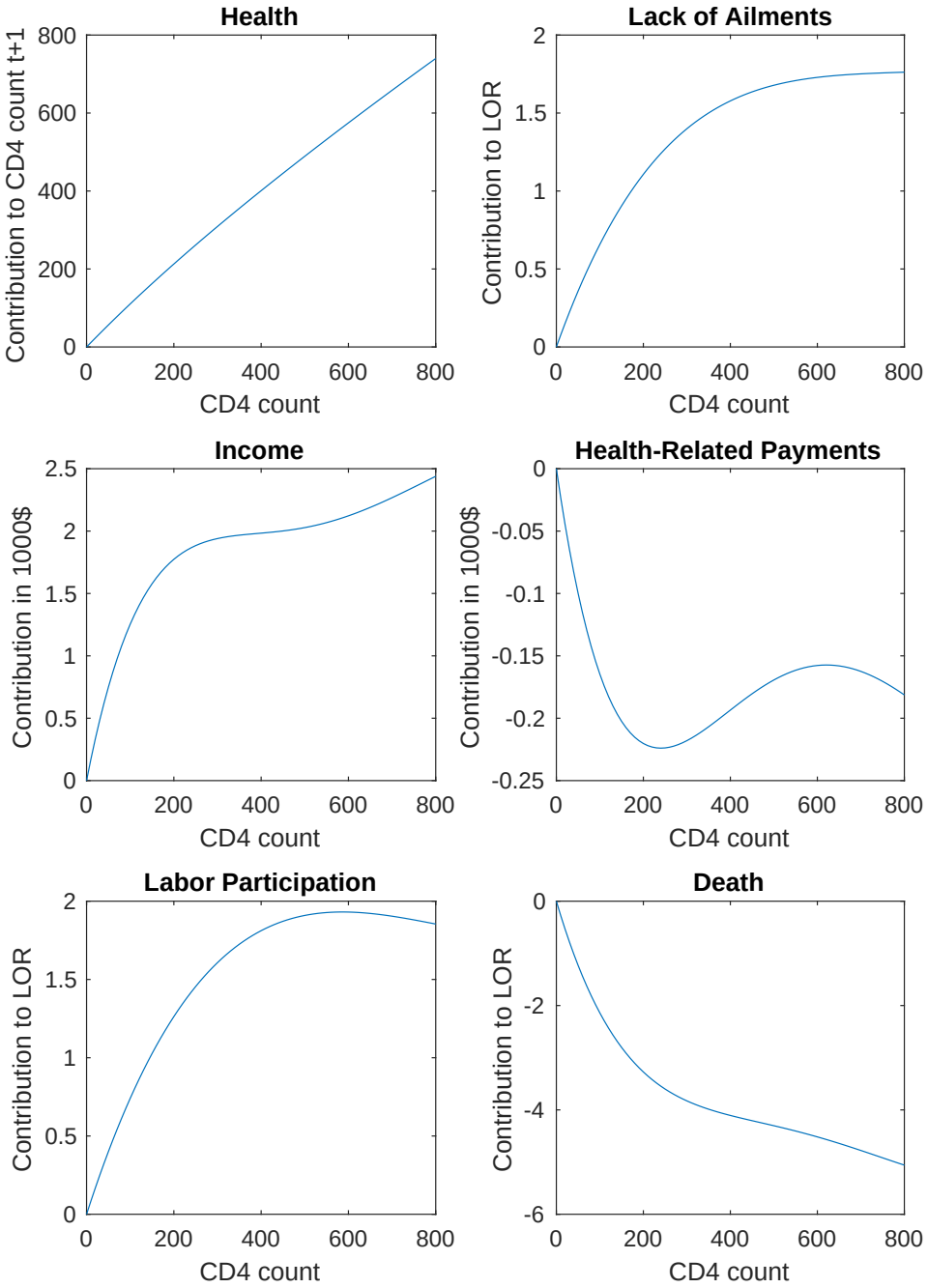


Figure 8: Health Effect on Future Health and Outcomes

Notes: CD4 Count measured in hundreds of cells per microliter. LOR stands for log odds ratio. Semestral income measured in thousands of dollars of 2000.

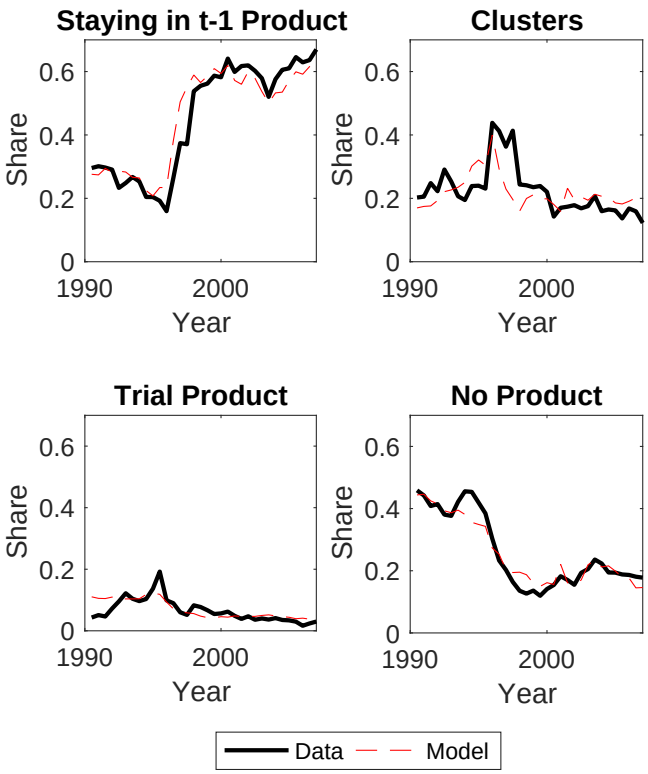


Figure 9: Goodness of Fit Figures

Notes: Simulated and empirical choice rates over time.

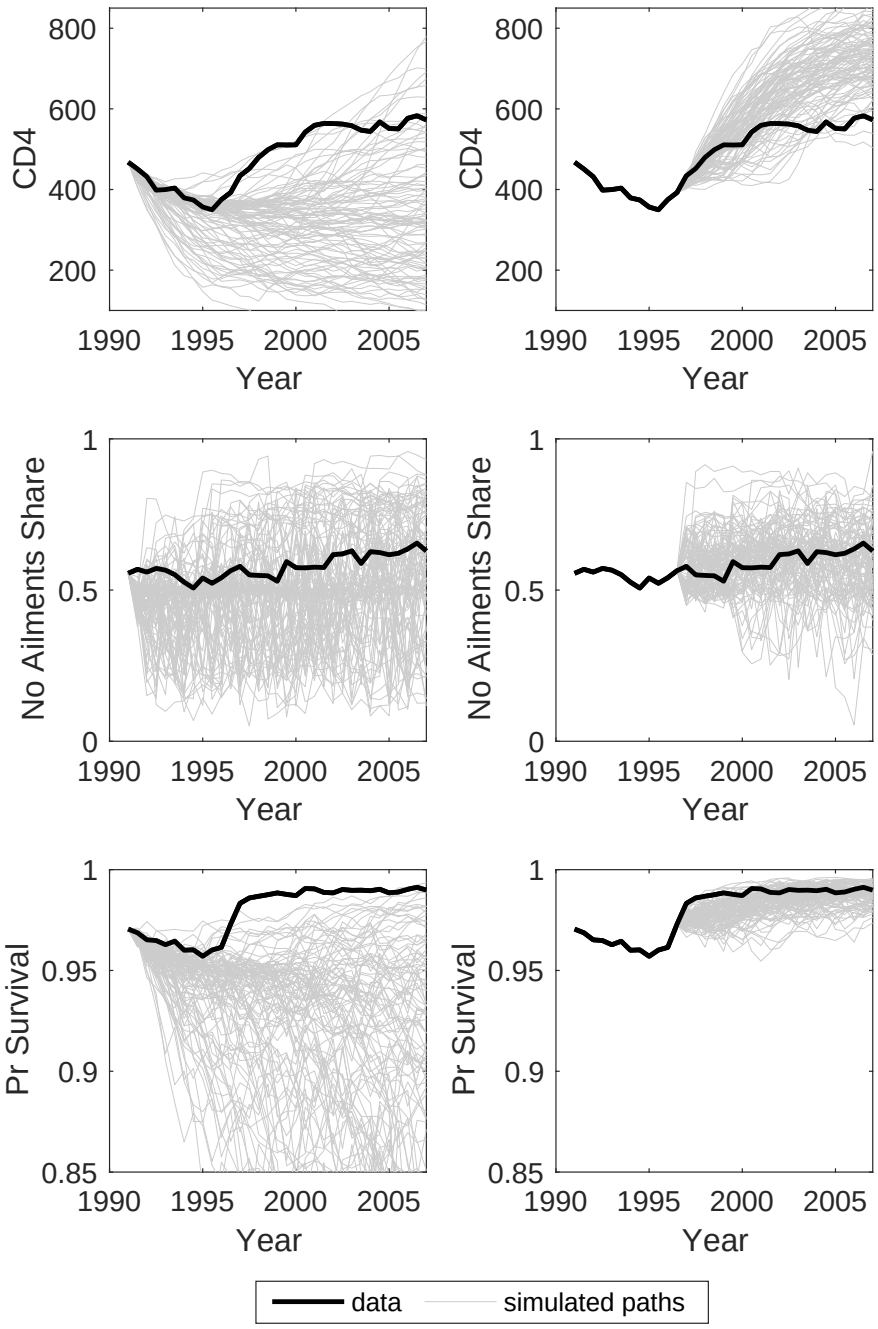


Figure 10: Distribution of Technology Paths: Consumers

Notes: 100 simulated paths conditional on the state of the world at 1991 and 1996.

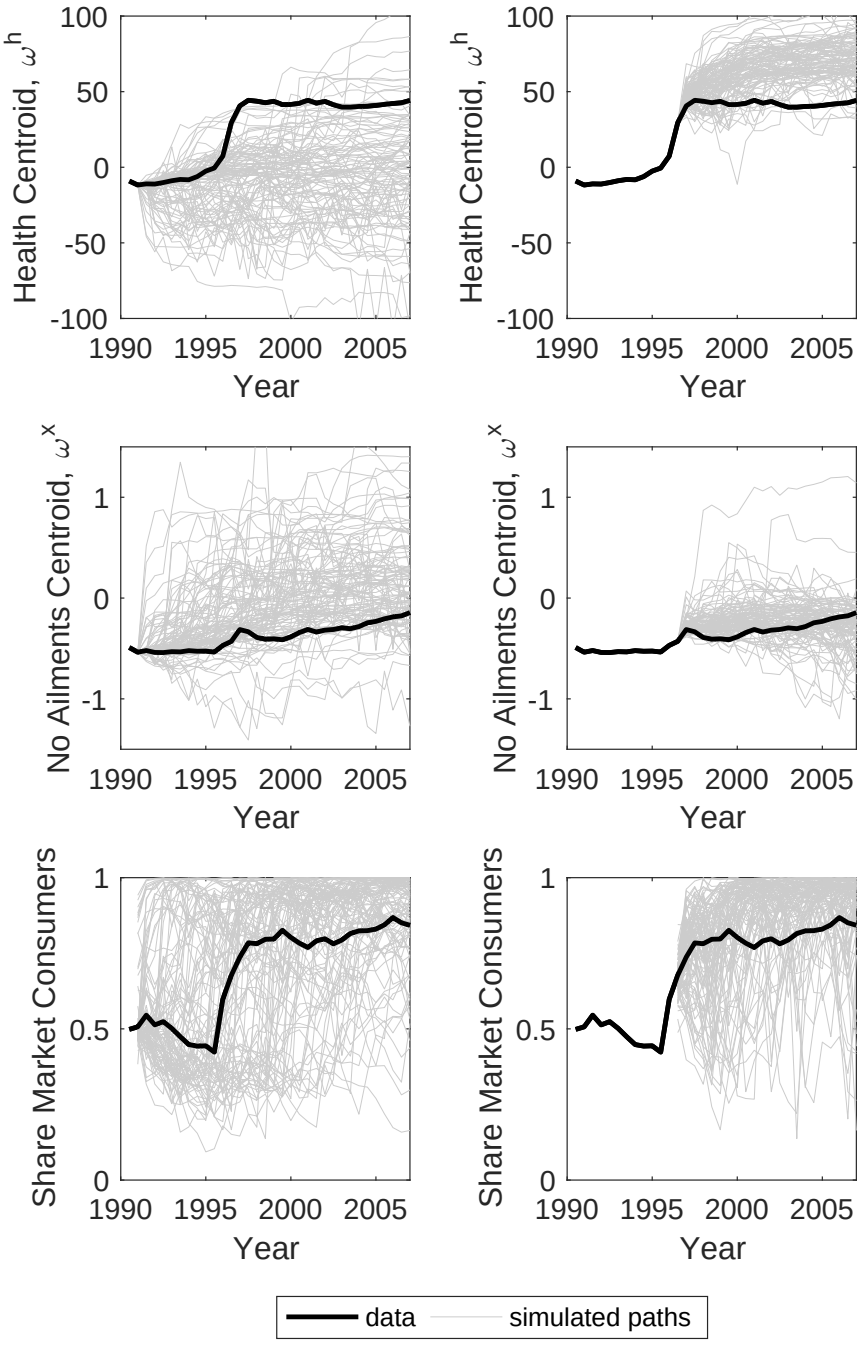


Figure 11: Distribution of Technology Paths: Technology and Product Consumption

Notes: 100 simulated paths conditional on the state of the world at 1991 and 1996.

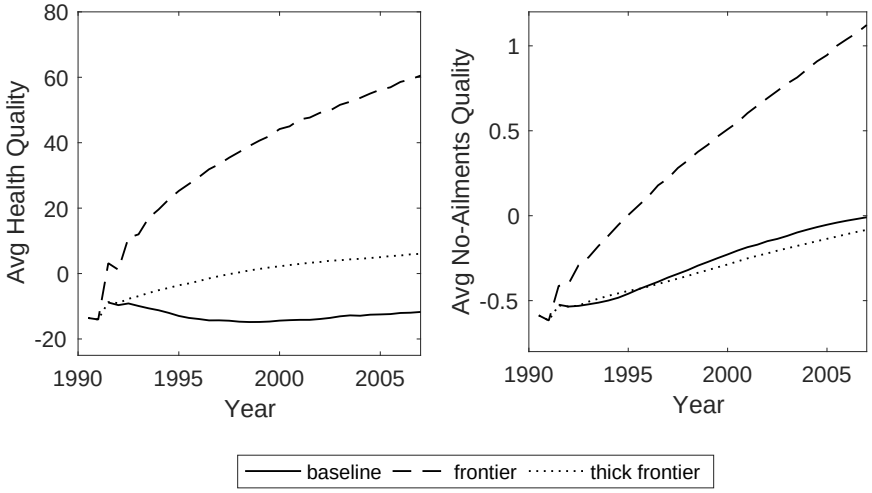


Figure 12: Alternative Regimes: Exogenous Scientific Intervention

Notes: Figure shows differences across regimes in terms of the average quality of products in the market. The *baseline* is the estimated model where products are dropped in response to low demand. In the *frontier* regime all dominated products in terms of quality are exogenously dropped from the market every period. The *thick frontier* sets the exit rate of products at the average baseline rate and exogenously drops the worst products. Statistics are computed from 500 simulations that are conditional on the state of the world at the first semester of 1991.

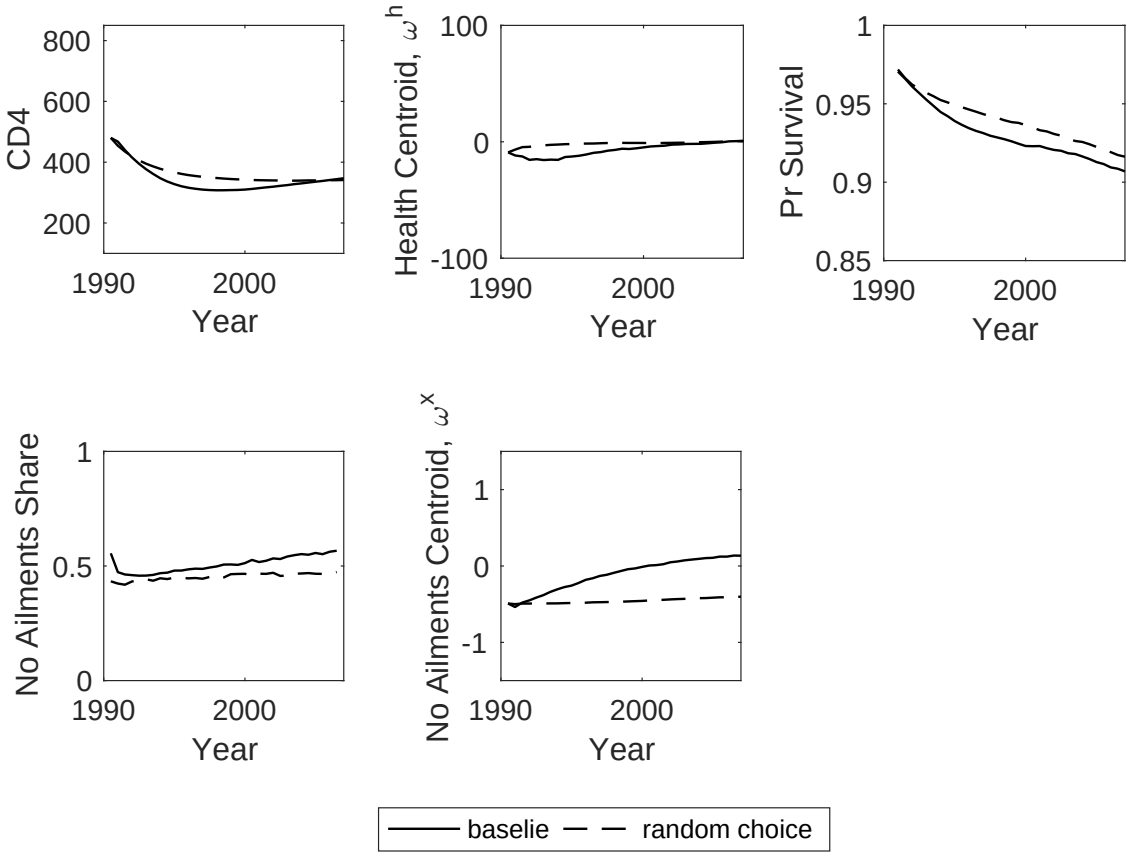


Figure 13: Alternative Regimes: Random Choice

Notes: Alternative choice regimes are: (i) baseline and (ii) random choice. The *baseline* regime is the estimated model where individuals make optimal dynamic choices. Individuals in the *random choice* regime select randomly using the aggregate shares on the baseline model to randomize. Averages computed from 500 simulations that are conditional on the state of the world at 1991.

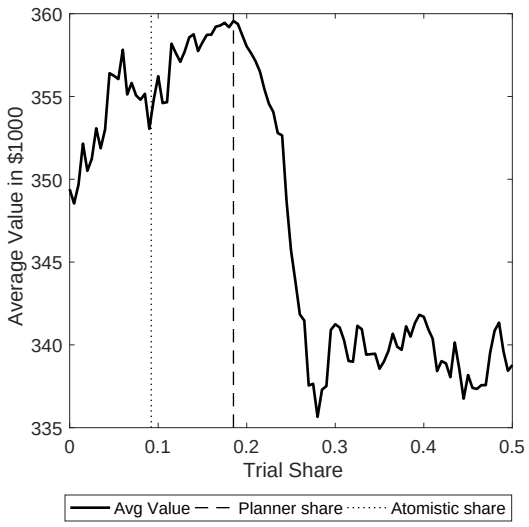


Figure 14: Constrained Planner: Random Assignment to Clinical Trials

Notes: Average welfare generated by a constrained planner in the second semester of 1996 that sends individuals to trials according to a rank based on how individuals like going to trials relative to their individually optimal choice. An individual can only access a clinical trial if he is assigned to one. If he is not sent to a clinical trial, he can choose among the remaining alternatives. The dotted line indicates the atomistic share. The dashed line indicates the planner's optimal share.

A Data Appendix

Beginning in 1984, the Multi-Center AIDS Cohort Study (MACS) started gathering information regarding natural and treated histories of HIV infection in homosexual and bisexual men. The study is conducted in Baltimore, Chicago, Pittsburgh and Los Angeles. At each semi-annual visit, data are collected on: demographics, psychosocial characteristics, sexual behavior, and specially important for our purposes, antiretroviral (AV henceforth) drugs consumption and trial participation. In addition, blood tests are administered to measure health status and serostatus (whether the individual is HIV+). Data collection started with 4,954 men enrolled. Two more enrollments have taken place: one in 1987-1991 (668 additional men) and another in 2001-2003 (1,350 additional men). We only use data from the first two enrollments.

A.1 Main Variables

Health (h_{it-1}): At every visit individuals go through a physical examination in which several health measurements are taken. As our measure of underlying health status, we use the CD4 count obtained from a blood sample. "CD4 is a glycoprotein found on the surface of immune cells [...]. If CD4 cells become depleted, for example in untreated HIV infection, or following immune suppression prior to a transplant, the body is left vulnerable to a wide range of infections that it would otherwise have been able to fight. [...] Normal blood values are usually expressed as the number of cells per microliter (or cubic millimeter, mm^3) of blood, with normal values for CD4 cells being 500-1200 cells/mm" (Wikipedia). We denote as h_{it-1} the CD4 count at of the individual at the start of period t.

Labor supply (l_{it-1}): Whether the individual was working full time (35 hours or more) in visit t.

Income (m_{jit}): Starting at visit 14, individuals answer the following question: "Which of the following categories describes your annual individual gross income before taxes"? For visit 14, categories are: less than 10000, 10000-19999, 20000-29999, 30000-39999, 40000-49999, 50000-59999, 60000-69999, 70000 or more, Doesn't wish to answer. For visits 15 to 35, categories are: less than 10000, 10000-19999, 20000-29999, 30000-39999, 40000-49999, 50000 or more, Doesn't wish to answer. For visits 36 to 41, categories are: less than 10000, 10000-19999, 20000-29999, 30000-39999, 40000-49999, 50000-99999, 60000 or more, Doesn't wish to answer.

We censor all periods at 50000 or more to obtain a uniform question over time. Then we assign the middle point to individuals in the bracket. For the highest bracket we assign

the upper limit (50000). In our model gross income is divided by two since the survey asks about annual income. Gross income as well as out-of-pocket payments (below) are in constant dollars of 2000.

Out-of-pocket payments (o_{jit}): Starting from visit 14, individuals are given the following direction "Please estimate the TOTAL out-of-pocket expenses that you or other personal sources (your lover, family or friends) paid for prescription medications since your last visit."[44] As opposed to the gross income question, this question is open so values are not categorized.

Ailments (x_{jit}): Starting from at visit 4, individuals are asked about physical symptoms. Even though other ailments are recorded, we focus on unusual bruises lasting at least two weeks, unintentional weight loss of at least 10 pounds, fatigue, diarrhea, fever, night sweats, and tender/enlarged glands. The last 5 ailments must be felt for at least 3 days.

Even though individuals are asked explicitly about side effects starting from visit 13, we choose not to use such data because it is less consistent and, more importantly, because we do not think individuals are able to differentiate correctly between side effects and symptoms. Therefore, in our model x_{it} takes the value of 1 if individual reports having any of the problems mentioned above.

Race (b_i): Individuals in the sample are either white, black or hispanic.

Age (a_{it}): Age of the individual at the beginning of period t.

A.2 Products and Product Components

At every visit after visit 6, individuals are asked whether they took any medication to fight AIDS. Starting from visit 13, as the number of medications becoming available for HIV exploded, separate surveys were administered for antiretroviral drugs (ARVs) and non antiretroviral drugs (NARVs). We focus on ARVs since these are the drugs used to treat HIV infection. Further, since our analysis includes estimating the health and ailments of people using different drugs, we focus on observations where individuals have reported a treatment along with h_{it}, h_{it-1}, and x_{it}.

Individuals are asked to name specifically which drugs they took as well as whether or not they took the drug as part of a research study (the exact wording of the question regarding research studies changes slightly over time). Some of the reported drugs are themselves coded as trials; we regard these instances as individuals participating in trials (see Table S1). If at individual i at period t is consuming one of his drugs as part of a trial we regard

[44] Wording changes slightly in visits 14 and 15.

individual i as consuming a trial product at period t.

Next, we define market products as treatments with no components consumed in trial. Given that the sum of effects of individual drugs is not equal to the effect of a treatment formed by the sum of the drugs, the relevant market products consumed in our data correspond to combinations of components. For instance a product is AZT and another is AZT plus 3TC plus ddI. Table S2 describes the individual components of market products. Some components, listed separately in Table S3, are in fact fixed-dose combinations of other components. In our sample, if individual i is consuming the fixed-dose combination $(A+B)$ and individual i' is consuming components A and B, we assign consumers i and i' to the same treatment. One of the coded components in the data corresponds to "other ARVs". We add all uncoded components (96 instances) to "other ARVs" which results in 158 instances of "other ARVs". Finally, we treat α and β Interferons (177 instances and 33 instances, respectively) as one single component.

Our definition of market products, as combinations of drug components, generates 1835 different market treatments. We reduce the number of market products using the following algorithm:

1. We select our core market products as those treatments that overall have more than 40 instances.[45] We acknowledge that our definition of core treatments is biased against treatments appearing near the end of the time period studied. We address this issue by excluding the last 4 periods of data. Our core treatments are listed in Table S4 which shows that there are 70 core products overall and they have at most five components. Out of 20142 subject-visit observations of consumers taking market products, 13767 are covered by core treatments and 6375 correspond to non-core treatments.

2. Second, we assign non-core treatments to core treatments in the following fashion. Each step is used sequentially to assign remaining non core treatments that were not assigned in previous steps.

   (a) Assignment of Non-core: Non core treatment A is assigned to core treatment B if B is the core treatment with the highest number of components that is contained by A. This procedure yields both non-unique assignments or null assignments. Of the remaining 6375 subject-visit observations of non core treatments, 2963 are assigned uniquely in this step. This means that we are left with 3412 subject-visit observations with non core treatments, 1647 that are assigned to multiple core treatments and 1765 that are not assigned to any core treatment.

[45] We can change this to a different number and main results remain robust.

(b) Assignment of Multiple Assignments:

i. First, we use the past history of the individual. If at period t individual i is consuming non core treatment W that was assigned to both core treatments A and B in previous steps, and he was observed consuming core treatment A in period $t-1$, then his treatment at t is assigned uniquely as A. We repeat this procedure until no further gains are obtained. Out of the remaining 1647 subject-visit observations of non core treatments with multiple assignments, 428 are assigned uniquely in this step.

ii. Second, we use the future history of the individual. If at period t individual i is consuming non core treatment W that was assigned to both core treatments A and B in previous steps, and he was observed consuming core treatment B in period $t+1$, then his treatment at t is assigned uniquely as B. We repeat this procedure until no further gains are obtained. Out of the remaining 1219 subject-visit observations of non core treatments with multiple assignments, 274 are assigned uniquely in this step.

iii. Third, we assign the reaming 945 subject-visit observations of non core treatments with multiple assignments using the core treatment with the highest share at t: if at period t individual i is consuming non core treatment W that was assigned to both core treatments A and B in previous steps, and treatment A's market share at t is greater than B's, his treatment at t is assigned uniquely as A. This final step assigns uniquely the remaining 945 observations.

(c) Next, we regard all 1765 not assigned treatment observations as "fringe" treatments since they do not contain any core treatment. We aggregate them in the following fashion. We aggregate all fringe treatments that appear at period t and assign to this "cohort" fringe treatment, all users consuming this product over time. Similarly as we do with core treatments, we only consider fringe cohort treatments that have at least 40 users. This reduces the number of observations by 345 (which represents 1.6% of the number of observations of treatment consumers). This aggregations leads to 17 fringe cohort treatments that we will treat in the same way we treat core treatments: as innovations from the trials distribution. This amounts to a total of 87 treatments over all. From this point on fringe treatments are included in the denomination of core treatments.

3. We have specified that a treatment gets withdrawn from the market if it has zero share for $X = 2$ consecutive periods. However, in the data, a treatment may have zero share

for $Y > X$ periods and then reappear again. 78 out of 87 core treatments have unique spells; we regard the remaining treatments with multiple spells as measurement error and follow the next procedure to ensure that treatments have one single spell from entry to exit. Consider a core treatment with multiple spells B.

(a) We identify all spells that treatment B has in the data.

(b) Among treatment B's spells, we select the spell that contains the period in which treatment B's share was the highest. We drop all observations of market consumers of treatment B that are not in this spell.

(c) We follow the same steps for all 9 core treatments with multiple spells. Out of 19797 $(20142 - 345)$ subject-visit observations of consumers taking market products, this smoothing procedure drops 42 observations leaving 19755 subject-visit observations of consumers taking market products.

As evidence of the relevance of the spells selected by this procedure we compute the difference between the maximum share in the selected spell and the maximum share in each of the other spells, as a percentage of the maximum share in the other spell. The mean value of this measure is 2401, which suggests that the maximum share in the selected spell is on average about 24 times larger that the maximum share in other spells. We also try the following criteria: (i) selecting the spell with the highest average share and (ii) selecting the spell with the highest sum of shares. All criteria result in closely similar entry and exit dates so we stick to the maximum-share criteria.

Appendix Table S1: Trial Components

Name	Observations
AZT/ddI Blinded Trial	91
AZT/ddC Blinded Trial	69
ddI/ddC Blinded Trial	6
AZT/ddI/ddC Blinded Trial	31
AZT/d4T trial	4
AZT/3-TC Blinded Trial	23
AZT/ddI/protease inhibitor Blinded Trial	1
AZT/protease inhibitor Blinded Trial	2
d4T/protease inhibitor Blinded Trial	1
AZT/3-TC/protease inhibitor Blinded Trial	1
Combivir/Trizivir Blinded Trial	5
Trizivir + Sustiva/Combivir + Sustiva Blinded Trial	3
Generic AIDS Vaccine Trial	1

Appendix Table S2: Chemical Formulae of Product Components

Component	Chemical Formula	Observations
Isoprinosine	$C_{52}H_{78}N_{10}O_{17}$	87
Ribavirin	$C_8H_{12}N_4O_5$	62
Interferons (α and β)		210
Foscarnet	CH_3O_5P	92
AZT	$C_{10}H_{13}N_5O_4$	7436
ddC	$C_9H_{13}N_3O_3$	1123
AL-721 egg lecithin		147
Dextran-Sulfate	$H(C_6H_{10}O_5)_xOH$	65
Acyclovir	$C_8H_{11}N_5O_3$	2550
ddI	$C_{10}H_{12}N_4O_3$	3069
d4T	$C_{10}H_{12}N_2O_4$	3807
Nevirapine	$C_{15}H_{14}N_4O$	2210
Delavirdine	$C_{22}H_{28}N_6O_3S$	176
3TC	$C_8H_{11}N_3O_3S$	5250
Saquinavir	$C_{38}H_{50}N_6O_5$	1279
Ritonavir	$C_{37}H_{48}N_6O_5S_2$	3230
Indinavir	$C_{36}H_{47}N_5O_4$	2255
Nelfinavir	$C_{32}H_{45}N_3O_4S$	1278
Kaletra	$C_{37}H_{48}N_4O_5$	1883
Abacavir	$C_{14}H_{18}N_6O$	1549
Agenerase	$C_{25}H_{35}N_3O_6S$	372
Efavirenz	$C_{14}H_9CIF_3NO_2$	3362
Adefovir	$C_8H_{12}N_5O_4P$	44
Enfuvirtide (T-20)	$C_{204}H_{301}N_{51}O64$	160
Tenofovir	$C_9H_{14}N_5O_4P$	2488
Emtricitabine	$C_8H_{10}FN_3O_3S$	263
Atazanavir	$C_{38}H_{52}N_6O_7$	1583
Lexiva	$C_{25}H_{36}N_3O_9PS$	418
Etravirine	$C_{20}H_{15}BrN_6O$	155
Darunavir	$C_{27}H_{37}N_3O_7S$	315
Raltegravir	$C_{20}H_{21}FN_6O_5$	384
Ampligen	Double-stranded RNA compound	25
Peptide T	$C_{35}H_{55}N_9O_{16}$	30
DTC	$C_5H_{10}NS_2Na$	10
CD4		2
Other protease		31
Vistide (cidofovir)	$C_8H_{14}N_3O_6P$	2
Tipranavir (PNU-140690)	$C_5H_{10}NS_2Na$	30
Other Avs		158

Notes: Source: Wikipedia (November, 2014)

Appendix Table S3: Combination Components

Name	Combination	Instances
Combivir	AZT + 3TC	2673
Trizivir	AZT + 3TC + Abacavir	778
Truvada	Emtricitabine + Tenofovir	1933
Epzicom	Abacavir + 3TC	724
Atripla	Efavirenz + Emtricitabine + Tenofovir	968

Appendix Table S4: Products in the Market, Entry and Exit

Treatment Id	Treatment	Haart	Entry (visit)	Exit (visit)
3	AZT	0	6	-
13	Interferons (α and/or β), AZT	0	7	23
9	AL-721 egg lecithin	0	7	15
34	AZT, Acyclovir	0	11	32
33	Acyclovir	0	11	32
47	AZT, Acyclovir, ddI	0	12	26
51	Acyclovir, ddI	0	12	32
14	AZT, ddC	0	12	35
39	AZT, ddI	0	12	41
46	ddI	0	12	-
69	AZT, ddC, Acyclovir, ddI	0	14	26
65	AZT, ddC, Acyclovir	0	14	31
67	AZT, ddC, ddI	0	14	23
63	ddC, Acyclovir	0	14	27
64	ddC	0	14	30
85	d4T	0	18	-
117	AZT, Acyclovir, 3TC	0	21	32
124	AZT, 3TC	0	22	-
146	Acyclovir, d4T, 3TC	0	23	32
161	AZT, 3TC, Saquinavir	1	24	42
157	d4T, 3TC	0	24	-
185	AZT, 3TC, Saquinavir, Ritonavir	1	25	-
164	AZT, Acyclovir, 3TC, Indinavir	1	25	32
171	Acyclovir, d4T, 3TC, Indinavir	1	25	32
169	AZT, 3TC, Ritonavir, Indinavir	1	25	45
214	d4T, 3TC, Ritonavir, Indinavir	1	25	45
254	d4T, 3TC, Saquinavir, Ritonavir	1	25	41
202	ddI , d4T, Indinavir	1	25	41
175	d4T, 3TC, Indinavir	1	25	48
165	AZT, 3TC, Indinavir	1	25	-
242	d4T, Nevirapine, 3TC	1	26	-
236	AZT, Nevirapine, 3TC	1	26	-
268	AZT, 3TC, Nelfinavir	1	26	-
377	ddI , d4T, Nelfinavir	1	26	43
292	d4T, 3TC, Nelfinavir	1	27	-
349	ddI , d4T, Nevirapine	1	27	-
311	ddI , 3TC, Nelfinavir	1	27	-
615	ddI , d4T, Efavirenz	1	29	48
644	3TC, Abacavir, Efavirenz	1	29	-
573	AZT, Nevirapine, 3TC, Abacavir	1	30	-
720	AZT, 3TC, Abacavir, Efavirenz	1	30	-

548	AZT, 3TC, Efavirenz	1	30	-
701	AZT, 3TC, Abacavir	0	30	-
532	d4T, 3TC, Efavirenz	1	30	44
581	Nevirapine, 3TC, Abacavir	1	31	-
782	d4T, 3TC, Kaletra	1	34	44
940	3TC, Kaletra, Abacavir	1	35	-
869	AZT, 3TC, Kaletra	1	35	-
987	AZT, 3TC, Kaletra, Abacavir	1	36	-
963	3TC, Abacavir, Efavirenz, Tenofovir	1	36	-
921	AZT, 3TC, Abacavir, Tenofovir	1	36	-
909	AZT, 3TC, Kaletra, Tenofovir	1	36	-
923	Nevirapine, 3TC, Tenofovir	1	36	46
949	3TC, Kaletra, Tenofovir	1	36	-
919	Kaletra, Efavirenz, Tenofovir	0	36	-
926	3TC, Efavirenz, Tenofovir	1	36	-
1010	AZT, 3TC, Kaletra, Abacavir, Tenofovir	1	37	-
1020	ddI , Kaletra, Tenofovir	1	37	-
976	ddI , Efavirenz, Tenofovir	1	37	-
1011	Abacavir, Efavirenz, Tenofovir	1	37	-
994	Kaletra, Abacavir, Tenofovir	1	37	-
1230	3TC, Ritonavir, Abacavir, Atazanavir	1	39	-
1071	Efavirenz, Tenofovir, Emtricitabine	1	39	-
1227	Ritonavir, Efavirenz, Tenofovir, Emtricitabine, Atazanavir	1	40	-
1245	3TC, Ritonavir, Abacavir, Tenofovir, Atazanavir	1	40	-
1303	ddI , Ritonavir, Tenofovir, Atazanavir	1	40	-
1222	Ritonavir, Tenofovir, Emtricitabine, Atazanavir	1	40	-
1128	Nevirapine, Tenofovir, Emtricitabine	1	40	-
1253	Kaletra, Tenofovir, Emtricitabine	1	41	-
1342	Ritonavir, Tenofovir, Emtricitabine, Lexiva	1	42	-
10006		0	6	16
10026		0	26	46
10027		0	27	45
10028		0	28	45
10030		1	30	43
10031		0	31	-
10035		0	35	49
10037		1	37	-
10038		0	38	-
10040		0	40	-
10041		1	41	-
10042		1	42	-
10043		1	43	-
10046		1	46	-

10048	1	48	-
10049	1	49	-

B Model Appendix

B.1 k-means Clustering Algorithm

Our k-means clustering algorithm approximates the solution of the following objective function:[46]

$$\min_{1\{k\in g\}_{k\in\mathcal{P}_t}|\mathcal{G}_t} \quad \sum_{g=1}^{\mathcal{G}_t}\sum_{k\in\mathcal{P}_t} 1\{k\in g\}\left\|\tilde{\theta}_k-\tilde{\theta}_k^c\right\|^2$$
$$s.t.\sum_{g\in\mathcal{G}_t} 1\{k\in g\}=1 \text{ for all } k\in\mathcal{P}_t \tag{27}$$

where the centroid of cluster k, $\tilde{\theta}_k^c$, is defined as

$$\tilde{\theta}_k^c=\frac{\sum_{k\in\mathcal{P}_t} 1\{k\in g\}\tilde{\theta}_k}{\sum_{k\in\mathcal{P}_t} 1\{k\in g\}} \tag{28}$$

We implement the following version of the k-means algorithm. At every period t:

1. We select the products that have not yet being applied the *exit switching* rule. In other words, we select products that are still available for people to swith into at period t. Denote this set of products available for clustering at t, $\mathcal{A}_t$.

2. In order to avoid issues emerging from differences in scales, we re-scale the characteristics of all products available for clustering at t. In order to do this we compute

$$\tilde{\theta}^r=\frac{\theta^r}{\max_{\delta\in\mathcal{A}_t}|\delta^r|}, \text{ for } r=h,x$$

   Therefore, by construction $\tilde{\theta}^r\in[-1,1]$.

3. We choose the first k centroids using k initial $\tilde{\theta}$'s in $\mathcal{A}_t$ randomly selected.

4. We allocate all remaining points in $\mathcal{A}_t$ sequentially. At each step the point selected is the one that is closest to one of the existing clusters. This point is then allocated to the correspondent cluster and the centroid of the cluster is updated. This process is repeated until all points are allocated to a cluster.

5. We undertake a reallocation step in which, taken the centroids as given, all points are allocated to their closest centroid.

[46] See Duda and Hart (1973) and Andrew W. Moore's *K-means and Hierarchical Clustering* tutorial at http://www.cs.cmu.edu/∼awm/tutorials.html.

6. We calculate the value of (27) for the current allocation.

7. We repeat the process 200 times using different random initial $\tilde{\theta}$'s in $\mathcal{A}_t$. The allocation with the lowest value of (27) is chosen. When simulating clusters in estimation we only repeat the process 50 times to speed up the process.

B.2 Timing

The aggregate state in period t is denoted Ξ_t and consists of current and previous product characteristics $\mathbb{P}_t$, previous market shares $\mathbb{S}_t$, and the distribution of current-period consumer characteristics $\mathcal{F}_t$. Together, these factors determine a summary of the state of technology ω_t, entry (the number of new products and their characteristics), and exit of products that are withdrawn from the market prior to the start of the next period.

The consumer observes his individual state $\mathcal{Z}_{it}$, along with his choice set $\mathcal{C}_t$, upon entering period t. His state consists of individual-level components $z_{it}^{\mathcal{I}}$ (e.g., health) along with aggregate market components $z_{it}^{\mathcal{M}}$ that he uses for forecast. When choosing an alternative, he takes account of how each choice affects current outcomes (e.g., side effects, income) and future states (e.g., health, labor participation). He also forecasts the characteristics of future alternatives, which may affect the relative payoffs to his current choice. The consumer's choice of treatment maximizes his expected discounted lifetime utility. Once a consumer makes a choice, outcome variables are realized and he receives his flow utility. Thereafter, their state variables update and the consumer enters the next period.

C Estimation Appendix

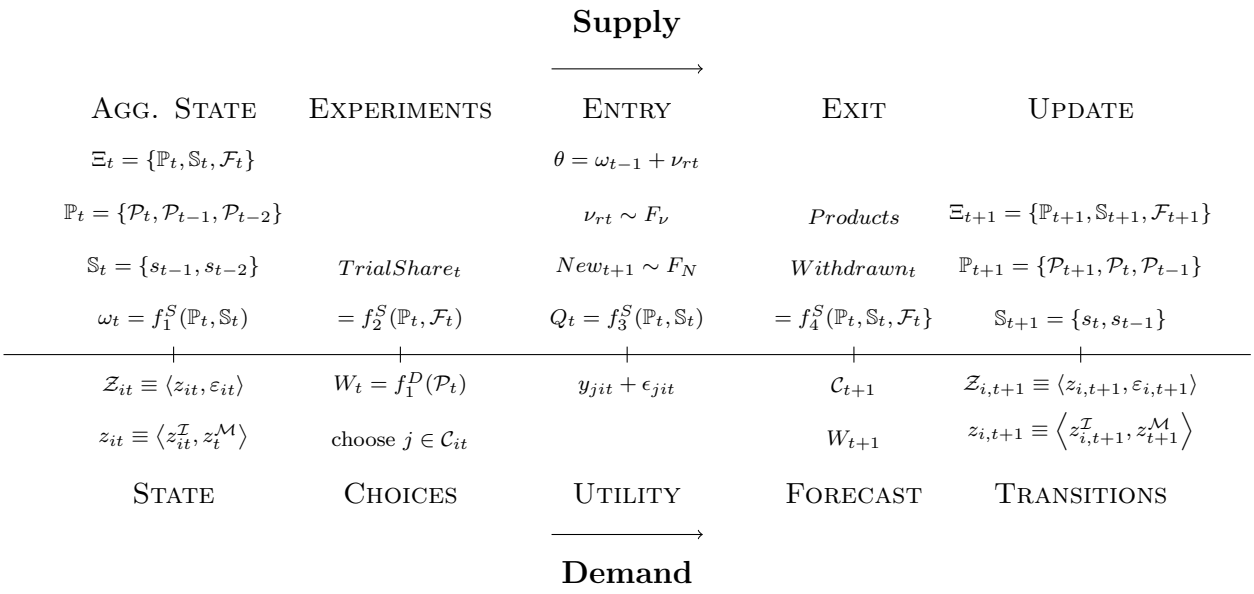
C.1 Product Characteristics

We estimate product characteristics using data on individual treatment usage and subsequent reports of health and ailments. Our estimation equations mimic equations (19) and (20), which individuals use to form expectations over their health and ailments conditional on their choice. The key difference between equations (19) and (20) and our estimation equations is that here our aim is to obtain characteristics of each individual treatment.

Let δ_{rit} be an indicator that treatment r was used by individual i at time t. The characteristics of treatment r are denoted

$$\theta_r = \left\{\theta_r^x, \theta_r^h\right\} \in \mathbb{R}^2 \tag{29}$$

Appendix Figure S1: Timing



The components of θ_r are estimated as the coefficients of δ_{rit} in the health and no-ailments regressions

$$\Pr\left[x_{it} = 1|\cdot\right] = \frac{\exp\left(\sum_{m=0}^{5} \alpha_m^x h_{it-1}^m + \sum_r \theta_r^x \delta_{rit}\right)}{1 + \exp\left(\cdot\right)} \tag{30}$$

$$h_{it} = \sum_{m=0}^{5} \alpha_m^h h_{it-1}^m + \sum_r \theta_r^h \delta_{rit} + \epsilon_{it} \tag{31}$$

C.2 GMM Estimation Algorithm

Using the fact that we observe the underlying stochastic process that generates the stochastic process of cluster characteristics we can write the moment condition in equation (26) can be

written as

$$\mathbb{E}\left\{ w\left(z_{it}\right) \otimes \left[\begin{array}{c} \vdots \\ \ln\left(\frac{p_{oit}(z_{it})}{p_{jit}(z_{it})}\right) + \mathbb{E}_{\mathcal{P}}\left[y_{jit}\right] - \mathbb{E}_{\mathcal{P}}\left[y_{oit}\right] \\ + \sum_{s=1}^{T^*} \beta^s P_j^{o(s-1)}\left(z_{it}\right) \\ \mathbb{E}_{\mathcal{P}}\left[D_{it+s}\left(z_{it+s}\right) \sum\limits_{k \in C_{t+s}} p_{kit}\left(z_{it+s}\right)\left[y_{kit+s}\left(z_{it+s}\right) + \psi_{kit+s}\left(z_{it+s}\right)\right] \middle| \cdot, j, \mathcal{P}_t \right] \\ - \sum_{s=1}^{T^*} \beta^s P_o^{o(s-1)}\left(z_{it}\right) \\ \mathbb{E}_{\mathcal{P}}\left[D_{it+s}\left(z_{it+s}\right) \sum\limits_{k \in C_{t+s}} p_{kit}\left(z_{it+s}\right)\left[y_{kit+s}\left(z_{it+s}\right) + \psi_{kit+s}\left(z_{it+s}\right)\right] \middle| \cdot, o, \mathcal{P}_t \right] \\ \vdots \end{array} \right] \right\} = 0 \tag{32}$$

Equation (32) is crucial for our simulation estimation method explained below. The key fact is that we observe the characteristics of the underlying process of product evolution and we are then able to use it to generate the stochastic evolution of clusters. We undertake simulation in order to obtain the value of

$$\begin{array}{c} \sum_{s=1}^{T^*} \beta^s P_j^{o(s-1)}\left(z_{it}\right) \times \\ \mathbb{E}_z\left[D_{it+s}\left(z_{it+s}\right) \sum\limits_{k \in C_{t+s}} p_{kit+s}\left(z_{it+s}\right)\left[y_{kit+s}\left(z_{it+s}\right) + \psi_{kit+s}\left(z_{it+s}\right)\right] \middle| z_{it}, d_{jit}=1, S_{it}^{(s-1)}=1, d_i^o, \mathcal{P}_t \right] \end{array} \tag{33}$$

for each individual i and choice j at every period t. Let NS denote the number of simulated technology paths for each individual at every period and let the superscript ns indicate that a quantity has being simulated. For individual i and decision j at period t we write the simulated counterpart of equation (33) as

$$\begin{aligned} & \frac{1}{NS} \sum_{ns} \sum_{s=1}^{T^*} \beta^s P_j^{o(s-1),ns}\left(z_{it}\right) D_{it+s}\left(z_{it+s}^{ns,j}\right) \sum_{k \in C_{t+s}^{ns,j}} d_{kit+s}^{ns,j}\left(z_{it+s}^{ns,j}\right)\left[y_{kit+s}\left(z_{it+s}^{ns,j}\right) + \psi_{kit+s}\left(z_{it+s}^{ns,j}\right)\right] \\ = & \frac{1}{NS} \sum_{ns} \sum_{s=1}^{T^*} \beta^s \left(\prod_{\tau=1}^{s} D_{it+\tau}\left(z_{it+\tau}^{ns,j}\right) \right) \sum_{k \in C_{t+s}^{ns,j}} d_{kit+s}^{ns,j}\left(z_{it+s}^{ns,j}\right)\left[y_{kit+s}\left(z_{it+s}^{ns,j}\right) + \psi_{kit+s}\left(z_{it+s}^{ns,j}\right)\right] \end{aligned} \tag{34}$$

For a given vector of parameters of the utility function, the above simulation must be undertaken NS times for each individual i available at period t, and for all t, and for $J-1$ choices as well as for choice o, which means it must be repeated at least $NS \times T \times N \times J$. Further, notice that within each individual simulation we must simulate N optimal paths, one for every person, in order to obtain the aggregate behavior. In other words, even though we simulate only $NS \times T \times N \times J$ technology paths, we simulate $NS \times T \times N \times J \times N$ individual paths. Given our numbers we will be simulating at most $NS \times 33 \times 1669 \times 6 = NS \times 330,462$

technology paths of length T^* and $NS \times 33 \times 1669 \times 6 \times 1669 = NS \times 551,541,078$ individual paths of length T^*. Relying on Hotz et al. (1994) we could set $NS = 1$ and still obtain consistency. We set $NS = 10$ after trying different values of NS for robustness.

The sample moment conditions will then be

$$\frac{1}{\sum_i \sum_t \delta_{it}} \sum_{i=1}^{N} \sum_{t=1}^{T} \delta_{it} w\left(z_{it}\right) \otimes \left[\begin{array}{c} \vdots \\ \ln\left(\frac{p_{oit}(z_{it})}{p_{jit}(z_{it})}\right) + y_{jit} - y_{oit} \\ + \frac{1}{NS} \sum_{ns} \sum_{s=1}^{T^*} \beta^s \left(\prod_{\tau=1}^{s} D_{it+\tau}\left(z_{it+\tau}^{ns,j}\right) \right) \times \\ \sum\limits_{k \in C_{t+s}^{ns,j}} d_{kit+s}^{ns,j}\left(z_{it+s}^{ns,j}\right) \left[y_{kit+s}\left(z_{it+s}^{ns,j}\right) + \psi_{kit+s}\left(z_{it+s}^{ns,j}\right) \right] \\ - \frac{1}{NS} \sum_{ns} \sum_{s=1}^{T^*} \beta^s \left(\prod_{\tau=1}^{s} D_{it+\tau}\left(z_{it+\tau}^{ns,o}\right) \right) \times \\ \sum\limits_{k \in C_{t+s}^{ns,j}} d_{kit+s}^{ns,o}\left(z_{it+s}^{ns,o}\right) \left[y_{kit+s}\left(z_{it+s}^{ns,o}\right) + \psi_{kit+s}\left(z_{it+s}^{ns,o}\right) \right] \\ \vdots \end{array} \right] = 0 \qquad (35)$$

where δ_{it} is an indicator of availability of individual i at period t. Estimation follows the simulation strategy described below. Simulation will be undertaken in order to obtain

$$\sum_{s=1}^{T^*} \beta^s P_j^{o(s-1)}\left(z_{it}\right) \mathbb{E}_z \left[D_{it+s}\left(z_{it+s}\right) \sum_{k \in C_{t+s}} p_{ikt+s}\left(z_{it+s}\right) \left[y_{ikt+s}\left(z_{it+s}\right) + \psi_{ikt+s}\left(z_{it+s}\right) \right] \middle| z_{it}, d_{jit} = 1, S_{it}^{(s-1)} = 1, d_i^o \right] \qquad (36)$$

and

$$\sum_{s=1}^{T^*} \beta^s P_o^{o(s-1)}\left(z_{it}\right) \mathbb{E}_z \left[D_{it+s}\left(z_{it+s}\right) \sum_{k \in C_{t+s}} p_{ikt+s}\left(z_{it+s}\right) \left[y_{ikt+s}\left(z_{it+s}\right) + \psi_{ikt+s}\left(z_{it+s}\right) \right] \middle| z_{it}, d_{iot} = 1, S_{it}^{(s-1)} = 1, d_i^o \right] \qquad (37)$$

for each individual i at every period t. Let the superscript ns indicate that a quantity has been simulated. Also let subscript j denote the decision made at time t to be compared against the base choice o.

For individual i at period t who chose j, the simulation algorithm to obtain (36) entails the following steps for each simulated path ns (again, we set the number of simulated paths for every data point (i,t) at $NS = 1$):

1. **Number of new products**. If $s = 1$, define $Q_{t+s-1}^{ns} \equiv Q_t$. Using Q_{t+s-1}^{ns} we draw number of new products, New_{t+s}^{ns}, using a negative binomial process. First we draw

$$\mu_{t+s}^* \sim Gamma\left(1/\alpha, \alpha\mu_{t+s}\right)$$

where

$$\mu_{t+s} = \beta_0^N + \beta_1^N Q_{t+s-1}$$

Then we draw

$$New_{t+s}^{ns}\big|_{\mu^*} \sim Poisson\left(\mu_{t+s}^*\right)$$

$\left(\alpha, \beta_0^N, \beta_1^N\right)$ are parameters estimated in a first stage.

2. **Characteristics of new products**. If $New_{t+s}^{ns} > 0$, for each simulated new product we obtain simulated product characteristics. Consistent with our model, new products at $t+s$ are characterized by simulated realizations of the bivariate random vector

$$\omega_{t+s-1} + \nu_{t+s-1} \tag{38}$$

where ω_{t+s-1} is the centroid at $t+s-1$, $\nu_{t+s-1} \sim F_\nu$ and F_ν is our innovations distribution which is estimated non parametrically.

As a by-product of steps 1 and 2 we obtain Q_{t+s}^{ns} using equation (6).

3. **Exit**.

   ↪ *Overall exit rule.* If the ratio of people consuming product k (either by staying or switching) relative to the number of people consuming a market product falls bellow $\tilde{\sigma}_2$ during the last 2 consecutive periods (i.e. $t+s-1, t+s-2$), the product is withdrawn from the market and cannot be consumed at any $\tau \geq t+s$. $\tilde{\sigma}_2$ is chosen as the minimum conditional share observed in the data.

   ↪ *Switching exit rule.* If the product satisfies the overall exit rule or if the ratio of people switching and being assigned product k relative to the number of people switching falls bellow $\tilde{\sigma}_1$ during the last 3 consecutive periods (i.e. $t+s-1, t+s-2, t+s-3$), the product is no longer available for switchers and therefore cannot be used to form clusters at any $\tau \geq t+s$. $\tilde{\sigma}_1$ is chosen as the minimum conditional share observed in the data. These products may still be used by "staying" individuals who consumed the product last period.

   Old products minus exits plus simulated new products yields the simulated set of products in period $t+s$, $\mathcal{P}_{t+s}^{ns}$.

4. **Clusters.** From the simulated set of products $\mathcal{P}_{t+s}^{ns}$, we select those products that can be used for clustering and along with the grouping algorithm we obtain simulated clusters $\mathcal{G}_{t+s}^{ns}$. We then compute characteristics for the simulated clusters, W_{t+s}^{ns}.

5. **Centroid.** If $s = 1$ define $\mathcal{P}_{t+s-1}^{ns} \equiv \mathcal{P}_t$. Using the characteristics of products in $\mathcal{P}_{t+s-1}^{ns}$, unconditional choice probabilities ($\mathbb{E}_i\left[p_{jit+s-1}\left(z_{it}\right)\right]$), within-cluster product weights at

$t+s-1$, and $t+s-1$ shares of products conditional on staying, we compute the simulated centroid ω_{t+s}^{ns} using equation (1).

Steps 1 through 5 provide the aggregate part of the simulated state, $z_{t+s}^{\mathcal{P},ns}$. Denote the future choice set induced by the simulated evolution of products as $\mathcal{C}_{t+s}^{ns}$.

6. **Future state for** i. **(i)** If $s=1$, define $h_{jit+s-1}^{ns}$as the observed $h_{jit+s-1}$. If $s>1$, draw $\epsilon_{it+s-1}^{h,ns}$ from the non parametric distribution of ϵ^h; then, using d_{it+s-1}^{ns}, and when necessary, the realization of the within cluster treatment assigned at $t+s-1$, we compute simulated health at the beginning of period $t+s$, $h_{jit+s-1}^{ns}$, using equation (31). If d_{it+s-1}^{ns} involves the trial alternative, trial-product characteristics for computing equation (31) are drawn from the trial distribution at $t+s-1$, $F_{\theta|\omega_{t+s-1}}$; which is equivalent to using equation (38) and the innovations distribution, F_ν. **(ii)** We draw a simulated out-of-pocket payment shock $\epsilon_{it+s}^{o,ns} \sim N\left(0,\sigma_o^2\right)$. **(iii)** We draw a simulated labor state l_{it+s}^{ns} using equation (17). **(iv)** We compute deterministic state variables for i.

7. **Future state for all** $i' \neq i$. **(i)** If $s=1$, define $h_{i't+s-1}^{ns}$as the observed $h_{i't+s-1}$. If $1<s<T^*$, draw $\epsilon_{i't+s-1}^{h,ns}$ from the non parametric distribution of ϵ^h. Then, using $d_{i't+s-1}^{ns}$, and when necessary, the realization of the within cluster treatment assigned at $t+s-1$, we compute simulated health at the beginning of period $t+s$, $h_{i't+s-1}^{ns}$, using equation (31). If $d_{i't+s-1}^{ns}$ involves the trial alternative, trial-product characteristics for computing equation (31) are drawn from the trial distribution at $t+s-1$, $F_{\theta|\omega_{t+s-1}}$. We have deliberately written $h_{i't+s-1}^{ns}$ instead of $h_{i'jt+s-1}^{ns}$ as it is explained below. **(ii)** We draw a simulated labor state $l_{i't+s}^{ns}$ using equation (17). **(iii)** We compute deterministic state variables for i'.

Steps 6 and 7 provide the relevant pieces of the individual-specific part of the simulated state, $z_{jit+s}^{o,ns}$ for i and $z_{i't+s}^{o,ns}$ for all $i' \neq i$.

8. **Probability of Survival up to** $t+s-1$**.** If $s=1$, by definition, $P_j^{o(s-1)}\left(z_{it}\right)=1$ for all i available at t. If $s>1$, using $z_{jit+s-1}^{o,ns}$, and $P_j^{o(s-2),ns}\left(z_{it}\right)$ we obtain $P_j^{o(s-1),ns}\left(z_{it}\right)$ using

$$
\begin{aligned}
P_j^{o(s-1),ns}\left(z_{it}\right) &= \prod_{\tau=1}^{s-1} D_{it+\tau}\left(z_{it+\tau}^{ns}\right) \\
&= D_{it+s-1}\left(z_{jit+s-1}^{ns}\right) P_j^{o(s-2),ns}\left(z_{it}\right) \qquad (39)
\end{aligned}
$$

9. **CCPs and simulated choice for** i. Using $z_{t+s}^{\mathcal{P},ns}$, $z_{jit+s}^{o,ns}$, and equations (42), (44), and (43), we compute simulated $t+s$ ccps, $p_{ikt+s}^{ns}\left(z_{jit+s}^{ns}\right)$, for every alternative $k \in C_{t+s}^{ns}$. Then, using the simulated ccps we draw a decision $d_{it+s}^{ns}\left(z_{jit+s}^{ns}\right)$ for i.

10. **CCPs and simulated choice for all** $i' \neq i$**.** Using $z_{t+s}^{\mathcal{P},ns}$, $z_{i't+s}^{o,ns}$ for all $i' \neq i$, and equations (42), (44), and (43), we compute simulated $t+s$ ccps, $p_{i'kt+s}^{ns}\left(z_{i't+s}^{ns}\right)$, for every alternative $k \in C_{t+s}^{ns}$. Then, using the simulated ccps we draw a decision $d_{i't+s}^{ns}\left(z_{i't+s}^{ns}\right)$ for all $i' \neq i$.

11. **Static payoff for** i**.** **(i)** We compute $\bar{m}_{it+s}^{s} = X_{it+s}^{m,ns}\theta^m + \nu_i^m$ using equation (15). Even though individuals know their idiosyncratic shocks in the income equation, ϵ_{it}^m, we do not need to simulate these as they are iid and have mean zero an enter linearly in the flow utility, which will result in them averaging out to zero in the moment condition. **(ii)** Using the simulated choice $d_{it+s}^{ns}\left(z_{jit+s}^{ns}\right)$ we compute expected simulated out-of-pocket payments using

$$
o_{it+s}\left(d_{it+s}^{ns}\right) = \begin{cases} o_{it+s}^{*,ns} & \text{if } o_{it+s}^{*,ns} > 0 \\ 0 & \text{if } o_{it+s}^{*,ns} \leq 0 \end{cases}
$$

where

$$
o_{it+s}^{*,ns}\left(d_{it+s}^{ns}\right) = X_{it+s}^{o,ns}\left(d_{it+s}^{ns}\right)\theta^o + \epsilon_{it+s}^{o,ns}
$$

and $X_{it+s}^{o,ns}\left(d_{it+s}^{ns}\right)$ are given in equation (16). Hence

$$
\mathbb{E}\left[o_{it+s}\left(d_{it+s}^{ns}\right)\middle|\, d_{it+s}^{ns}\right] = \Phi\left(X_{it+s}^{o,ns}\left(d_{it+s}^{ns}\right)\theta^o/\sigma^o\right) X_{it+s}^{o,ns}\left(d_{it+s}^{ns}\right)\theta^o + \sigma^o\phi\left(X_{it+s}^{o,ns}\left(d_{it+s}^{ns}\right)\theta^o/\sigma^o\right)
$$

(iii) We compute the expected probability of no-ailments as

$$
\mathbb{E}\left[x_{it+s}\middle|\, d_{it+s}^{ns}\right]
$$

using equation (19) and the relevant distribution: cluster, trial, or degenerate. Notice that here we exploit again the fact that we observe the underlying stochastic process. Whenever the choice is a cluster, we use the within cluster weights. **(iv)** Using above

components and i's simulated decision we compute flow payoffs $y^{ns}_{it+s}\left(z^{ns}_{it+s}, d^{ns}_{it+s}\right)$ using equation (13). **(v)** We compute the probability of survival from $t+s-1$ into $t+s$, $D_{it+s}\left(z^{ns}_{it+s}\right)$, using equation (21) and the term $\psi_{it+s}\left(z^{ns}_{it+s}, d^{ns}_{it+s}\right)$ using equation (25).

12. **Repeat all steps above until $s = T^*$.**

In order to obtain all other simulated counterparts of (36) for individual i at period t we do not repeat all the steps above. Instead, we use the same simulated aggregate evolution of the market and repeat only those steps involving individual i's path conditional on choice $j' \neq j$ at t; this is the reason why we deliberately write $h^{ns}_{i't+s-1}$ instead of $h^{ns}_{i'jt+s-1}$ for all $i \neq i'$, as their simulated individual paths do not depend on i's decision at period t. We abstain from generating a path of product innovation following counterfactual choice k by individual i as the impact of his decision at period t on the overall aggregate evolution of the market is negligible.

When simulating the path following counterfactual choice j' we need counterfactual health when $s = 1$, $h^{ns}_{ij't+s-1}$; for this we need to compute the realized residuals of the health equation at t

$$\hat{\epsilon}^h_{it} = h_{it} - \sum_{m=0}^{5} \alpha^h_m h^m_{it-1} - \sum_r \theta^h_r \delta_{it-1r}$$

Then, using the realized residual $\hat{\epsilon}^h_{it}$ and equation (31) we obtain $h^{ns}_{ij't}$. When individual i is in a trial in period t we do not observe the characteristics of the trial ex post; hence, we draw a health shock as well as trial characteristics and compute future simulated health, $h^{ns}_{ij'}$.

Current period payoffs. On the one hand, in order to obtain y_{jit} we need $\mathbb{E}_j\left[x_{jit+s}\right]$. Here, when j corresponds to a cluster alternative, we exploit again the fact that we observe the underlying stochastic process and use the within cluster weights. On the other hand, in order to obtain counterfactual y_{ikt} we need the realized error term of the out-of-pocket payment equation at t given by

$$\hat{\epsilon}^o_{it} = o^*_{jit} - X^o_{jit}\theta^o$$

However, we only observe o^*_{jit} if $o^*_{jit} > 0$. Hence, if $o^*_{jit} \leq 0$, we need to draw a simulated error $\epsilon^{o,ns}_{it}$ from a truncated normal conditional on

$$\epsilon^{o,ns}_{it} \leq -X^o_{jit}\theta^o$$

The sample simulated counterpart of (36) is

$$\frac{1}{NS}\sum_{ns}\sum_{s=1}^{T^*}\beta^s P_j^{o(s-1),ns}\left(z_{it}\right)D_{it+s}\left(z_{it+s}^{ns,j}\right)\sum_{k\in C_{t+s}^{ns,j}}d_{ikt+s}^{ns,j}\left(z_{it+s}^{ns,j}\right)\left[y_{ikt+s}\left(z_{it+s}^{ns,j}\right)+\psi_{ikt+s}\left(z_{it+s}^{ns,j}\right)\right] \quad (40)$$

One potential issue with our simulation algorithm is that in reality individuals die and others become potential consumers. This two phenomena are likely to affect the aggregate joint distribution of individual characteristics and therefore the ccps and the evolution of the market. In order to control for death when computing i's continuation value we could simulate death conditional on optimal behavior for all $i' \neq i$, i.e. some people will leave the sample in the simulated paths. However, we would also need to create people to be introduced into the market. We decide to simulate neither people into the absorbing state nor the stream of people into the sample. Instead, we condition on the aggregate distribution of characteristics at any period t in order to simulate ahead and on optimal future behavior.

Also, a related issue is that our sample is refreshed at least once as new subjects are surveyed. Figures not shown here present no special effect of this refreshing in terms of the aggregate ccps suggesting that the aggregate distribution of characteristics of the new surveyed people matches that of the surveyed individuals at the time.

C.3 Estimator

We use a GMM estimator to obtain our structural parameters. Define B as the $K-$dimensional vector of parameters.Following Hotz et al. (1994) we want to obtain the parameter vector that solves

$$\left((NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\delta_{it}w\left(z_{it}\right)\otimes\bar{v}_{it}(z_{it},B)\right)'W_n\left((NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\delta_{it}w\left(z_{it}\right)\otimes\bar{v}_{it}(z_{it},B)\right) \quad (41)$$

where

$$\bar{v}_{it}(z_{it},B)=\left[\begin{array}{c}\vdots\\ \ln\left(\frac{p_{oit}(z_{it})}{p_{jit}(z_{it})}\right)+y_{jit}-y_{oit}\\ +\frac{1}{NS}\sum_{ns}\sum_{s=1}^{T^*}\beta^s\left(\prod_{\tau=1}^{s}D_{it+\tau}\left(z_{it+\tau}^{ns,j}\right)\right)\times\\ \sum_{k\in C_{t+s}^{ns,j}}d_{kit+s}^{ns,j}\left(z_{it+s}^{ns,j}\right)\left[y_{kit+s}\left(z_{it+s}^{ns,j}\right)+\psi_{kit+s}\left(z_{it+s}^{ns,j}\right)\right]\\ -\frac{1}{NS}\sum_{ns}\sum_{s=1}^{T^*}\beta^s\left(\prod_{\tau=1}^{s}D_{it+\tau}\left(z_{it+\tau}^{ns,o}\right)\right)\times\\ \sum_{k\in C_{t+s}^{ns,j}}d_{kit+s}^{ns,o}\left(z_{it+s}^{ns,o}\right)\left[y_{kit+s}\left(z_{it+s}^{ns,o}\right)+\psi_{kit+s}\left(z_{it+s}^{ns,o}\right)\right]\\ \vdots\end{array}\right]$$

and W_n is a square weighting matrix. Using the linear structure of our utility function we collect and factor terms in order to write the jth component of the vector $\bar{v}_{it}(z_{it},B)$ as the linear form

$$\tilde{y}_{jit}-\tilde{x}_{jit}'B$$

Define Y as the $[(J-1)NT\times 1]$ −dimensional vector that stacks all $\tilde{y}_{jit}$, X the matrix of dimensions $[(J-1)NT\times K]$ that stacks all $\tilde{x}_{jit}$. Define Z as the $[NT\times R]$ −dimensional matrix the columns of which contain the R instruments orthogonal to the difference in alternative representations—which renders W_n as a $(J-1)R-$dimensional square matrix. Finally, let $\mathbf{I}_{[J-1]}$ be a $(J-1)-$dimensional identity matrix

$$Y=\left[\begin{array}{c}\tilde{y}_{1,1,1}\\ \tilde{y}_{1,1,2}\\ \vdots\\ \tilde{y}_{1,N,T-1}\\ \tilde{y}_{1,N,T}\\ \vdots\\ \tilde{y}_{J-1,1,1}\\ \tilde{y}_{J-1,1,2}\\ \vdots\\ \tilde{y}_{J-1,N,T-1}\\ \tilde{y}_{J-1,N,T}\end{array}\right],\quad X=\left[\begin{array}{ccc}\tilde{x}_{1,1,1,1}&\cdots&\tilde{x}_{1,1,1,K}\\ \tilde{x}_{1,1,2,1}&\cdots&\tilde{x}_{1,1,2,K}\\ \vdots&&\vdots\\ \tilde{x}_{1,N,T-1,1}&\cdots&\tilde{x}_{1,N,T-1,K}\\ \tilde{x}_{1,N,T,1}&\cdots&\tilde{x}_{1,N,T,K}\\ \vdots&&\vdots\\ \tilde{x}_{J-1,1,1,1}&\cdots&\tilde{x}_{J-1,1,1,K}\\ \tilde{x}_{J-1,1,2,1}&\cdots&\tilde{x}_{J-1,1,2,K}\\ \vdots&&\vdots\\ \tilde{x}_{J-1,N,T-1,1}&\cdots&\tilde{x}_{J-1,N,T-1,K}\\ \tilde{x}_{J-1,N,T,1}&\cdots&\tilde{x}_{J-1,N,T,K}\end{array}\right],\quad Z=\left[\begin{array}{ccc}w\left(z_{11}\right)_1&\cdots&w\left(z_{11}\right)_R\\ w\left(z_{12}\right)_1&\cdots&w\left(z_{12}\right)_R\\ \vdots&&\vdots\\ w\left(z_{NT}\right)_1&\cdots&w\left(z_{NT}\right)_R\end{array}\right]$$

And define

$$\tilde{Z}=\mathbf{I}_{[J-1]}\otimes Z$$

Then we can write the objective function in (41) as

$$\left((NT)^{-1}\tilde{Z}'\left(Y-XB\right)\right)'W_n\left((NT)^{-1}\tilde{Z}'\left(Y-XB\right)\right)$$

From where we can obtain a close form solution for $\hat{B}$ as the optimal GMM estimator. It entails a first stage estimator given by

$$\hat{B}^{1S} = \left(X'\tilde{Z}\tilde{Z}'X\right)^{-1}\left(X'\tilde{Z}\tilde{Z}'Y\right)$$

and a second stage estimator given by

$$\hat{B}^{2S} = \left(X'\tilde{Z}\hat{S}^{-1}\tilde{Z}'X\right)^{-1}\left(X'\tilde{Z}\hat{S}^{-1}\tilde{Z}'Y\right)$$

where

$$\hat{S} = \frac{1}{N^*}\tilde{Z}'D\tilde{Z}$$

and D is the $N(J-1) \times N(J-1)$ diagonal matrix with elements $\hat{u}_{jit}^2 = \left(y_{jit} - x'_{jit}\hat{B}^{1S}\right)^2$ in its diagonal. The variance-covariance matrix of the second stage estimator is

$$\hat{V}^{2S} = N^*\left(X'\tilde{Z}\hat{S}^{-1}\tilde{Z}'X\right)^{-1}$$

and

$$N^* = \sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{j=1}^{J-1} 1\{\text{Decision } j \text{ available for } i \text{ at } t\}$$

which accounts for the fact that some individuals cannot stay in their lagged treatments at some periods (for instance, if lagged decision was no treatment or trial treatment).

C.4 CCP Estimation and Fit

The probability that an individual chooses one of the alternatives depends on the elements of his state. As such, the CCPs needed to simulate choices in our estimation method are functions of individual-specific variables as well as market-level variables.

Individuals decide between one of $\mathcal{G}$ clusters, yesterday's product (if any), a trial product, and no product. Let W_{jit} be the characteristics describing alternative j for individual i at period t: mean health, mean ailments, and the variance matrix. Let $W_{jit}W_{jit}$ denote a vector of interactions between the elements of W_{jit}. Let $\tilde{x}_{it}$ and $\tilde{z}_{it}$ be subsets of the individual-specific components of the state.[47] Let $\omega_t W_{jit}$ denote a vector of interactions between the centroid and the elements of W_{jit}. Similarly, let $W_{jit}\tilde{z}_{it}$ be a vector of interactions between the components of W_{jit} and individual-specific state components and let $\omega_t W_{jit}\tilde{z}_{it}$ be defined in a similar fashion. Finally, let $\tilde{\mathcal{F}}_t$ denote a set of non parametric moments describing the

[47] $\tilde{z}_{it}$ includes h_{it-1}, a_{it-1}, b_i, l_{it} while $\tilde{x}_{it}$ includes a constant, a_{it-1}, b_i.

joint distribution of aggregate characteristics, $\mathcal{F}_t$.[48]

For each of the alternatives, the CCPs are expressed as follows:

Cluster ccps $(j = 1, \ldots, \mathcal{G})$

$$p_{jit} = \frac{\exp\left(\gamma_0 \tilde{x}_{it} + \beta_0 W_{jit} + \beta_1 W_{jit} W_{jit} + \beta_2 \omega_t W_{jit} + \beta_3 W_{jit} \tilde{z}_{it} + \beta_4 \omega_t W_{jit} \tilde{z}_{it} + \beta_5 W_{jit} \tilde{\mathcal{F}}_t\right)}{1 + \sum_{k=1}^{\mathcal{G}+2} \exp(\cdot)} \tag{42}$$

γ_0 is constant across clusters and over time. For a given cluster j and period t, W_{jit} is in fact constant across individuals so $W_{jit} = W_{jt}$.

Trial ccps $(j = \mathcal{G} + 1)$

$$p_{jit} = \frac{\exp\left(\gamma_j \tilde{x}_{it} + \beta_0 W_{jit} + \beta_1 W_{jit} W_{jit} + \beta_3 W_{jit} \tilde{z}_{it} + \beta_5 W_{jit} \tilde{\mathcal{F}}_t\right)}{1 + \sum_{k=1}^{\mathcal{G}+2} \exp(\cdot)} \tag{43}$$

For the trial alternative, W_{jit} is constant across individuals so $W_{\mathcal{G}+1it} = W_{\mathcal{G}+1t}$. In fact, two of the components of W_{jt} are $\omega_{t-1} + \mu_\nu$, where μ_ν is the mean of the innovations distribution. Therefore, to avoid collinearity we do not include terms $\omega_t W_{jt}$ and $\omega_t W_{jt} \tilde{z}_{it}$ in the trials ccps.

Staying ccps $(j = \mathcal{G} + 2)$

$$p_{jit} = \frac{\exp\left(\gamma_j \tilde{x}_{it} + \beta_0 W_{jit} + \beta_1 W_{jit} W_{jit} + \beta_2 \omega_t W_{jit} + \beta_3 W_{jit} \tilde{z}_{it} + \beta_4 \omega_t W_{jit} \tilde{z}_{it} + \beta_5 W_{jit} \tilde{\mathcal{F}}_t\right)}{1 + \sum_{k=1}^{\mathcal{G}+2} \exp(\cdot)} \tag{44}$$

When individuals choose to stick to their previous product $W_{\mathcal{G}+1it}$ becomes heterogeneous—individuals may have consumed different products last period.

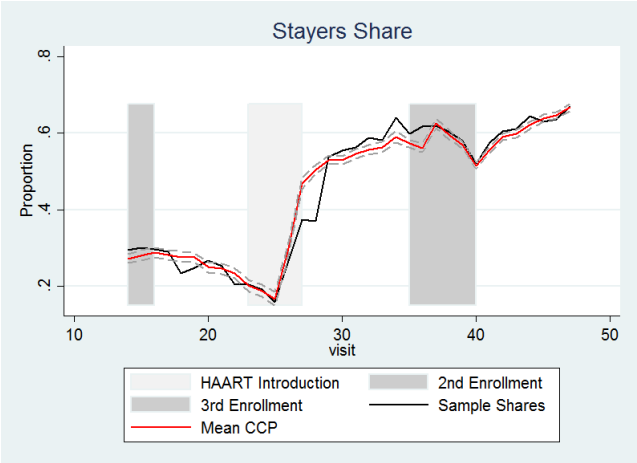
No product ccps $(j = 0)$

$$p_{jit} = 1 - \sum_{k=1}^{\mathcal{G}+2} p_{kit} \tag{45}$$

Even though the characteristics of the choice set are non stationary, by interacting our time-varying regressors $\tilde{z}_{it}$ with the characteristics of the choice for individual i, W_{jit}, we are able to control for the state of the world inside the ccps. As a consequence of this we do not have to run period-specific logits and we can have ccps for any simulated world as long as our observed worlds cover the space of possible worlds reasonably well. We also include parameters that are invariant to the state of the technology, γ, which capture stationary taste differences between staying in current choice, trying a new market product, going to a

[48] We specify these moments as shares of people with different sets of characteristics.

Appendix Figure S2: CCPs Goodness of fit: Stayers

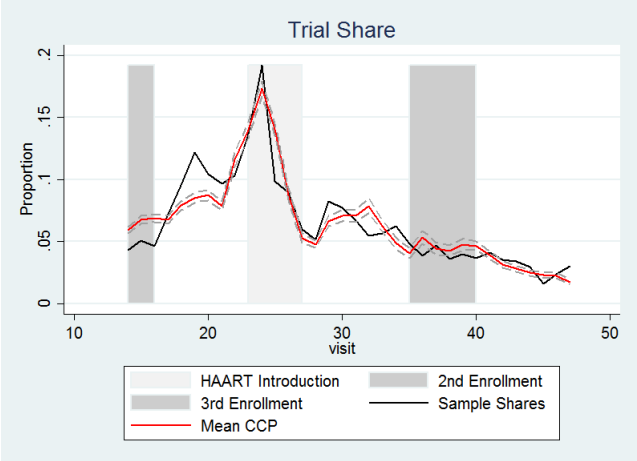


Notes: Figure shows the average estimated conditional choice probability against the share of people choosing the alternative. Dashed lines represent 95 percent confidence intervals around the predicted CCPs. Figure highlights three periods that are of special relevance in the period we study. It depicts periods during which enrollment into the sample was undertaken and more importantly, it displays the period in which products belonging to the HAART family were introduced.

trial, or not consuming anything. Also, since all clusters correspond to the action of "trying a market product" we impose $\gamma_j = \gamma_{j'} = \gamma_0$ for any $j, j' = 1, \ldots, \mathcal{G}$.

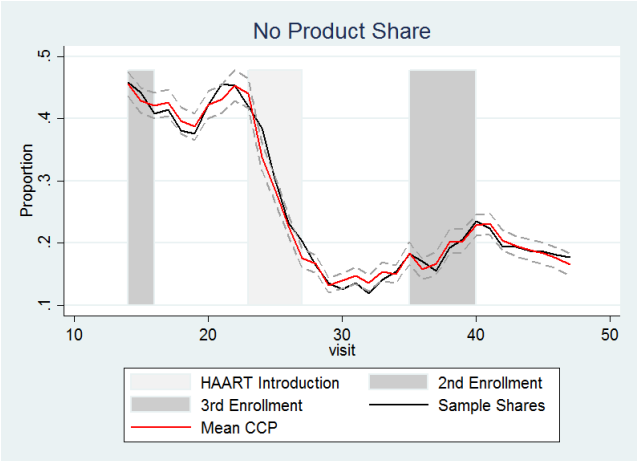
Figures S2, S3, and S4 display the mean predicted conditional choice probability using equations (42), (44), (43) and (45) over time against the correspondent share of the population who chose the alternative. Our ccps map the choices in the data relatively well. In fact, we further explore the fit of our ccp estimates comparing the relatives shares that clusters received in reality against our the predictions from our estimated ccps. We do this by ranking the three clusters at every period by the share they received and comparing this ranking with the ranking obtained from our estimated ccps. A cross tabulation of these rankings—not shown here—suggests that the predicted ranks match the real ranks in more than 79 percent of the periods. In fact, the lowest-ranking cluster matches the predicted lowest-ranking cluster 88 percent of the times.

Appendix Figure S3: CCPs Goodness of fit: Trial



Notes: Figure shows the average estimated conditional choice probability against the share of people choosing the alternative. Dashed lines represent 95 percent confidence intervals around the predicted CCPs. Figure highlights three periods that are of special relevance in the period we study. It depicts periods during which enrollment into the sample was undertaken and more importantly, it displays the period in which products belonging to the HAART family were introduced.

Appendix Figure S4: CCPs Goodness of fit: No Product



Notes: Figure shows the average estimated conditional choice probability against the share of people choosing the alternative. Dashed lines represent 95 percent confidence intervals around the predicted CCPs. Figure highlights three periods that are of special relevance in the period we study. It depicts periods during which enrollment into the sample was undertaken and more importantly, it displays the period in which products belonging to the HAART family were introduced.

D Results Appendix

D.1 Alternative Regimes

In the paper we explore the consequences of alternative regimes on the innovation process. Here we describe them in more detail:

1. *Science regimes*. In these regimes we separate the process of innovation from demand. On the entry margin we transform the centroid to be just a simple average of the characteristics of products currently available in the market—as opposed to the share weighted average in the baseline model. Because this definition changes the realized innovation values in equation (2), we also estimate new parameters for equation (3), and new distributions of innovations and number of new products, which are associated with the realized innovations directly and through Q_t in equation (5). However, since we still need a trial participation path to determine the distribution of the number of new products, we set the trial participation path at the average from the baseline simulated paths. In this way we keep that part of the comparison constant relative to the baseline. On the exit margin we exogenously drop products off the market based on their quality. For this we follow one of two procedures as explained below:

   ↪ *Frontier*. Any product that is not in the technological frontier is dropped from the market.

   ↪ *Thick frontier*. The exit rate path is set at the average from the baseline simulated paths. The exit rate then determines the number of products to be dropped. Finally, the products that are dropped from the market are chosen from inside the *thick frontier*. For a given number of products to be dropped n_t, this frontier is formed with the following algorithm. Let $\mathcal{P}_t$ define the set of products θ available at t, and define the set $I_1 = \mathcal{P}_t$. Then starting from iteration $k = 1$ follow the steps:

   (a) Build the kth frontier as:

   $$F_k = \{\theta \in I_k : \nexists \theta' \in I_k \text{ s.t. } \theta' \geq \theta\}$$

   (b) Define the new inside set as:

   $$I_{k+1} = I_k \setminus F_k$$

   (c) If $\#I_{k+1} > n_t$, set $k = k + 1$ and go back to Step (a).

(d) If $\#I_{k+1} \leq n_t$, drop all products in I_{k+1} and randomly drop $(n_t - \#I_{k+1})$ from F_k. Stop.

2. *Random choice.* In this regime we study the evolution of product quality when the process of innovation responds to demand but demand is random. Random demand neutralizes the dependence of the technological path on the preferences and characteristics of consumers without changing the nature of the process on the supply side. In practical terms, we maintain the definition for the centroid as a share-weighted average. As a consequence, the distributions of innovations and number of new products remain unchanged. Moreover, we aim to avoid a spurious effect of arbitrary aggregate shares on the process of innovation. Therefore, instead of allocating an arbitrary distribution for choices (f.i. $1/G$ for a choice set of size G), we fix the distribution for random choices to match the unconditional shares in the baseline.

D.2 One-Time Planners

(Describe here how the planner problems are solved using continuation values.)

E Proofs

E.1 Proof of Proposition 1

$$
\begin{aligned}
v_{jit}(z_{it}) &= \mathbb{E}_y[y_{jit}|z_{it}] + \beta\mathbb{E}\left[V\left(z_{it+1},\varepsilon_{it+1}\right)|z_{it},j\right] \\
&= \mathbb{E}_y[y_{jit}|z_{it}] + \beta\mathbb{E}\left[\left.S_{it+1}\left(z_{it+1}\right)\mathbb{E}_\varepsilon\left[\sum_{k\in C_{t+1}} d^o_{ikt+1}\left(z_{it+1}\right)\left[y_{ikt+1}\left(z_{it+1}\right)+\varepsilon_{ikt+1}\right]\right]\right| z_{it},j\right] \\
&\quad +\beta^2\mathbb{E}\left[S_{it+1}\left(z_{it+1}\right)V\left(z_{it+2},\varepsilon_{it+2}\right)|z_{it},j,d^o_i\right] \\
&= \mathbb{E}_y[y_{jit}|z_{it}] + \beta\mathbb{E}\left[\left.S_{it+1}\left(z_{it+1}\right)\mathbb{E}_\varepsilon\left[\sum_{k\in C_{t+1}} \mathbb{E}_\varepsilon\left[d^o_{ikt+1}\left(z_{it+1}\right)\left[y_{ikt+1}\left(z_{it+1}\right)+\varepsilon_{ikt+1}\right]\middle| d^o_{ikt+1}\left(z_{it+s}\right)=1\right]\right]\right| z_{it},j\right] \\
&\quad +\beta^2\mathbb{E}\left[S_{it+1}\left(z_{it+1}\right)V\left(z_{it+2},\varepsilon_{it+2}\right)|z_{it},j,d^o_i\right] \\
&= \mathbb{E}_y[y_{jit}|z_{it}] + \beta\mathbb{E}\left[\left.S_{it+1}\left(z_{it+1}\right)\mathbb{E}_\varepsilon\left[\sum_{k\in C_{t+1}} d^o_{ikt+1}\left(z_{it+s}\right)\left[y_{ikt+1}\left(z_{it+1}\right)+\mathbb{E}_\varepsilon\left[\varepsilon_{ikt+1}\middle| d^o_{ikt+1}\left(z_{it+1}\right)=1\right]\right]\right]\right| z_{it},j\right] \\
&\quad +\beta^2\mathbb{E}\left[S_{it+1}\left(z_{it+1}\right)V\left(z_{it+2},\varepsilon_{it+2}\right)|z_{it},j,d^o_i\right] \\
&= \mathbb{E}_y[y_{jit}|z_{it}] + \beta\mathbb{E}\left[\left.S_{it+1}\left(z_{it+1}\right)\mathbb{E}_\varepsilon\left[\sum_{k\in C_{t+1}} d^o_{ikt+1}\left(z_{it+1}\right)\left[y_{ikt+1}\left(z_{it+1}\right)+\psi_{ikt+1}\left(z_{it+1}\right)\right]\right]\right| z_{it},j\right] \\
&\quad +\beta^2\mathbb{E}\left[S_{it+1}\left(z_{it+1}\right)V\left(z_{it+2},\varepsilon_{it+2}\right)|z_{it},j,d^o_i\right] \\
&= \mathbb{E}_y[y_{jit}|z_{it}] + \beta\mathbb{E}\left[\left.S_{it+1}\left(z_{it+1}\right)\sum_{k\in C_{t+1}} p_{ikt+1}\left(z_{it+1}\right)\left[y_{ikt+1}\left(z_{it+1}\right)+\psi_{ikt+1}\left(z_{it+1}\right)\right]\right| z_{it},j\right] \\
&\quad +\beta^2\mathbb{E}\left[S_{it+1}\left(z_{it+1}\right)V\left(z_{it+2},\varepsilon_{it+2}\right)|z_{it},j,d^o_i\right] \\
&= \mathbb{E}_y[y_{jit}|z_{it}] + \beta\mathbb{E}\left[\left.S_{it+1}\left(z_{it+1}\right)\sum_{k\in C_{t+1}} p_{ikt+1}\left(z_{it+1}\right)\left[y_{ikt+1}\left(z_{it+1}\right)+\psi_{ikt+1}\left(z_{it+1}\right)\right]\right| z_{it},j\right] \\
&\quad +\beta^2\mathbb{E}\left[\left.S_{it+1}\left(z_{it+1}\right)S_{it+2}\left(z_{it+2}\right)\sum_{k\in C_{t+1}} p_{ikt+2}\left(z_{it+2}\right)\left[y_{ikt+2}\left(z_{it+2}\right)+\psi_{ikt+2}\left(z_{it+2}\right)\right]\right| z_{it},j,d^o_i\right] \\
&\quad +\beta^3\mathbb{E}\left[S_{it+1}\left(z_{it+1}\right)S_{it+2}\left(z_{it+2}\right)V\left(z_{it+3},\varepsilon_{it+3}\right)|z_{it},j,d^o_i\right] \\
&= \mathbb{E}_y[y_{jit}|z_{it}] + \sum_{s=1}^{T^*}\beta^s\mathbb{E}\left[\left.\left(\prod_{r=1}^{s} S_{it+r}\left(z_{it+r}\right)\right)\sum_{k\in C_{t+1}} p_{ikt+s}\left(z_{it+s}\right)\left[y_{ikt+s}\left(z_{it+s}\right)+\psi_{ikt+s}\left(z_{it+s}\right)\right]\right| z_{it},j,d^o_i\right] \\
&\quad +\beta^{T^*+1}\mathbb{E}\left[\left.\left(\prod_{r=1}^{T^*} S_{it+r}\left(z_{it+r}\right)\right)V\left(z_{it+T^*+1},\varepsilon_{it+T^*+1}\right)\right| z_{it},j,d^o_i\right] \\
&= \mathbb{E}_y[y_{jit}|z_{it}] + \sum_{s=1}^{T^*}\beta^s\mathbb{E}\left[\left.\left(\prod_{r=1}^{s} D_{it+r}\left(z_{it+r}\right)\right)\sum_{k\in C_{t+1}} p_{ikt+s}\left(z_{it+s}\right)\left[y_{ikt+s}\left(z_{it+s}\right)+\psi_{ikt+s}\left(z_{it+s}\right)\right]\right| z_{it},j,d^o_i\right] \\
&\quad +\beta^{T^*+1}\mathbb{E}\left[\left.\left(\prod_{r=1}^{T^*} D_{it+r}\left(z_{it+r}\right)\right)V\left(z_{it+T^*+1},\varepsilon_{it+T^*+1}\right)\right| z_{it},j,d^o_i\right]
\end{aligned}
$$

That

$$\psi_{kit}\left(z_{it}\right) = \gamma - \ln\left(p_{kit}\left(z_{it}\right)\right) \tag{46}$$

follows from the joint distribution of the taste shifter ε_{it}, which is Extreme Value Type-I. *Q.E.D.*

F Additional Tables and Figures

Appendix Table S5: Health Characteristics of Treatments

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	cd4	cd4	cd4	cd4	cd4	cd4
$CD4_{t-1}$	0.834***	1.064***	1.009***	1.021***	1.152***	1.136***
	(0.006)	(0.013)	(0.014)	(0.026)	(0.032)	(0.051)
$CD4^2_{t-1}/10^3$		-0.174***	-0.097***	-0.121**	-0.519***	-0.456**
		(0.012)	(0.018)	(0.059)	(0.098)	(0.212)
$CD4^3_{t-1}/10^7$			-0.274***	-0.112	4.375***	3.363
			(0.060)	(0.430)	(1.123)	(3.518)
$CD4^4_{t-1}/10^{10}$				-0.031	-2.016***	-1.288
				(0.080)	(0.502)	(2.598)
$CD4^5_{t-1}/10^{14}$					2.803***	0.482
					(0.718)	(8.325)
$CD4^6_{t-1}/10^{18}$						2.623
						(9.398)
DT3	-21.583***	-11.174***	-11.950***	-11.909***	-12.004***	-11.983***
	(2.840)	(2.707)	(2.700)	(2.699)	(2.697)	(2.697)
DT9	-20.319*	-19.561*	-19.089	-19.165	-19.655*	-19.623*
	(11.743)	(11.879)	(11.865)	(11.865)	(11.861)	(11.860)
DT13	-72.170***	-53.988***	-55.512***	-55.437***	-55.796***	-55.726***
	(11.798)	(12.504)	(12.348)	(12.364)	(12.455)	(12.455)
DT14	-15.506**	-4.315	-5.164	-5.115	-5.155	-5.140
	(6.241)	(6.105)	(6.100)	(6.098)	(6.094)	(6.094)
DT33	-21.629**	0.985	-2.034	-1.689	-0.017	-0.112
	(9.038)	(9.161)	(9.112)	(9.123)	(9.108)	(9.113)
DT34	-21.810***	-12.450***	-13.310***	-13.219***	-12.752***	-12.779***
	(4.900)	(4.755)	(4.761)	(4.764)	(4.764)	(4.765)
DT39	-31.246***	-15.492***	-17.057***	-16.924***	-16.615***	-16.607***
	(5.805)	(5.715)	(5.691)	(5.691)	(5.687)	(5.688)
DT46	7.741*	15.348***	14.581***	14.678***	15.263***	15.229***
	(4.679)	(4.566)	(4.577)	(4.581)	(4.574)	(4.573)
DT47	-34.371***	-15.583**	-17.510**	-17.327**	-16.474**	-16.521**
	(7.318)	(7.033)	(7.027)	(7.028)	(7.040)	(7.037)
DT51	-22.630***	-3.664	-6.022	-5.740	-4.159	-4.252
	(7.962)	(7.693)	(7.690)	(7.693)	(7.669)	(7.670)
DT63	-16.743	2.384	-0.183	0.162	2.415	2.275
	(14.637)	(13.594)	(13.649)	(13.659)	(13.746)	(13.735)
DT64	-37.988***	-17.449*	-19.583**	-19.387**	-18.630**	-18.656**
	(8.900)	(9.076)	(8.991)	(8.996)	(9.035)	(9.032)
DT65	-27.913***	-12.409*	-13.823**	-13.704*	-13.186*	-13.220*
	(7.203)	(7.007)	(7.006)	(7.006)	(6.993)	(6.994)
DT67	-50.755***	-31.179**	-33.087**	-32.938**	-32.700**	-32.673**
	(15.300)	(14.998)	(14.986)	(14.990)	(15.052)	(15.044)
DT69	-26.741*	-11.827	-13.331	-13.215	-13.351	-13.275
	(14.379)	(13.908)	(13.950)	(13.945)	(13.973)	(13.973)
DT85	34.619***	40.457***	39.721***	39.790***	39.776***	39.792***
	(6.424)	(6.319)	(6.311)	(6.308)	(6.299)	(6.299)
DT117	33.323***	42.736***	41.910***	41.991***	42.267***	42.277***
	(12.098)	(11.819)	(11.837)	(11.834)	(11.819)	(11.818)
DT124	33.711***	33.910***	33.804***	33.864***	34.398***	34.364***

	(6.284)	(6.229)	(6.234)	(6.235)	(6.227)	(6.228)
DT146	27.752*	34.323**	33.694**	33.761**	33.792**	33.831**
	(14.796)	(14.611)	(14.644)	(14.639)	(14.625)	(14.625)
DT157	34.353***	37.455***	37.258***	37.282***	37.173***	37.208***
	(6.945)	(6.861)	(6.862)	(6.862)	(6.856)	(6.857)
DT161	33.496**	38.559***	38.364***	38.340***	38.283***	38.259***
	(13.411)	(13.215)	(13.201)	(13.205)	(13.193)	(13.198)
DT164	55.089**	64.825**	64.314**	64.302**	63.734**	63.798**
	(27.560)	(27.365)	(27.365)	(27.370)	(27.414)	(27.419)
DT165	60.168***	64.722***	65.220***	65.337***	65.041***	65.045***
	(7.077)	(6.246)	(6.215)	(6.225)	(6.220)	(6.222)
DT169	33.129**	34.545**	34.182**	34.289**	35.032**	35.012**
	(16.388)	(16.316)	(16.316)	(16.317)	(16.339)	(16.334)
DT171	73.104***	78.825***	78.453***	78.478***	78.559***	78.548***
	(17.682)	(18.040)	(18.017)	(18.010)	(17.950)	(17.943)
DT175	44.728***	52.470***	52.730***	52.619***	53.128***	53.153***
	(8.770)	(8.233)	(8.202)	(8.198)	(8.176)	(8.172)
DT185	50.899***	58.842***	57.833***	57.922***	57.776***	57.825***
	(12.661)	(12.659)	(12.642)	(12.638)	(12.608)	(12.608)
DT202	32.648**	32.522**	33.226**	33.107**	32.286**	32.338**
	(14.544)	(14.584)	(14.576)	(14.576)	(14.573)	(14.574)
DT214	33.330***	33.541***	34.154***	34.057***	33.510***	33.535***
	(12.245)	(12.162)	(12.166)	(12.164)	(12.163)	(12.161)
DT236	48.886***	46.186***	46.239***	46.267***	46.275***	46.281***
	(7.172)	(7.130)	(7.121)	(7.123)	(7.123)	(7.124)
DT242	47.980***	46.484***	46.110***	46.240***	46.846***	46.863***
	(9.266)	(9.144)	(9.154)	(9.160)	(9.161)	(9.162)
DT254	42.775***	42.587***	42.568***	42.601***	42.631***	42.656***
	(13.502)	(13.436)	(13.444)	(13.443)	(13.446)	(13.445)
DT268	47.316***	52.474***	51.249***	51.353***	50.776***	50.855***
	(10.457)	(10.436)	(10.415)	(10.407)	(10.417)	(10.415)
DT292	42.030***	48.796***	48.057***	48.109***	48.018***	48.069***
	(10.638)	(10.242)	(10.225)	(10.230)	(10.212)	(10.215)
DT311	39.770*	50.740**	49.168**	49.215**	47.816**	47.922**
	(23.206)	(22.720)	(22.698)	(22.709)	(22.774)	(22.780)
DT349	50.575***	42.467**	43.413**	43.408**	44.240***	44.156***
	(16.958)	(17.083)	(17.108)	(17.098)	(17.046)	(17.046)
DT377	56.809***	57.778***	57.727***	57.716***	57.227***	57.259***
	(19.614)	(19.566)	(19.530)	(19.538)	(19.552)	(19.555)
DT532	49.321***	47.631***	47.537***	47.614***	47.978***	47.990***
	(10.952)	(10.886)	(10.899)	(10.899)	(10.893)	(10.892)
DT548	45.842***	43.345***	43.281***	43.348***	43.526***	43.551***
	(5.368)	(5.331)	(5.329)	(5.330)	(5.327)	(5.329)
DT573	40.314***	39.595***	39.432***	39.485***	39.379***	39.426***
	(10.981)	(10.960)	(10.901)	(10.909)	(10.919)	(10.922)
DT581	19.612	18.387	18.413	18.417	17.866	17.935
	(14.499)	(14.316)	(14.341)	(14.341)	(14.376)	(14.378)
DT615	44.239***	40.856***	41.087***	41.122***	41.280***	41.301***
	(11.769)	(11.592)	(11.603)	(11.604)	(11.622)	(11.622)
DT644	54.543***	53.883***	53.615***	53.650***	53.341***	53.368***
	(8.639)	(8.512)	(8.504)	(8.505)	(8.516)	(8.515)
DT701	52.853***	55.916***	54.878***	54.997***	54.824***	54.870***
	(11.144)	(10.997)	(10.979)	(10.975)	(10.999)	(11.003)
DT720	60.713***	79.231***	78.995***	78.688***	78.914***	78.726***
	(13.046)	(14.550)	(14.500)	(14.464)	(14.412)	(14.405)

DT782	28.143*	35.924**	35.177**	35.267**	35.611**	35.633**
	(15.627)	(14.945)	(14.959)	(14.967)	(15.077)	(15.068)
DT869	50.005***	50.037***	49.904***	49.946***	49.838***	49.885***
	(13.110)	(12.947)	(12.940)	(12.946)	(12.997)	(12.999)
DT909	27.964**	33.525***	33.367***	33.310***	32.227***	32.320***
	(10.898)	(10.827)	(10.764)	(10.781)	(10.842)	(10.846)
DT919	47.628***	48.846***	48.522***	48.536***	47.617***	47.722***
	(13.308)	(13.619)	(13.486)	(13.499)	(13.453)	(13.466)
DT921	15.458	18.929	19.116	19.058	19.273	19.286
	(16.086)	(14.468)	(14.426)	(14.448)	(14.327)	(14.341)
DT923	30.619*	26.759	26.896	26.960	27.246	27.283
	(17.077)	(16.964)	(16.951)	(16.954)	(16.971)	(16.973)
DT926	47.776***	47.965***	47.952***	47.971***	47.790***	47.835***
	(10.277)	(9.953)	(9.995)	(9.993)	(10.024)	(10.021)
DT940	54.575***	50.873***	50.705***	50.821***	51.570***	51.537***
	(15.098)	(15.196)	(15.198)	(15.195)	(15.164)	(15.163)
DT949	53.752***	50.921***	51.203***	51.236***	51.672***	51.661***
	(11.818)	(11.668)	(11.706)	(11.701)	(11.705)	(11.701)
DT963	37.095***	30.953**	31.641**	31.628**	31.845**	31.829**
	(12.997)	(13.013)	(13.021)	(13.019)	(13.014)	(13.015)
DT976	-7.655	2.510	2.487	2.349	2.381	2.436
	(20.271)	(17.213)	(16.922)	(16.980)	(16.471)	(16.507)
DT987	4.115	10.199	9.583	9.654	9.855	9.870
	(14.474)	(14.526)	(14.496)	(14.498)	(14.503)	(14.500)
DT994	10.625	15.088	15.225	15.171	14.891	14.893
	(17.109)	(17.416)	(17.404)	(17.396)	(17.282)	(17.291)
DT1010	12.409	20.292**	19.891**	19.906**	19.980**	19.966**
	(9.769)	(9.701)	(9.687)	(9.686)	(9.676)	(9.676)
DT1011	43.817*	39.067*	38.498*	38.691*	39.457*	39.484*
	(22.599)	(22.024)	(22.150)	(22.142)	(22.163)	(22.157)
DT1020	20.973	17.603	18.253	18.220	18.396	18.375
	(13.204)	(13.121)	(13.141)	(13.135)	(13.111)	(13.111)
DT1071	58.721***	53.880***	54.012***	54.094***	54.798***	54.796***
	(4.578)	(4.475)	(4.469)	(4.478)	(4.453)	(4.453)
DT1128	40.782***	37.265***	37.397***	37.415***	37.227***	37.246***
	(9.919)	(9.662)	(9.682)	(9.683)	(9.722)	(9.720)
DT1222	53.239***	52.943***	52.719***	52.793***	53.028***	53.050***
	(5.409)	(5.301)	(5.306)	(5.307)	(5.309)	(5.310)
DT1227	83.132***	85.565***	84.437***	84.556***	83.823***	83.917***
	(20.468)	(21.138)	(21.037)	(21.031)	(20.842)	(20.859)
DT1230	25.312**	27.037**	27.504**	27.416**	26.850**	26.886**
	(12.040)	(12.112)	(12.093)	(12.093)	(12.079)	(12.081)
DT1245	37.822***	38.379***	38.357***	38.374***	38.313***	38.336***
	(13.418)	(13.334)	(13.326)	(13.328)	(13.347)	(13.347)
DT1253	46.066***	46.654***	46.213***	46.319***	46.723***	46.735***
	(7.946)	(7.735)	(7.745)	(7.747)	(7.767)	(7.765)
DT1303	51.942***	46.893***	47.631***	47.602***	47.800***	47.786***
	(16.434)	(16.225)	(16.276)	(16.269)	(16.284)	(16.279)
DT1342	32.840**	29.637**	30.481**	30.395**	30.226**	30.204**
	(14.069)	(14.124)	(14.137)	(14.132)	(14.115)	(14.116)
DT10006	-29.515	-21.709	-22.258	-22.209	-21.950	-21.961
	(19.930)	(20.278)	(20.256)	(20.251)	(20.191)	(20.194)
DT10026	64.425***	66.829***	65.194***	65.444***	65.353***	65.496***
	(24.136)	(22.649)	(22.765)	(22.778)	(23.021)	(23.023)
DT10027	0.210	7.741	7.165	7.179	6.457	6.562

	(14.742)	(14.802)	(14.701)	(14.715)	(14.739)	(14.748)
DT10028	26.450	32.481	31.616	31.629	30.293	30.414
	(19.796)	(20.521)	(20.367)	(20.371)	(20.276)	(20.282)
DT10030	20.031	19.261	19.703	19.654	19.278	19.315
	(17.621)	(17.572)	(17.592)	(17.586)	(17.546)	(17.548)
DT10031	34.205**	29.830**	30.781**	30.712**	31.044**	30.969**
	(15.053)	(14.878)	(14.911)	(14.901)	(14.838)	(14.843)
DT10035	44.294***	43.738***	43.648***	43.682***	43.495***	43.550***
	(15.320)	(15.368)	(15.337)	(15.340)	(15.357)	(15.356)
DT10037	28.525***	28.144***	28.115***	28.134***	27.893**	27.931**
	(11.035)	(10.856)	(10.855)	(10.857)	(10.893)	(10.892)
DT10038	48.755***	44.792***	44.735***	44.855***	45.683***	45.679***
	(13.769)	(13.693)	(13.692)	(13.695)	(13.673)	(13.674)
DT10040	26.314***	28.505***	28.742***	28.692***	28.440***	28.431***
	(8.531)	(8.329)	(8.333)	(8.335)	(8.334)	(8.337)
DT10041	43.028***	41.990***	42.154***	42.158***	42.050***	42.074***
	(12.657)	(12.467)	(12.470)	(12.470)	(12.474)	(12.473)
DT10042	30.254**	32.127**	31.743**	31.779**	31.824**	31.811**
	(12.900)	(13.008)	(13.007)	(12.996)	(12.924)	(12.922)
DT10043	28.589**	26.499**	26.919**	26.894**	26.678**	26.715**
	(12.874)	(12.711)	(12.704)	(12.707)	(12.739)	(12.739)
DT10046	36.196***	32.318**	32.455**	32.517**	32.865**	32.884**
	(13.618)	(13.720)	(13.651)	(13.662)	(13.672)	(13.678)
DT10048	33.017**	33.618**	33.783**	33.756**	33.352**	33.394**
	(15.278)	(14.856)	(14.884)	(14.888)	(14.943)	(14.943)
DT10049	49.474***	47.695***	48.034***	48.005***	47.736***	47.760***
	(11.002)	(10.687)	(10.698)	(10.703)	(10.757)	(10.753)
DT10050	38.954**	38.166**	38.394**	38.415**	38.933**	38.887**
	(17.897)	(18.043)	(18.036)	(18.037)	(18.096)	(18.090)
Constant	56.819***	-2.797	6.623**	5.233	-5.874*	-4.898
	(3.161)	(3.411)	(3.018)	(3.432)	(3.313)	(3.681)
Observations	33,258	33,258	33,258	33,258	33,258	33,258
R-squared	0.728	0.736	0.736	0.736	0.736	0.736

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table S6: No Ailments Characteristics of Treatments

VARIABLES	(1) NoSfx	(2) NoSfx	(3) NoSfx	(4) NoSfx	(5) NoSfx	(6) NoSfx
$CD4_{t-1}$	0.001***	0.003***	0.005***	0.006***	0.008***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
$CD4^2_{t-1}/10^3$		-0.001***	-0.005***	-0.007***	-0.013***	-0.017***
		(0.000)	(0.001)	(0.001)	(0.002)	(0.003)
$CD4^3_{t-1}/10^7$			0.013***	0.033***	0.109***	0.166***
			(0.003)	(0.004)	(0.019)	(0.040)
$CD4^4_{t-1}/10^{10}$				-0.005***	-0.040***	-0.084***
				(0.001)	(0.010)	(0.028)
$CD4^5_{t-1}/10^{14}$					0.054***	0.203**
					(0.016)	(0.092)
$CD4^6_{t-1}/10^{18}$						-0.186*
						(0.106)
DT3	-0.576***	-0.515***	-0.500***	-0.498***	-0.500***	-0.501***
	(0.040)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
DT9	-0.402*	-0.404*	-0.421**	-0.427**	-0.433**	-0.434**
	(0.208)	(0.212)	(0.213)	(0.213)	(0.212)	(0.212)
DT13	-0.738***	-0.627**	-0.594**	-0.593**	-0.600**	-0.603**
	(0.260)	(0.259)	(0.260)	(0.260)	(0.260)	(0.260)
DT14	-0.523***	-0.457***	-0.439***	-0.437***	-0.439***	-0.439***
	(0.099)	(0.100)	(0.100)	(0.101)	(0.101)	(0.101)
DT33	-1.039***	-0.900***	-0.819***	-0.799***	-0.783***	-0.781***
	(0.127)	(0.128)	(0.130)	(0.130)	(0.131)	(0.132)
DT34	-0.622***	-0.569***	-0.549***	-0.544***	-0.539***	-0.538***
	(0.079)	(0.079)	(0.080)	(0.080)	(0.080)	(0.081)
DT39	-0.713***	-0.618***	-0.580***	-0.573***	-0.571***	-0.571***
	(0.105)	(0.106)	(0.107)	(0.108)	(0.108)	(0.108)
DT46	-0.457***	-0.411***	-0.390***	-0.383***	-0.375***	-0.374***
	(0.069)	(0.070)	(0.070)	(0.071)	(0.071)	(0.071)
DT47	-1.016***	-0.907***	-0.866***	-0.858***	-0.851***	-0.850***
	(0.157)	(0.159)	(0.162)	(0.162)	(0.163)	(0.163)
DT51	-0.577***	-0.456***	-0.388**	-0.369**	-0.348**	-0.344**
	(0.161)	(0.164)	(0.166)	(0.167)	(0.168)	(0.168)
DT63	-0.567**	-0.445	-0.367	-0.341	-0.310	-0.304
	(0.269)	(0.274)	(0.280)	(0.282)	(0.284)	(0.285)
DT64	-0.566***	-0.436**	-0.379*	-0.367*	-0.358	-0.357
	(0.210)	(0.213)	(0.218)	(0.220)	(0.222)	(0.222)
DT65	-0.650***	-0.557***	-0.525***	-0.519***	-0.514***	-0.512***
	(0.133)	(0.133)	(0.135)	(0.135)	(0.136)	(0.137)
DT67	-1.582***	-1.473***	-1.439***	-1.436***	-1.440***	-1.442***
	(0.306)	(0.303)	(0.305)	(0.306)	(0.307)	(0.307)
DT69	-0.916***	-0.827***	-0.790***	-0.785***	-0.789***	-0.793***
	(0.261)	(0.261)	(0.262)	(0.263)	(0.263)	(0.264)
DT85	-0.772***	-0.737***	-0.718***	-0.715***	-0.717***	-0.718***
	(0.091)	(0.091)	(0.091)	(0.092)	(0.092)	(0.092)
DT117	-0.609***	-0.555***	-0.535**	-0.530**	-0.527**	-0.528**
	(0.205)	(0.208)	(0.210)	(0.211)	(0.212)	(0.212)
DT124	0.036	0.040	0.050	0.055	0.064	0.065
	(0.093)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)
DT146	-0.568**	-0.530**	-0.513**	-0.509**	-0.509**	-0.511**
	(0.223)	(0.226)	(0.227)	(0.227)	(0.227)	(0.227)

DT157	-0.132	-0.111	-0.103	-0.102	-0.104	-0.105
	(0.112)	(0.113)	(0.114)	(0.114)	(0.114)	(0.114)
DT161	-0.302*	-0.270	-0.270	-0.272	-0.271	-0.270
	(0.180)	(0.182)	(0.182)	(0.182)	(0.182)	(0.182)
DT164	-0.532***	-0.475**	-0.468**	-0.471**	-0.479**	-0.482**
	(0.184)	(0.185)	(0.186)	(0.187)	(0.187)	(0.187)
DT165	-0.106	-0.084	-0.078	-0.073	-0.075	-0.076
	(0.080)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)
DT169	-0.604**	-0.600**	-0.585**	-0.577**	-0.567**	-0.566**
	(0.244)	(0.246)	(0.248)	(0.249)	(0.250)	(0.250)
DT171	-0.342*	-0.308	-0.299	-0.297	-0.295	-0.295
	(0.190)	(0.195)	(0.197)	(0.198)	(0.199)	(0.199)
DT175	-0.424***	-0.377***	-0.399***	-0.402***	-0.395***	-0.397***
	(0.099)	(0.100)	(0.100)	(0.100)	(0.100)	(0.100)
DT185	-0.671***	-0.621***	-0.592***	-0.588***	-0.591***	-0.594***
	(0.174)	(0.175)	(0.176)	(0.176)	(0.177)	(0.177)
DT202	0.003	-0.002	-0.027	-0.036	-0.048	-0.050
	(0.226)	(0.227)	(0.228)	(0.228)	(0.229)	(0.229)
DT214	-0.720***	-0.730***	-0.754***	-0.761***	-0.767***	-0.768***
	(0.267)	(0.268)	(0.269)	(0.269)	(0.269)	(0.268)
DT236	0.125	0.107	0.109	0.110	0.109	0.109
	(0.112)	(0.112)	(0.112)	(0.111)	(0.111)	(0.111)
DT242	-0.415***	-0.425***	-0.403***	-0.393***	-0.386***	-0.387***
	(0.121)	(0.120)	(0.121)	(0.120)	(0.121)	(0.121)
DT254	-0.446***	-0.450***	-0.447***	-0.444***	-0.444***	-0.445***
	(0.160)	(0.159)	(0.159)	(0.159)	(0.160)	(0.160)
DT268	-0.508***	-0.466***	-0.426***	-0.423***	-0.432***	-0.436***
	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)
DT292	-0.941***	-0.900***	-0.882***	-0.879***	-0.881***	-0.883***
	(0.128)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)
DT311	-0.913***	-0.830***	-0.785***	-0.788***	-0.810***	-0.813***
	(0.214)	(0.213)	(0.214)	(0.213)	(0.213)	(0.213)
DT349	0.809**	0.756**	0.736**	0.740**	0.753**	0.757**
	(0.332)	(0.327)	(0.325)	(0.324)	(0.324)	(0.325)
DT377	-1.043***	-1.040***	-1.039***	-1.041***	-1.049***	-1.050***
	(0.219)	(0.220)	(0.219)	(0.220)	(0.220)	(0.220)
DT532	-0.353**	-0.366**	-0.356**	-0.350**	-0.346**	-0.346**
	(0.146)	(0.148)	(0.149)	(0.149)	(0.149)	(0.149)
DT548	0.340***	0.327***	0.337***	0.341***	0.342***	0.341***
	(0.084)	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)
DT573	0.031	0.027	0.038	0.040	0.038	0.036
	(0.233)	(0.231)	(0.232)	(0.233)	(0.235)	(0.235)
DT581	-0.454**	-0.463**	-0.460**	-0.462**	-0.470***	-0.473***
	(0.181)	(0.180)	(0.180)	(0.180)	(0.180)	(0.179)
DT615	-0.605***	-0.631***	-0.632***	-0.628***	-0.626***	-0.627***
	(0.163)	(0.164)	(0.164)	(0.164)	(0.163)	(0.163)
DT644	0.106	0.102	0.113	0.113	0.108	0.107
	(0.128)	(0.126)	(0.125)	(0.125)	(0.125)	(0.125)
DT701	-0.508***	-0.481***	-0.444***	-0.438***	-0.442***	-0.444***
	(0.127)	(0.128)	(0.128)	(0.128)	(0.128)	(0.128)
DT720	0.263	0.387**	0.349*	0.337*	0.348*	0.355*
	(0.190)	(0.181)	(0.186)	(0.188)	(0.186)	(0.185)
DT782	-0.393	-0.345	-0.321	-0.315	-0.310	-0.311
	(0.262)	(0.265)	(0.269)	(0.270)	(0.271)	(0.271)
DT869	-0.661***	-0.664***	-0.656***	-0.653***	-0.655***	-0.657***

	(0.183)	(0.183)	(0.182)	(0.181)	(0.180)	(0.180)
DT909	-0.560***	-0.528***	-0.530***	-0.537***	-0.552***	-0.556***
	(0.197)	(0.196)	(0.194)	(0.193)	(0.193)	(0.193)
DT919	-0.974***	-0.966***	-0.951***	-0.952***	-0.966***	-0.971***
	(0.274)	(0.268)	(0.261)	(0.260)	(0.261)	(0.262)
DT921	-0.659***	-0.641***	-0.656***	-0.657***	-0.652***	-0.653***
	(0.204)	(0.207)	(0.206)	(0.206)	(0.205)	(0.205)
DT923	-0.244	-0.270	-0.266	-0.261	-0.258	-0.260
	(0.212)	(0.213)	(0.214)	(0.214)	(0.214)	(0.214)
DT926	-0.015	-0.013	-0.009	-0.008	-0.011	-0.013
	(0.153)	(0.153)	(0.153)	(0.153)	(0.154)	(0.154)
DT940	-0.940***	-0.967***	-0.952***	-0.943***	-0.934***	-0.933***
	(0.207)	(0.206)	(0.207)	(0.208)	(0.208)	(0.208)
DT949	-0.081	-0.100	-0.102	-0.098	-0.092	-0.092
	(0.171)	(0.173)	(0.174)	(0.174)	(0.174)	(0.174)
DT963	-0.251	-0.296*	-0.311*	-0.311*	-0.308*	-0.307*
	(0.178)	(0.179)	(0.179)	(0.179)	(0.178)	(0.178)
DT976	-0.463*	-0.396	-0.418	-0.422*	-0.420*	-0.424*
	(0.253)	(0.259)	(0.255)	(0.254)	(0.253)	(0.253)
DT987	0.214	0.262	0.287	0.294	0.298	0.297
	(0.260)	(0.266)	(0.271)	(0.272)	(0.274)	(0.275)
DT994	-0.814***	-0.798***	-0.813***	-0.817***	-0.820***	-0.820***
	(0.244)	(0.246)	(0.248)	(0.248)	(0.249)	(0.249)
DT1010	-0.778***	-0.739***	-0.738***	-0.739***	-0.738***	-0.738***
	(0.209)	(0.212)	(0.214)	(0.215)	(0.215)	(0.215)
DT1011	-0.793***	-0.820***	-0.785***	-0.770***	-0.762***	-0.763***
	(0.279)	(0.279)	(0.276)	(0.275)	(0.275)	(0.275)
DT1020	-0.234	-0.261	-0.278	-0.279	-0.276	-0.275
	(0.240)	(0.237)	(0.238)	(0.238)	(0.239)	(0.239)
DT1071	0.129*	0.098	0.102	0.110	0.118*	0.118*
	(0.066)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
DT1128	-0.178	-0.203	-0.202	-0.202	-0.205	-0.205
	(0.134)	(0.134)	(0.133)	(0.133)	(0.132)	(0.132)
DT1222	0.114	0.116	0.130	0.135	0.138	0.137
	(0.088)	(0.089)	(0.090)	(0.090)	(0.090)	(0.090)
DT1227	0.254	0.275	0.315	0.318	0.306	0.303
	(0.310)	(0.311)	(0.310)	(0.309)	(0.309)	(0.310)
DT1230	-0.040	-0.032	-0.048	-0.054	-0.061	-0.063
	(0.209)	(0.211)	(0.211)	(0.211)	(0.210)	(0.210)
DT1245	-0.406**	-0.405**	-0.403*	-0.402*	-0.403*	-0.404*
	(0.204)	(0.205)	(0.206)	(0.207)	(0.208)	(0.208)
DT1253	-0.223*	-0.217	-0.196	-0.189	-0.183	-0.184
	(0.133)	(0.134)	(0.134)	(0.134)	(0.135)	(0.135)
DT1303	0.101	0.065	0.047	0.046	0.049	0.049
	(0.251)	(0.255)	(0.255)	(0.254)	(0.252)	(0.251)
DT1342	-0.310	-0.339*	-0.366*	-0.371*	-0.372*	-0.371*
	(0.194)	(0.197)	(0.199)	(0.199)	(0.199)	(0.199)
DT10006	-1.059***	-1.025***	-1.020***	-1.019***	-1.017***	-1.017***
	(0.260)	(0.266)	(0.269)	(0.269)	(0.269)	(0.269)
DT10026	-0.153	-0.126	-0.062	-0.048	-0.054	-0.061
	(0.332)	(0.330)	(0.324)	(0.323)	(0.325)	(0.326)
DT10027	0.010	0.063	0.080	0.079	0.068	0.063
	(0.291)	(0.288)	(0.285)	(0.285)	(0.285)	(0.285)
DT10028	-0.735***	-0.690***	-0.665**	-0.669**	-0.689***	-0.694***
	(0.268)	(0.267)	(0.264)	(0.263)	(0.261)	(0.262)

DT10030	-1.082***	-1.099***	-1.114***	-1.117***	-1.121***	-1.123***
	(0.276)	(0.277)	(0.278)	(0.279)	(0.279)	(0.279)
DT10031	-0.631**	-0.671**	-0.701**	-0.704**	-0.697**	-0.693**
	(0.291)	(0.300)	(0.303)	(0.303)	(0.302)	(0.301)
DT10035	-0.411*	-0.416*	-0.409*	-0.407*	-0.410*	-0.413*
	(0.242)	(0.242)	(0.243)	(0.243)	(0.243)	(0.243)
DT10037	-0.462***	-0.467***	-0.463***	-0.463***	-0.467***	-0.468***
	(0.170)	(0.172)	(0.173)	(0.173)	(0.173)	(0.172)
DT10038	-1.266***	-1.301***	-1.287***	-1.277***	-1.265***	-1.266***
	(0.231)	(0.233)	(0.232)	(0.231)	(0.230)	(0.230)
DT10040	-0.452***	-0.445***	-0.458***	-0.462***	-0.465***	-0.465***
	(0.164)	(0.165)	(0.166)	(0.166)	(0.167)	(0.167)
DT10041	-0.597***	-0.609***	-0.611***	-0.611***	-0.612***	-0.613***
	(0.228)	(0.229)	(0.229)	(0.229)	(0.229)	(0.229)
DT10042	-0.694***	-0.681***	-0.668***	-0.666***	-0.665***	-0.664***
	(0.190)	(0.193)	(0.193)	(0.192)	(0.191)	(0.191)
DT10043	-0.178	-0.194	-0.205	-0.206	-0.210	-0.212
	(0.225)	(0.226)	(0.226)	(0.226)	(0.226)	(0.226)
DT10046	0.084	0.060	0.064	0.068	0.072	0.071
	(0.327)	(0.328)	(0.327)	(0.326)	(0.325)	(0.324)
DT10048	0.042	0.046	0.042	0.039	0.032	0.030
	(0.233)	(0.234)	(0.234)	(0.234)	(0.234)	(0.234)
DT10049	-0.191	-0.206	-0.215	-0.217	-0.221	-0.222
	(0.167)	(0.168)	(0.168)	(0.167)	(0.167)	(0.167)
DT10050	-0.375	-0.386	-0.390*	-0.387	-0.379	-0.377
	(0.231)	(0.235)	(0.236)	(0.236)	(0.236)	(0.236)
Constant	0.091***	-0.320***	-0.638***	-0.754***	-0.929***	-0.981***
	(0.031)	(0.045)	(0.065)	(0.057)	(0.067)	(0.073)
Observations	33,258	33,258	33,258	33,258	33,258	33,258

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1