The Economic Impact of AIDS Treatment: Labor Supply in Western Kenya*

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Abstract

Using longitudinal survey data collected in collaboration with a treatment program, this paper is the first to estimate the economic impacts of antiretroviral (ARV) treatment in Africa. The responses in two important outcomes are studied: (1) labor supply of adult AIDS patients receiving treatment; and (2) labor supply of children and adults living in the patients' households. We find that within six months after the initiation of treatment, there is a 20 percent increase in the likelihood of the patient participating in the labor force and a 35 percent increase in weekly hours worked. Since patient health would continue to decline without treatment, these labor supply responses are *underestimates* of the impact of treatment on the treated. The upper bound of the treatment impact, which is based on plausible assumptions about the counterfactual, is considerably larger and also implies that the wage benefit from treatment is roughly equal to the costs of treatment provision. The responses in the labor supply of patients' household members are heterogeneous. Young boys work considerably less after initiation of treatment, while girls and other adults in the household do not change their labor supply. In multiple-patient households, only the labor supply of girls remains unaffected. These results suggest that ARV treatment influences intrahousehold time allocation decisions and that it has non-health benefits for patients and their household members.

1. Introduction

Sub-Saharan Africa is home to 25 million of the nearly 40 million people living with HIV/AIDS (UNAIDS, 2004). In the next decade, AIDS-related mortality will continue to increase the number of orphans in the region (currently 12 million) and reduce life expectancy (already at 35 years in some countries). Following increases in donor support and substantial reductions in the prices of medicines, antiretroviral (ARV) therapy has recently become an important part of the policy response to combat AIDS.[1] As of June 2005, roughly one-half million HIV-positive individuals were receiving ARV therapy in sub-Saharan Africa (WHO, 2005). Since this represents only 11 percent of the number of people needing treatment, scaling-up of treatment programs poses a major challenge in many countries.[2] At the same time, however, some have questioned the investment in ARV therapy since most low-income countries have limited resources and many competing needs (Marseille, Hofmann, and Kahn, 2002; Kremer, 2002).[3]

Numerous studies have shown that ARV therapy dramatically reduces morbidity and mortality among HIV-infected individuals, in both industrialized countries (Hammer et al., 1997, Hogg et al., 1998; Palella et al., 1998) and developing countries (Laurent et al., 2002; Marins et al., 2003; Koenig, Leandre, and Farmer, 2004; Wools-Kaloustian et al., 2005). These health benefits have the potential to significantly improve economic well-being, as suggested by a growing literature that shows linkages between health and income in developing countries.[4] While this literature examines the economic impacts of several dimensions of health such as nutritional status and morbidity, it provides little guidance when it comes to a highly debilitating and chronic disease like HIV/AIDS. One exception is the recent study by Fox et al. (2004), who analyze retrospective data from a Kenyan tea estate and find significant declines in the labor productivity of HIV-positive workers prior to their death or medical retirement. However, the extent to which treatment can reverse such declines in labor productivity remains to be determined. Little is known about the impact of this important intervention on a broad range of other socio-economic outcomes as well, both at the individual and household level.

[1] For example, in 2003 the World Health Organization (WHO) launched the prominent "3 by 5" campaign, with the goal of treating three million people by 2005 (WHO, 2003).
[2] As explained below, not all HIV-positive individuals are currently in need of ARV therapy.
[3] Furthermore, advocates of treatment have also noted that questions concerning economic effectiveness have served as obstacles to obtaining greater donor support (Binswanger, 2003; Clinton, 2003).
[4] See Strauss and Thomas (1998), Ruger, Jamison, and Bloom (2001), and Thomas and Frankenberg (2002) for reviews and discussions of the micro-economic literature on linkages between health and income.

In this paper, we use survey data from Kenya to present the first estimates of how quickly and to what degree ARV therapy affects the labor supply of treated patients and their household members. These estimates are a preliminary step in understanding the socio-economic impacts of ARV therapy, which in turn is critical for properly evaluating treatment programs and efficiently allocating resources. For example, if ARV therapy for adult AIDS patients increases the likelihood that their children attend school, then such impacts belong in any cost-benefit analysis. Estimates of these impacts can also contribute to the growing literature on the long-term micro- and macro-economic consequences of AIDS (Bell, Devarajan, and Gersbach (2003) and Young (2005).

Labor is the central productive asset of the poor in most developing countries. Indeed, labor supply and related outcomes like income have been the focus of many studies that examine the impacts of nutrition, morbidity, and AIDS-related mortality.[5] Because it is an important outcome, changes in the labor supply of adult AIDS patients can also generate intrahousehold spillover effects on time allocation patterns and influence other measures of household welfare.

Our analysis is based on data from a household survey we conducted in collaboration with a rural treatment program in western Kenya. Over the course of one year, longitudinal socio-economic data were collected from AIDS patients who receive treatment. These data have been linked to longitudinal medical data containing clinical and laboratory measures of the patients' health status. The presence of individuals whose HIV status is known, the ARV treatment program, and the linked medical data combine to offer us a unique opportunity to measure the effects of treatment.

To identify the response to treatment, we examine changes over time in the labor supply of treated patients and their household members. Since ARV treatment eligibility is defined by biological markers that are not easily influenced by the behavior of patients with late-stage HIV disease, treatment and the resulting changes in health are exogenous. Using data collected simultaneously from a large random sample of non-patient households, we control for time-varying factors (such as seasonality) that could bias the estimates. The analysis is strengthened by variation in the length of time that patients had been exposed to treatment *prior* to the survey. As we show with the linked medical data, health has a non-linear temporal response to

[5] Yamano and Jayne (2004) examine the impacts of working-age adult mortality on a range of household outcomes including crop and non-farm income. Beegle (2005) examines the impacts of adult mortality on the labor supply of household members.

treatment—it improves dramatically in the first months of treatment but more gradually thereafter. We exploit this non-linearity to test for heterogeneous treatment responses in the labor supply of patients.

We find that the provision of ARV therapy leads to a large and significant increase in the labor supply of AIDS patients. This increase occurs very soon after the initiation of ARV therapy: within six months, there is a 20 percent increase in the likelihood of participating in the labor force and a 35 percent increase in hours worked during the past week. Since AIDS patients left untreated will experience continued declines in health and possibly death within six months, our estimated labor supply responses are underestimates of the impact of treatment on the treated. It is important to note that due to the clinical effectiveness and life-saving nature of ARV therapy, randomized evaluations of treatment interventions are not feasible on ethical grounds. Thus, the results here represent the best available method of studying the impact of treatment. However, we also calculate an upper bound of the impact of treatment on the treated by assuming that patients would be too sick to work (or even dead) without treatment. Clinical evidence on the evolution of untreated HIV disease suggests that this is a reasonable assumption, and that the upper bound estimate is close to the 'true' impact of treatment on the treated. This upper bound is very large: labor force participation for those initiating therapy in Round 1 increases by 85 percentage points and hours worked increases by 26 hours per week relative to what would have happened if AIDS had progressed untreated.

Given this effect on patients' labor supply, treatment can also have spillover benefits within the household. However, an analysis of how ARV therapy influences the labor supply of treated patients' household members is complicated, as the effects are theoretically ambiguous. On the one hand, the increase in a patient's labor supply has an *income effect* that allows other household members to work less. On the other hand, the improvement in the patient's health reduces the care-taking and housework burden on family members, thereby having a *time endowment effect* that allows for more work and leisure. We find that the labor supply of younger boys in patients' households declines after the initiation of ARV therapy. In multiple-patient households, both younger and older boys, as well as other adults in the household, work less after patients receive treatment. This suggests that intrahousehold decisions about time allocation are influenced by the provision of treatment, and that the welfare of some household members beyond the patient may increase considerably as a result.

This paper is organized as follows: in Section 2, we provide a brief overview of the key stages of HIV infection and the role of ARV therapy in treating infected individuals. We then discuss our survey data in Section 3. Section 4 uses medical data from the HIV clinic where this study was conducted to show that measurable dimensions of patient health improve after initiation of treatment. We discuss our strategy for estimating the response in treated patients' labor supply in Section 5 and present the results in Section 6. In Section 7, we examine the labor supply of children and adults living with ARV recipients. Section 8 concludes and discusses the policy implications of this research.

2. Background on HIV/AIDS and Antiretroviral Therapy

The human immunodeficiency virus (HIV) affects the health of individuals and eventually causes acquired immune deficiency syndrome (AIDS) because it destroys white blood cells that are essential to the immune system. In sub-Saharan Africa, which is home to 25 million of the nearly 40 million people living with HIV/AIDS, most HIV transmission among adults occurs through sexual intercourse between men and women (UNAIDS, 2004). Soon after transmission, infected individuals enter a clinical latent period of many years during which health status declines gradually and few symptoms are experienced. Median time from seroconversion to AIDS in east Africa is estimated to be 9.4 years (Morgan et al., 2002).[6] During this latency period, most HIV-positive individuals are unaware of their status and physically capable of performing all normal activities.

Over time, almost all HIV-infected individuals will experience a weakening of the immune system and progress to developing AIDS. This later stage is very often associated with substantial weight loss (wasting) and opportunistic infections such as P. carinii pneumonia, Kaposi's sarcoma, and tuberculosis. In resource-poor settings, absent treatment with ARV therapy, death usually occurs within one year after progression to AIDS. One study in Uganda reports a median survival time of 9.2 months (Morgan et al., 2002) and another study in Brazil reports a median survival time of 5.1 months (Chequer et al., 1992). Opportunistic infections are generally the cause of death in AIDS cases.

[6] Conversion to HIV-positive serology normally occurs 4-10 weeks after transmission. The duration of the clinical latent period has been found to vary considerably, depending upon the mode of transmission and age at transmission (Collaborative Group on AIDS Incubation and HIV Survival including the CASCADE EU Concerted Action, 2000). In developing countries, limited access to health care and greater burden of other infectious diseases may expedite the progression of HIV.

Highly active antiretroviral therapy[7] has been proven to reduce the likelihood of opportunistic infections and prolong the life of HIV-infected individuals. After several months of treatment, patients are generally asymptomatic and have improved functional capacity. As we discuss in Section 4, individuals are considered eligible for ARV therapy after they progress to AIDS. Numerous studies in various countries and patient populations have reported positive results.[8] In Haiti, patients had weight gain and improved functional capacity within one year after the initiation of ARVs (Koenig, Leandre, and Farmer, 2004). In Brazil, median survival time after developing AIDS rose to 58 months with ARV therapy (Marins et al., 2003). Section 4 summarizes the results obtained by Wools-Kaloustian et al. (2004) for the treatment program we collaborated with in Kenya and documents similar health impacts for patients in our sample.

The price of ARV therapy in developing countries is an important issue in discussions about treatment provision. First-line ARV regimens used to cost more than $10,000 per patient per year. However, since 2000 widespread generic production of medicines has reduced these prices significantly, to as low as $140 (negotiated by the Clinton Foundation for treatment in selected countries) in 2004 (Gutierrez et al., 2004; Campaign for Access to Essential Medicines, 2005). Further declines may be possible with greater generic competition and bulk purchasing agreements. Expenditures on lab tests and HIV clinic operations can also be sizable, with the sum of these drug provision costs dependent on the treatment setting.

3. Sampling Strategy and Survey Data

The socio-economic data used in this paper come from a household survey we conducted in Kosirai Division, a rural region near the town of Eldoret, in western Kenya (see Figure 1).[9] The Division has an area of 76 square miles and a population of 35,383 individuals living in 6,643 households (Central Bureau of Statistics, 1999). Households are scattered across more than 100 villages where crop farming and animal husbandry are the primary economic activities and maize is the major crop.

[7] In this paper, we use the terms "ARV therapy" and "ARV treatment" to refer to highly active antiretroviral therapy (HAART), which was introduced in 1996. HAART always consists of three antiretroviral medications, with a common first-line regimen of nevirapine, stavudine, and lamivudine. Generic medications that combine 3 medications in 1 pill (such as Triomune) have recently become available.

[8] Since placebo-controlled randomized trials of ARV therapy are ethically infeasible, these studies are either observational cohort studies or randomized trials that compare regimens composed of different antiretroviral medications.

[9] Kenya has an estimated 1.5 million HIV-infected adults and a prevalence rate of 6.7 percent (UNAIDS 2004).

The largest health care provider in the survey area is the Mosoriot Rural Health Training Center, a government health center that offers primary care services. The health center also contains a clinic that provides free medical care (including ARV therapy) to HIV-positive patients. This rural HIV clinic (one of the first in sub-Saharan Africa) was opened in November 2001 by the Academic Model for the Prevention and Treatment of HIV/AIDS (AMPATH).[10] Following increased funding since late-2003, the Mosoriot HIV clinic has experienced rapid growth: the number of patients has risen from about 150 in early-2003 to 2,149 in September 2005 (communication with AMPATH), with many patients coming from outside Kosirai Division.[11] During this period, adequate funding has been available to treat all patients requiring ARV therapy.[12,13]

We implemented two rounds of a comprehensive socio-economic survey between March 2004 and March 2005, with an interval of roughly six months between rounds.[14] The survey sample contains two different groups of households: 503 households chosen randomly from a census of households in Kosirai Division without an AMPATH patient (random sample households) and 266 households with at least one AMPATH patient (HIV households).[15] The HIV sample includes *all* non-pregnant patients who entered the Mosoriot HIV clinic before April 2004 and resided in Kosirai Division. To obtain a larger sample size, we also conducted in-clinic interviews with non-pregnant patients who entered the clinic before April but resided outside Kosirai Division and too far away from the clinic to be visited at home. In total, 81 percent of all survey households were visited at home. Refusal rates for in-clinic interviews with AMPATH patients were less than 1 percent.

[10] AMPATH is a collaboration between the Indiana University School of Medicine and the Moi University Faculty of Health Sciences (Kenya). Descriptions of AMPATH's work in western Kenya can be found in Mamlin, Kimaiyo, Nyandiko, and Tierney (2004) and Cohen et al. (2005).

[11] For reasons including limited funding, AMPATH's clinic had very few patients during its first two years of operation. Early entrants to the HIV clinic had often progressed to AIDS at the time of their first visit. In contrast, later entrants are often in early stages of the disease and do not require ARV therapy.

[12] The availability of funding and criteria for treating patients has evolved over time. Before 2003, funding for purchasing ARVs was limited and treatment could only be provided to the sickest few patients.

[13] As of June 2005, ARV therapy was being provided to an estimated 38,000 out of 250,000 Kenyans needing treatment (WHO 2005). About 17 percent of the Kenyans receiving ARV therapy are patients at one of AMPATH's eight urban and rural clinics (based on figure of 6,375 patients receiving ARV therapy as of June 2005).

[14] Round 1 was between March and August 2004. Round 2 was between September 2004 and March 2005.

[15] In the random sample, the HIV status of respondents is usually unknown, unless the respondent gives a self-report of having gone for an HIV test and testing HIV-positive or HIV-negative.

Within the 266 HIV households, there are 320 individuals (including children) who are HIV-positive and known to be receiving care at the Mosoriot HIV clinic.[16] Using the AMPATH identification numbers obtained from patients, we have established with the AMPATH Medical Records System (AMRS) that 224 of the 320 patients (from 206 households) began receiving ARV therapy sometime prior to the round 2 interview (we report the distribution of treatment start dates in Section 4).[17] The remaining HIV-positive patients in our sample were not sick enough to require ARV therapy before round 2. Attrition of households and individuals between rounds is minimal in the random sample, either due to refusal/relocation (7 out of 503 households) or mortality (7 out of 3,009 individuals). In the HIV sample, a total of 26 patients attrite from the sample between rounds (14 due to mortality and 12 due to loss to follow-up). In the analysis below, we attempt to correct for bias that may be introduced by this attrition.

The survey focused on various issues and included questions about demographic characteristics, health, agriculture, income and employment.[18] Height and weight measurements were made for children under the age of 5 years. Relevant outcomes such as asset sales and purchases, child anthropometrics, school enrollment and attendance, income, employment, and food consumption were recorded in each round to obtain longitudinal data.

Table 1 summarizes the main demographic characteristics of households in the random sample and HIV sample during round 1. On average, households in the survey area have 6 members. HIV households tend to be smaller, with 5.4 members on average. There is a significant difference in the sex and marital status of household heads and the orphan status of children: HIV households are more likely to be headed by a woman who has lost her husband, whereas random sample households are generally headed by a married man. HIV households

[16] 274 of these 320 HIV-positive individuals were interviewed; HIV-positive children of adult patients and HIV-positive spouses of in-clinic respondents were not interviewed. Included among these individuals are household members of respondents who were reported to be HIV-positive. The figure of 320 HIV-positive individuals excludes 15 household members who were reported to be HIV-positive by the respondent but for whom no AMPATH identification number was made available.

[17] In this paper, we refer to the sample of ARV patients as the "ARV sample" and their households as "ARV households." There are 7 HIV-positive individuals whose AMPATH identification number cannot be found in the AMRS. The ARV status of these patients is therefore unknown.

[18] In the household visits, teams of male and female enumerators interviewed the household head and spouse as well as a youth in the household. For in-clinic interviews, all information was obtained from the AMPATH patient.

also own significantly less land and livestock, which is one of several indications from the survey that they are worse off than other households in the community.[19]

4. ARV Therapy and Patient Health

The AMRS contains longitudinal information on the health status of patients at AMPATH's eight HIV clinics in western Kenya. Before estimating how labor supply responds to ARV therapy, we discuss evidence from the AMRS on the health response to treatment. We also summarize relevant medical data for patients in our sample.

Since HIV enters and destroys T cells with the protein CD4 on their surface, the CD4+ T cell count is an important indicator of disease progression among HIV-infected individuals.[20] According to definitions of the Centers for Disease Control and Prevention (CDC), individuals develop AIDS when they have one of several opportunistic infections or a CD4 count below 200/mm^3. It is at this stage when functional capacity deteriorates and patients should begin ARV therapy—according to WHO guidelines (WHO, 2002), ARV therapy should be administered for all patients who have a CD4 count below 200/mm^3 or an AIDS-indicating condition.[21]

Although most AMPATH patients receiving treatment come to the HIV clinics every month, their CD4 count is monitored at intervals of roughly six months.[22] However, since the weight and height of patients are recorded at almost every clinic visit, the AMRS contains more frequent measures of the body mass index (weight/height^2, BMI), a well-known indicator of short-term health and nutritional status (WHO, 1995). Wools-Kaloustian et al. (2005) have recently analyzed the CD4 counts and weights of all non-pregnant adult patients treated with ARV therapy at AMPATH's HIV clinics (including Mosoriot). They find significant improvements in both outcomes, including a rapid increase in CD4 count during the first six weeks of ARV therapy followed by slower increases thereafter.[23] In addition, the CD4 count at the time of treatment initiation (baseline) is found to be a significant predictor of subsequent

[19] For further details on the household survey and the first round data, see Goldstein, Graff Zivin, Nangami, and Thirumurthy (2005).
[20] Most uninfected individuals have a CD4+ T cell count of 800 to 1000 per mm^3 of blood.
[21] These guidelines have been followed by many treatment programs in developing countries, including AMPATH. See Grubb, Perriens, and Schwartlander (2003) and Mamlin et al. (2004).
[22] The CD4 count was obtained less frequently and at unspecified intervals prior to 2004, when funding was more limited.
[23] The reported gains in CD4 count are similar to those found by studies in Senegal and South Africa (Laurent et al. 2002; Coetzee et al. 2004).

survival: the risk of death for patients with baseline CD4 count below 100/mm^3 is three times higher than for patients with baseline CD4 count above 100/mm^3.

Using AMRS data for adult ARV recipients at only the Mosoriot HIV clinic, Figure 2 shows the dramatic improvement in health status experienced by patients. We plot the median CD4 count in cells of ten weeks before and after initiation of treatment.[24] The response of CD4 count is highly non-linear: at 10-20 weeks, the median CD4 count has risen to levels at which patients are generally asymptomatic. Subsequent changes are smaller and less consistent. Figure 3 shows a similar non-linear relationship for the BMI.[25]

Since patients do not have a CD4 count or BMI in every cell of Figures 2 and 3, the cross-sectional relationship shown may differ from the average experience of individual patients. Thus, restricting the analysis to all post-treatment outcomes for the 191 adult ARV recipients who appear in both rounds of our survey, the following equation is estimated using patient fixed effects:

$$H_{it} = \alpha_i + \beta_1 ARV_{i,t-3} + \beta_2 ARV_{i,t-6} + \beta_3 ARV_{i,t-9} + \beta_4 ARV_{i,t-12} + \varepsilon_{it}. \quad (1)$$

α_i is a patient fixed effect, H_{it} is a measure of patient i's health status (CD4 count or BMI) during the appointment at time t, and $ARV_{i,t-\tau}$ indicates whether or not patient i was receiving ARV therapy τ months prior to the appointment when health status is measured.[26,27] The omitted time period is the span of three months after initiation of treatment. Table 2 reports results from estimating equation 1 with CD4 and BMI as the dependent variables (columns 1 and 2, respectively). The increase in CD4 count during the first three to six months of ARV therapy is substantial (127/mm^3) and statistically significant. After six months of treatment, marginal increases are smaller. For BMI (which is measured more frequently), we are able to estimate a

[24] Due to the low frequency at which CD4 count is measured, we chose a group size that is large enough to produce a relatively smooth curve. When median CD4 counts are calculated for intervals of less than 10 weeks, the figure looks similar. Likewise, a similar pattern is evident when mean CD4 count is calculated in each time interval.

[25] These figures do not correct for mortality bias, which will lead to an overestimate of trends in CD4 count and BMI. Since mortality rates are low in the period immediately following treatment, the short-term trends should be relatively accurate. But mortality is more of a concern for long-term trends. Since patients who die are generally those who presented with advanced disease and very low baseline CD4 counts, the long-term trends displayed here will be more applicable to patients who begin treatment before becoming very sick.

[26] Since there are very few patients with *multiple* measurements of CD4 counts during the pre-treatment period, it is not possible to estimate the trajectory of CD4 count in this period with patient fixed effects. In cross-sectional regressions of CD4 count on weeks before initiation of ARV therapy, however, there is a significant overall negative trend in CD4 count prior to initiation (as shown in Figure 2).

[27] Following Wools-Kaloustian et al. (2005) and other studies, if a CD4 count is not available at the time ARV therapy is initiated, the baseline CD4 count is taken to be nearest available CD4 count in the 3 months before or 15 days after the time of initiation.

more continuous version of equation 1 with additional time intervals. Here again, the largest increase occurs soon after initiation of treatment, but there are also significant increases in subsequent months.[28]

Finally, for ARV recipients in our sample, in Table 3 we summarize the CD4 count and BMI linked to three different points in time: baseline, round 1, and round 2.[29] We also report the number of days that patients in our sample had been receiving ARV therapy *at the time of the round 1 interview*. While the average number of days is 172, we find substantial variation here: 19 percent had not yet initiated ARVs at the time of the round 1 interview, and 26 percent had been on ARVs for fewer than 100 days. This means that due to the non-linear temporal response of health status to ARV therapy, treated patients in our sample experienced varying amounts of health improvement between the survey rounds. In the next section, we exploit this variation to test for heterogeneous treatment responses in labor supply.

5. Estimation Strategy for Patients' Labor Supply Response

We primarily study two outcomes that measure an individual's labor supply: an indicator of participation in any economic activity during the past week and the total number of hours worked in the past week. For all household members older than 8 years, the survey recorded this information in each round for three types of activities: wage and salaried jobs, farming on the household's owned or rented land, and non-farm self-employed work.

The first indication that ARV therapy influences labor supply is provided by Figures 4 and 5, which combines data from the two survey rounds and plots the relationship between adult ARV recipients' labor supply outcomes and time on treatment. The temporal pattern of labor force participation rates (Figure 4) and weekly hours worked (Figure 5) closely resembles the non-linear response of medical outcomes. In this section, we discuss the main estimation strategies used to test the hypothesis that ARV therapy results in increased labor supply.

The motivation for our empirical work comes from the following labor supply function, which is drawn from Strauss and Thomas (1998) and can be used to describe the relationship between health and labor supply:

[28] The results are similar when equation 1 is estimated for the entire sample of adult ARV recipients in the Mosoriot HIV clinic.

[29] In constructing the CD4 and BMI for round 1 and round 2, we again use the nearest available measure within 3 months before and 15 days after the round 1 and round 2 interview date. This still results in several patients for whom we cannot link a CD4 count and BMI to the interview date.

$$L = L(H, p_c, w(H, X, \alpha, e_w), X, \xi). \quad (2)$$

Labor supply (L) is affected by health (H) due to two factors: first, health can influence an individual's productivity or real wage (w), and second, independent of its effect on wages, health can influence the marginal rate of substitution between consumption goods and leisure (if we assume that health, consumption, and leisure are all directly valued by the individual). A host of other factors will also influence labor supply, such the price of consumption goods (p_c), a vector of individual and family characteristics (X) such as education, schooling, family background, and wealth, unexpected events (e_w) such as weather shocks that influence labor demand and wage rates, as well as unobservables such as ability (α) and tastes (ξ).

Estimating the total effect of health in a reduced form equation for labor supply is difficult for well-known reasons that are discussed in the literature (see Strauss and Thomas, 1998): bias from omitted variables (such as ability) that are correlated with both wages and health, simultaneity problems that arise from health and income influencing each other contemporaneously, and errors in the measurement of health status. In our case, however, since we are interested in estimating the effect of ARV treatment on labor supply, we overcome these problems by taking advantage of the panel structure our data and the exogenous health improvement that occurs due to treatment. First, we estimate reduced form equations that measure the response of labor supply to ARV treatment. Second, we estimate the total effect of health on labor supply (as described in equation 2) by instrumenting for health status with the length of time on ARV treatment. The latter strategy allows us to test whether the reduced form effect of treatment is indeed due to changes in health status. It also allows us to examine the relationship between the health measures of AIDS patients and their labor supply.

5.1 Reduced Form Estimation of the Response to Treatment

We identify the response to ARV therapy by examining changes in the treatment group's labor supply between rounds. Since labor supply is also influenced by several time-varying factors such as seasonality in agriculture (which influences local prices and labor demand) and aggregate health shocks (greater malaria burden in specific months, for example), we include data from the random sample of adults to control for secular trends in the survey area. This strategy is similar to a difference-in-difference estimation strategy in which the "comparison

group" is the sample of adults from the random sample.[30] We thus estimate individual fixed effects regressions in which a time interaction for ARV recipients measures the change in their labor supply. The first equation estimated is the following:

$$L_{it} = \alpha_i + \beta_1(ARV_i * ROUND2_t) + \beta_2 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{it}. \quad (3)$$

L_{it} is the labor supply outcome of interest for individual i in time t (round 1 or 2), α_i is a fixed effect for individual i that captures the effects of time-invariant variables like demographic characteristics, schooling, family background, as well as unobservables such as ability and tastes, ARV_i is an indicator variable equal to 1 if individual i is an ARV recipient, and $ROUND2_t$ indicates whether the observation is from round 2.[31] The round 2 indicator and ten month-of-interview indicator variables (with one month from each round omitted to avoid singularity) together control for monthly fluctuations in labor supply in the entire community. The coefficient of interest, β_1, measures the change in labor supply (between rounds) due to ARV therapy, after controlling for time-varying factors.

Equation 3 assumes that the response to treatment will be identical for all ARV recipients in the sample. However, as noted earlier, patients have been on treatment for varying lengths of time during round 1 and the largest health improvement occurs for those just beginning treatment. Thus, we also estimate an equation in which ARV recipients who had been on ARVs for less than 100 days in round 1 (represented by $ARV_{<100,i}$) can experience a different change in labor supply than ARV recipients who had been on ARVs for more than 100 days in round 1 ($ARV_{>100,i}$). This distinction divides the ARV sample into two roughly equal samples, and distinguishes between patients experiencing large and small health improvements. The following modified version of equation 3 is thus estimated:

$$L_{it} = \alpha_i + \beta_1(ARV_{<100,i} * ROUND2_t) + \beta_2(ARV_{>100,i} * ROUND2_t) + \beta_3 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{it}. \quad (4)$$

[30] This also resembles the estimation strategy used by Jacobson, LaLonde, and Sullivan (1993). The authors use a longitudinal dataset to estimate the temporal pattern in earnings losses of displaced workers. In their estimation strategy, one reason why nondisplaced workers are used as a comparison group to displaced workers is that it is important to control for macroeconomic factors that can cause changes in workers' earnings.

[31] This equation could also be approximated without individual fixed effects as:

$$L_{it} = \alpha + \beta_1 ARV_i + \beta_2(ARV_i * ROUND2_t) + \beta_3 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{it}, \quad (3')$$

in which the individual fixed effect is assumed to vary systematically by ARV status.

While the division of ARV recipients into two samples will indicate whether there are heterogeneous responses during the post-treatment period, the use of 100 days as a cutoff for determining long and short duration of ARV therapy can be seen as arbitrary. To trace the response of labor supply more carefully, we construct indicators of whether or not the patient has been receiving ARVs for incremental durations of three months. The random sample is again used as a "comparison" group in this analysis to control for seasonality. Specifically, the following equation is estimated:

$$L_{it} = \alpha_i + \beta_1 ARV_{i,t-3} + \beta_2 ARV_{i,t-6} + \beta_3 ARV_{i,t-9} + \beta_4 ARV_{i,t-12} + \beta_5 ARV_{i,t-15} + \beta_6 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{it}. \quad (5)$$

$ARV_{i,t-\tau}$ indicates whether or not individual i was receiving ARVs τ months prior to the interview at time t (round 1 or round 2). In this specification, the outcomes of patients are compared at different times in the post-treatment period, with the baseline period of three months before and after treatment serving as the omitted time period.[32] Data from adults in the random sample again control for monthly fluctuations in labor supply.

The individual fixed effects in all of the equations estimated will allow for ARV recipients to have different *levels* of labor supply than other adults in the sample. While time varying factors such as seasonality are dealt with using the time indicators, the key assumption in identifying the treatment response is that the ARV recipients in the sample do not have characteristics that influence the *change* in labor supply between rounds. The only form of heterogeneity in the treatment response allowed by the equations above is in the temporal pattern of the response. In the analysis below, however, we also test for heterogeneity in the treatment response according to the gender of the ARV recipient.

5.2 Instrumental Variables Estimation

The equations above provide reduced form estimates of the labor supply response to treatment and suggest a strong linkage between health and labor supply. To show that treatment influences labor supply through the mechanism of improvements in health status and to further establish the link between health and labor supply, we take advantage of AMRS data on patients' medical

[32] Note that the definition of the indicator variables implies that the coefficients are *marginal* effects of completing additional months of ARV therapy. That is, patients who have completed 6-9 months of ARV therapy will experience an average increase in labor supply (relative to baseline) that is equal to $\beta_1+\beta_2$.

outcomes. Restricting the analysis to only ARV recipients, we estimate a slightly modified version of equation 2:

$$L_{it} = \alpha_i + \beta_1 H_{it} + \beta_2 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{it}, \quad (6a)$$

where α_i is a fixed effect for patient i and H_{it} is the health status (CD4 count or BMI) of patient i at time t (round 1 or round 2).[33]

The endogeneity of health can result in biased estimates of the coefficient β_1, even with individual fixed effects. Moreover, random measurement error in the health status variables will cause attenuation bias in the coefficient β_1. To overcome these estimation problems, we employ an instrumental variables (IV) strategy to estimate the effect of health status, based only on variation generated by the availability of ARV therapy. In particular, we instrument for health status using indicator variables of treatment duration (similar to equation 1):

$$H_{it} = \alpha_i + \beta_1 ARV_{i,t-3} + \beta_2 ARV_{i,t-6} + \beta_3 ARV_{i,t-9} + \beta_4 ARV_{i,t-12} + \varepsilon_{it} + \beta_5 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{it}. \quad (6b)$$

One shortcoming of this IV approach is that the number of observations is limited by the availability of CD4 counts and BMI measures at the time of the round 1 and round 2 interviews.[34] To overcome this problem, we use the point estimates of the coefficients in equation 6b to construct predicted values of the CD4 count and BMI for *all* patients in the ARV sample. These predicted values are based solely on the relationship between health outcomes and treatment duration. Using these predicted values, we then estimate equation 6a for a larger sample than is possible under the IV strategy.

6. Results for Adult Patients' Labor Supply Response

We restrict the analysis of labor supply to individuals between the ages of 18 and 65 who appear in both rounds.[35] Table 4 presents summary statistics from the first round for 191 adult ARV

[33] A drawback of this strategy is that it does not use information from the random sample to fully control for time-varying factors that determine labor supply.

[34] As noted earlier, measurements of CD4 counts at the HIV clinic are not done with enough frequency for us to obtain measures near the round 1 and round 2 interview for *all* patients in our sample.

[35] Adults who move into the household between rounds are thus excluded, as are adults who move out permanently. A small number of observations are dropped because the respondent did not know how many hours a specific household member worked in the past week. The role of attrition due to mortality is discussed in Section 6.4.

recipients and 1,286 adults in the random sample.[36] Crop farming is the primary economic activity of households in the survey area, as 84 percent of the random sample adults and 60 percent of the HIV sample reported having worked on their farm in the past 7 days. A non-trivial fraction of adults also report working off-farm for a wage (17-18%) or in a household enterprise (16-17%).

Table 4 shows that in the first round, ARV recipients are significantly more likely to *not* have done any work in the past week (24 percent of ARV recipients compared to 11 percent of adults in the random sample). ARV recipients also work significantly fewer hours than other adults, unconditional on participating in the labor force (24 hours compared to 35 hours) and conditional on participating (32 hours compared to 40 hours). Table 5 summarizes the respondents' reported reasons for not having worked in the past week. Only 8 percent of unemployed adults in the random sample report being sick as the reason for not having worked. In contrast, being sick is the reported reason for 85 percent of unemployed adult ARV recipients.

The data also show it is important that our analysis control for seasonal variations in labor supply. Figure 6 plots the median of weekly hours worked in each month of the survey. There is a peak during the maize planting and harvesting seasons—the months of April and May (in round 1) and November through January (in round 2), respectively.[37] Because of the seasonality in agriculture and the reliance of most people on self-employed farming, we do not focus on outcomes such as income or wages. Instead, most of our analysis below examines individuals' labor force participation and hours worked.

To contrast adults from the HIV clinic and random sample over time, we estimate labor supply regressions in each round separately. Table 6 reports the results for the indicator of labor force participation and Table 7 reports results for hours worked in the past week. Both tables show that age has a non-linear effect on labor supply and women have significantly lower levels of labor supply. We find that ARV recipients have significantly lower labor force participation

[36] Household members of the ARV recipients are not included in any of this analysis. To the extent that labor supply of these adult household members is affected by the changing health status of the ARV recipient, pooling them with adults in the random sample may produce biased results.

[37] Due to the seasonality of agriculture, income tends to be concentrated after harvest periods. We find that household income shows a sharp peak during December and January, when most households sell maize after the annual harvest (not reported). It is therefore not very meaningful to compare changes in income between rounds. Furthermore, since agricultural income is generally reported for only the household head and spouse, it is not surprising that income differences in Table 4 between ARV recipients and all other adults are not statistically significant.

rates than adults in the random sample (column 1). Also noteworthy, however, is that ARV recipients in early stages of ARV treatment are the worst off group in round 1 (column 2). Their labor force participation rate is 28 percentage points lower than comparable adults in the random sample, whereas the participation rate of ARV recipients in later stages of treatment (more than 100 days) is only 7.9 percentage points lower. In the second round, while ARV recipients are still significantly less likely to be economically active, the differences are smaller than in the first round. This is particularly true for ARV recipients who had just initiated treatment prior to round 1.

6.1 Individual Fixed Effects Results

In the regression results just presented, omitted characteristics of ARV patients could influence labor supply and thereby produce biased estimates of the ARV coefficient. To mitigate such identification problems, we estimate labor supply regressions with individuals fixed effects, as discussed in Section 5.1. Table 8 reports results from estimating equations 3 and 4. We find that ARV therapy leads to a large and statistically significant increase in labor supply. Adults receiving treatment are 8.2 percentage points more likely to participate in the labor force in round 2 than in round 1 (column 1), controlling for time-varying factors that are evident in both the ARV sample and the random sample. Hours worked in the past week also increases by 3.7 hours (column 2). Relative to the levels in round 1, this implies a large increase in labor supply for the entire sample of ARV patients: labor force participation rates rise by almost 11 percent, and weekly hours worked rise by 15 percent.

Columns 3 and 4 of Table 8 show an even stronger result. The individuals with the largest increase in labor supply between the two rounds are patients who began receiving ARVs less than 100 days prior to the round 1 interview. The magnitude of these increases is substantial: over the course of six months, patients who have just initiated ARV therapy show a 16.7 percentage point increase in labor force participation rates and an 6.9 hour increase in hours worked. Given round 1 levels of 65.1 percent and 20.3 hours for this group, the estimates imply a 26 percent increase in participation rates and a 34 percent increase in hours worked. In contrast, the other ARV recipients in our sample show no statistically significant improvement in outcomes between rounds.[38]

[38] Comparisons of socio-economic characteristics of the two groups of ARV recipients show that there are no statistically significant differences in the gender, education, and household characteristics such as household size

Since the regressions of hours worked includes individuals not participating in the labor force during round 1, the results do not clearly establish whether the labor supply response is also applicable to patients already working in round 1. In column 5 of Table 8, we present results for a restricted sample that includes only those adults who were participating in the labor force during round 1. Since we do not find a statistically significant effect on hours worked, the results suggest that the main treatment response occurs by allowing patients who were previously too sick and incapable of working to enter the labor force.

The results for ARV patients who have just initiated treatment are noteworthy since these patients are particularly sick before starting treatment and at the time of the round 1 interview. As discussed earlier, in the absence of treatment these patients have a small probability of living for another six months, until the round 2 interview date. In this sense, the estimated labor supply responses are likely to be *underestimates* of the impact of treatment on the treated.[39]

Table 9 reports the results from estimating equation 5, with a more complete set of indicators to identify the temporal response to treatment. As columns 1 and 2 show, the increase in labor supply is largest during the first three to six months of ARV therapy, with subsequent increases being smaller and statistically insignificant. The point estimates show that after three to six months on treatment, there is a 12.3 percentage point increase in labor force participation rates and a 6.9 hour increase in weekly hours worked. Compared to levels of labor supply for patients who are within three months before or after initiation of ARV therapy (the omitted group), this implies a 20 percent increase in the labor force participation rate and a 35 percent increase in hours worked.[40]

6.2 Effects of Health Status on Labor Supply

To estimate the impact of health improvements (as measured by the CD4 count and BMI) on labor supply in the context of AIDS, we estimate equation 6a using the instrumental variables strategy outlined in Section 5.2. We restrict the analysis to only ARV recipients since measures of CD4 count and BMI are obtained from the AMRS and therefore not available for adults in the random sample. Table 10a reports results from the first stage regression (equation 6b) in which

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and ownership of land and livestock (results not reported). This implies that such characteristics cannot explain the large difference in the labor supply changes of the two groups.

[39] Because HIV/AIDS is a chronic disease, the typical problem of mean reversion in the outcome variable (Ashenfelter and Card, 1985) does not apply here and therefore does not bias the estimates.

[40] For adult ARV recipients in our sample who have been on ARV therapy for fewer than three months, the labor force participation rate is 61.56 percent and the average weekly hours worked is 19.68.

indicators of treatment duration are used as instruments for CD4 count and BMI at the time of the two rounds of the survey. As earlier, we find that there is a large and statistically significant increase in both measures of health status after three months of treatment. However, the inclusion of a round 2 indicator and month-of-measurement indicators (as well as the restriction to health measures obtained only at the time of round 1 and round 2) makes the point estimates different from those in Table 2.

Table 10b shows that both CD4 count and BMI have a positive impact on the labor force participation rate. In column 1, we report the results from an individual fixed effects regression without instrumenting for CD4 count. Random measurement error in CD4 count most likely explains why we find a small and insignificant point estimate. After instrumenting for CD4 count (column 2), the point estimate increases considerably but remains insignificant, probably due to the limited number of patients with a CD4 count measure in both round 1 and round 2. In fact, expanding our sample size by using CD4 count predictions for the entire sample of ARV recipients (column 3) yields significant estimates that are similar in magnitude to the IV estimates with individual fixed effects. A 100 point increase in CD4 count is associated with an increase in labor force participation rates of 22 percentage points. These estimates are consistent with the reduced form estimates of the labor supply response, which show that patients experience a 20 percent increase in labor force participation in the first three to six months of treatment. Using BMI as our health measure, increases the sample size for our analysis, yielding highly significant results for our instrumental variables approach. The results for BMI (columns 4-6) are broadly consistent with those reported for the CD4 count.

6.3 Decomposition of the Impact of ARV Therapy

The composition of adults' economic activities exhibits considerable variation according to gender and seasons of the year. Moreover, households with ARV patients are less likely to be engaged in farming for reasons that may have to do with their past health history and lower landholdings. In light of such differences, this section examines changes in labor supply more carefully, focusing on the composition of economic activities and differences between men and women.

Composition of Activities

Instead of using an aggregate measure of labor supply, we estimate equation 4 separately for each of the three different types of labor supply that were recorded in the survey: wage labor,

farm labor, non-farm business labor. Data from adults in the random sample are used to control for seasonal patterns in *each* of the labor activities. The results in columns 1-3 of Table 11 indicate that much of the increase in labor supply occurs in non-farm business work. Patients are more likely to begin doing wage labor and farm labor as well, but these increases are not statistically significant.

The results for monthly income from each of the three labor activities (columns 4-6 in Table 11) underscore the significance of seasonality in interpreting income patterns. While farm income is known to be highly seasonal, non-farm business income is less variable during the year. As a result, business income should be more responsive to short-term changes in health status. Indeed, we find there is a statistically significant increase in non-farm business income for ARV recipients in the early stages of treatment (column 6 in Table 11).

Labor Supply Impacts by Gender

The survey data from each round show that men are more likely to be engaged in income-earning activities in the past week than women. In results not reported, we also find gender differences for some components of labor supply: women are much less likely to work for a wage, but equally likely to work in a non-farm business. Thus it is possible that the impacts of ARV therapy on labor supply will differ according to the gender of the patient. To test for such differences, we estimate equation 4 separately for men and women.

As columns 1 and 2 of Table 12 show, for male patients there is no significant increase in labor force participation rates but a large and significant increase in weekly hours worked. This suggests that patients already working prior to initiation of treatment are the ones who increase their labor supply after treatment. For women, there is a large and significant increase of 20.8 percentage points in the labor force participation rate, but no significant increase in weekly hours worked. Combining these results with baseline observations provides an intuitive explanation for this pattern. Since men have high levels of baseline participation to begin with, most of their response to improved health takes the form of additional hours worked. For women, baseline participation is low, so labor supply is the natural margin for change.

6.4 Controlling for Attrition in the HIV Sample

Since our analysis so far has excluded ARV recipients who do not appear in our sample for both rounds, the estimated labor supply responses apply only to those ARV patients who survived and

continued to come to the clinic until round 2. The average response to ARV therapy for all treated patients is therefore likely to be smaller.

In the HIV sample, mortality of patients and loss to follow-up are the main reasons for attrition of individuals (and households) between the two rounds of the survey. For patients who were interviewed at the HIV clinic in round 1 but subsequently died or were lost to follow-up, we were unable to obtain any household information in round 2. Patients who are lost to follow-up can be assumed to have either stopped seeking HIV care altogether, transferred to another clinic, or died. Of the 320 HIV-positive AMPATH patients in our sample from round 1, 14 patients are known to have died before round 2, and another 12 patients were not found in round 2 (nearly all were lost to follow-up by AMPATH).

A conservative approach to estimating the average labor supply response to ARV therapy is to analyze the panel data while treating all attrited patients as individuals with *zero* labor supply in round 2. Since it is unlikely that all missing patients are dead or not working in the labor market, this strategy provides us with a lower bound on the labor supply response.[41] As Table 13 shows, we find that even with the inclusion of zero labor supply for patients who are deceased or lost to follow-up, there is a statistically significant increase in labor supply. All patients who had been on ARVs for fewer than 100 days in round 1 experienced an 11.7 percentage point increase in labor force participation rates and a 5.9 hour increase in weekly hours worked (compare to 16.7 percentage points and 6.9 hours in Table 9, for the analysis without attrited patients).

The reduced effectiveness of ARV therapy when it is initiated in very sick patients has been widely reported in the literature (Hogg et al., 2001; Wools-Kaloustian et al., 2005). Rates of progression to death are considerably higher when baseline CD4 counts are below 100/mm^3, thus compromising the short-term effectiveness of ARV therapy. In fact, for the 9 patients in our sample who died between round 1 and 2 and for whom a baseline CD4 count can be obtained in the AMRS, the average baseline CD4 count was 35.5/mm^3 (and the average round 1 CD4 count was 67/mm^3). This influences how to interpret the role of mortality in our analysis. While our earlier results should be recognized as being valid only for patients who survive, the broader relevance of these results is heightened if HIV-positive patients begin receiving treatment before

[41] Attrited patients who have not died may be receiving care at other clinics. Alternatively, patients from far away may have missed several appointments and therefore not been included in the round 2 sample.

having advanced to late stages of the disease (as will be the case when ARV treatment programs are scaled-up and become more established).

6.5 Estimating the Impact of Treatment on the Treated

As noted earlier, there is strong evidence that the health of individuals who have developed AIDS will decline rapidly without treatment, generally leading to death in less than one year (Morgan et al., 2002; Chequer et al., 1992). Since the baseline CD4 counts of patients in our sample are well below 200/mm^3 (the level associated with developing AIDS), very few of the patients would be working (or even alive) in round 2 without treatment. While this counterfactual case is not observed by us, we can provide an upper bound of the impact of treatment on the treated by assuming that without treatment, all patients in the sample would not be participating in the labor force in round 2. While the 'true' impact of treatment lies somewhere between our earlier estimates and the upper bound figures presented in this section, the clinical evidence on disease progression suggests that the true impact will be only slightly below the upper bound. Comparing the observed treated group to this constructed control group, we can obtain difference-in-difference estimates of the treatment impact. For patients who are just beginning treatment in round 1, the impact of ARV therapy on labor supply is very large: an increase in the labor force participation rate of 85.4 percentage points, and an increase in hours worked of 26 hours (not reported). This represents a 5-fold increase in participation and a 4-fold increase in hours worked relative to our earlier estimates of the labor supply response to treatment (in Table 8). Moreover, this suggests that our earlier results are considerable underestimates of the true impact of treatment on the treated. While our earlier results are useful in understanding how labor supply responds to health improvements among previously sick AIDS patients, the fact that they are underestimates of the treatment impact should be borne in mind when evaluating treatment interventions. In the concluding section of the paper, we use this estimated impact of treatment on the treated to provide a rough comparison of the costs and benefits of ARV therapy.

7. Response of Family Labor Supply to ARV Therapy

Intrahousehold reallocation of time is known to be an important consumption smoothing mechanism of households in low-income countries. In settings with imperfect financial markets, households often adjust the time spent by children and adults in activities such as schooling,

housework, and employment in response to sudden changes in income and health. These adjustments can have differential effects according to the age and gender of household members. For example, Jacoby and Skoufias (1997) find that children's school attendance in rural India is responsive to seasonal fluctuations in income. Others have examined time allocation to household activities and labor market activities in response to income and health shocks, finding that responses depend on the gender of household members (Pitt and Rosenzweig, 1990; Kochar, 1995). Such intrahousehold decisions about time allocation suggest that ARV therapy can also influence the labor supply of patients' family members. Having estimated a large increase in patients' labor supply due to ARV therapy (own-effect of health), this section examines the labor supply of children and adults in the patients' households (cross-effects of health).

There is a large theoretical and empirical literature on the role of income and substitution effects in individual time allocation decisions (beginning with Becker, 1965) and family labor supply (beginning with Ashenfelter and Heckman, 1974). A simple model of family labor supply can be used to illustrate the role of ARV therapy in influencing labor supply within the family. Two effects are likely to be especially relevant. First, as the treated patient begins to work, there is an income effect for the family. Since leisure is most likely a normal good, the cross-income effect within the family is negative and the increase in patient income leads other household members to work less. Second, as the treated patient's health improves, the time demanded for taking care of the patient and performing additional housework is diminished, thereby expanding other household members' time endowment for work and leisure. Since this "reduced caregiving" or "time release" effect exerts a positive influence on the labor supply of the patients' family members, the net effect of treatment on family members' labor supply is therefore theoretically ambiguous. Finally, there is also a third, cross-substitution effect on family members' labor supply (in response to an income-compensated change in the patient's market productivity). In the standard model of family labor supply, this effect can be positive or negative depending on whether the nonmarket times of the treated patient and the other family member are complements or substitutes, respectively.

To estimate the net effect of treatment on child and adult labor in ARV households, we examine longitudinal data on the labor supply of non-patient individuals in these households and use data from random sample households to control for monthly fluctuations in labor supply.

Specifically, the following equation is estimated with longitudinal data for non-patient individuals in ARV households and others in the random sample:

$$L_{iht} = \alpha_i + \beta_1(ARVHH_{<100,h} * ROUND2_t) + \beta_2(ARVHH_{>100,h} * ROUND2_t) + \beta_3 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{iht}. \quad (7)$$

L_{iht} is the labor supply measure of interest for individual i in household h at time t (round 1 or 2), α_i is a fixed effect for individual i, $ROUND2_t$ indicates whether the observation is from round 2, and $ARVHH_{<100,h}$ and $ARVHH_{>100,h}$ are indicator variables equal to 1 if household h has an adult who was receiving ARV therapy for less than or more than 100 days, respectively, at the time of the round 1 interview. We estimate equation 7 separately for men, women, and young and old boys and girls.

Table 14 presents summary statistics from the first round for children and adults in ARV households and random sample households (excluding HIV-positive patients at the Mosoriot HIV clinic). A large fraction of boys and girls in the random sample had engaged in some income-generating activities during the past week (78 percent and 74 percent, respectively), although the mean number of hours is considerably lower than for adults.[42] In general, household members of ARV patients are equally or less likely to be working than others in the random sample, although the cross-sectional comparisons can be misleading given differences in wealth, education, and other characteristics between the two groups of households.

Table 15 contains results from estimating equation 7. Panel A reports results for the labor supply of men and women. As column 1 shows, soon after initiation of ARV treatment for adult patients, there is a negative but insignificant change in the labor force participation rates of adults in the patients' households. For women in these households, the decline in labor supply is greater—14.6 percentage points—and almost significant at the 10 percent level (column 3). This suggests that, at the margin, women are more likely to compensate for changes in the AIDS patients' labor supply by entering and exiting the labor force. As men are generally more likely to remain in the labor force at all times, we do not observe any significant adjustment of their labor force participation decisions (column 2).

Panels B and C of Table 15 contain results for the labor supply of boys and girls, respectively. We examine responses among young and old children (8-12 years and 12-18 years)

[42] The mean hours worked by children are low enough to be consistent with regular school attendance, which will be examined in subsequent work.

separately to capture potentially heterogeneous responses among them. The results indicate that there is a large decline in the labor supply of young boys after an adult household member begins to receive ARV therapy, but no significant change for older boys. Girls do not significantly change their labor supply, regardless of age. Column 2 of the Panel B shows that the decline in labor supply for younger boys in ARV households occurs gradually. In households with an adult who began receiving treatment shortly before round 1, the change is labor force participation rates of young boys is -15.9 percentage points but not statistically significant. However, in households with adults who began receiving treatment more than 100 days before round 1, labor force participation rates decline by 22.7 percentage points and this coefficient is statistically significant. Hours worked also declines significantly for younger boys, with a reduction of 8.6 hours in households exposed to treatment for more than 100 days at the time of round 1. Given that boys in ARV households have an average labor force participation rate of 74 percent and average weekly hours worked of 12.3 hours in round 1, the estimates in Table 14 imply extremely large declines in labor supply between round 1 and round 2.

All else equal, young children in Kenya are less likely to be engaged in economic activities since there are no official school fees for primary school and the productivity of young children is likely to be low. Older boys, on the other hand, are considerably more likely to be engaged in economic activities and less likely to be enrolled in school. This may explain why, at the margin, young boys are more likely to be pulled into the labor force when adults become very sick and then pulled out of the labor force when the adults become healthy.[43] Given that girls allocate fewer hours to income-generating activities and more hours to housework, ARV therapy is more likely to exert its influence on their time allocation in the domain of housework (not measured in labor supply), especially since adult women in the household appear to be adjusting their labor supply in response to disease and treatment.

Another way of examining the influence of ARV therapy on household members' labor supply is to take advantage of variation in the number of treated adults in ARV households. In nine percent of the ARV households, there are two adult patients receiving ARV therapy. These households are much more heavily burdened by AIDS in the months prior to round 1 and experience larger health improvements between rounds than households with only one ARV

[43] Future research will examine whether there are corresponding changes in school enrollment or attendance for boys.

patient. Thus, we examine whether there are larger changes in labor supply in these ARV household by estimating the following equation:

$$L_{iht} = \alpha_i + \beta_1(ARVHH_{2\,patient,h} * ROUND2_t) + \beta_2(ARVHH_{1\,patient,h} * ROUND2_t) + \beta_3 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{iht}. \quad (8)$$

The indicator variable $ARVHH_{2patient,h}$ equals 1 if household h has more than one adult ARV recipients and 0 otherwise. Likewise, $ARVHH_{1patient,h}$ equals 1 if household h has only one adult ARV recipient.

The results from estimating equation 8 are presented in Table 16. In panel A, we find that in double-patient households there is a significant decline over time in the number of hours worked by both men and women. In single-patient households, however, hours worked by adults do not change significantly. Panel B shows that for boys of all ages, there is a much larger decline in labor supply in the double-patient households than the single-patient households (columns 1 and 2). *For young boys in double-patient households*, the decline in labor force participation is 79.2 percentage points, as compared to 14.3 percentage points in single-patient households (column 2). Hours worked by young boys in all ARV households also declines significantly, but the responses are again larger in double-patient households (column 5). *For older boys in double-patient households*, there is a significant decline in both labor force participation and hours worked (columns 3 and 6). Older boys in single-patient households, however, do not experience any significant change in labor supply. Finally, Panel C shows that the labor supply of girls does not change significantly in both types of households.

These results suggest that in households with multiple adults who have developed AIDS, other household members (particularly boys and adults) are forced to do considerably more market work before treatment is initiated, possibly in the place of the patient. Upon initiation of treatment, these household members are able to work less. More generally, in contrast to the large positive changes in the labor supply of treated patients, the results in this section always show zero or negative changes in the labor supply of patients' household members. These results suggest that the income effect from the higher labor supply of treated patients is larger than the time release effect that comes from the treated patient no longer being sick, thus allowing some household members to decrease their labor supply. They also suggest that households are engaged in their customary function of smoothing total market and non-market labor supply over time as they face the negative health shock of AIDS and the offsetting, positive

health shock from ARV therapy. Finally, an important implication of these results is that ARV therapy influences outcomes of not just the treated patient but also individuals living with the patient.

8. Conclusion

This paper provides the first evidence on how ARV therapy affects the labor supply of AIDS patients and their household members. Using data from our household survey, we find that patients have significantly higher labor supply within six months after the initiation of treatment. This response is also large, with patients showing a 20 percent increase in labor force participation rates and a 35 percent increase in hours worked. Importantly, these results suggest that with treatment, the labor supply of AIDS patients can recover rapidly from periods of severe illness. We also find evidence that the labor supply of patients' family members (particularly young boys) declines after initiation of treatment. This suggests that family members may have been compensating for previously sick patients' diminished labor supply and that they too experience some of the benefits from treatment. These effects are larger and impact more household members in multiple-patient families. Taken together, the results providence evidence that ARV therapy has significant non-health benefits and influences a range of intrahousehold decisions.

In the absence of data from a randomly chosen sample of AIDS patients who do not receive ARV therapy, it will be difficult to estimate the full impact of treatment on the treated. Given ethical constraints to implementing such an evaluation, our strategy represents the best available method of estimating the response to treatment while controlling for important confounding factors (such as seasonality in labor supply). Moreover, especially for the case of patients' labor supply, we argue that our results are underestimates of the treatment effect because there is considerable medical evidence that untreated AIDS patients will die very quickly. Our conclusion that treatment results in significantly higher labor supply would only be strengthened if the analysis were based on comparison to a true counterfactual group.

Although the number of HIV-positive individuals requiring ARV therapy will continue to grow during the next decade, treatment programs have yet to be scaled up in many countries. The results presented in this paper are therefore highly relevant for evaluating such interventions. In fact, the labor supply response we have estimated can provide an important first step in

analyzing the costs and benefits of ARV therapy. Median daily wage rates for all adults doing casual wage labor in our sample are 100 Kenya shillings, or about $1.50. Since this daily wage is associated with six hours of work, the hourly wage is about 17 Kenya shillings, or $0.25. Using our base case estimates of a 6.9 hour average increase in weekly hours worked, treatment can thus be expected to yield an average wage benefit to patients of $86 per year (assuming individual work 50 weeks per year). This estimate is based on the labor supply impact relative to pre-treatment labor supply. However, for the purpose of a cost-benefit evaluation, it is essential to calculate benefits using the impact of treatment on the treated—based on a comparison to counterfactual outcomes rather than pre-treatment outcomes. Using our upper bound of the treatment impact (calculated by assuming that patients would have zero labor supply within six months if treatment were not provided), the average increase in weekly hours worked is 26 hours. In this case the average wage benefit to patients from treatment is $325 per year, which is considerably larger than the $150 annual per-patient cost of first-line ARV drugs. In addition to ARV drug expenditure, however, there are several additional costs associated with providing treatment, such as the costs of lab tests, treatment for opportunistic infections, clinic space, and medical personnel. AMPATH estimates these costs to be approximately $200 per-patient. Thus, the total patient wage benefit from providing treatment is roughly equal to the total cost of drugs and other associated expenses.

However, these are only the simple private wage gains for the patients. Since treatment expands the time endowment of patients by reducing sick time, patients are also consuming more leisure. Moreover, while the reduced market labor supply of children due to the provision of treatment does represent a loss in market income for the household, it is likely that the increased nonmarket activities of these household members have greater private value to the household as a whole. As a result, the fact that children reduce their labor supply suggests that the benefit of treatment is larger than the income gain from the parent's increased supply of labor (and leisure). In line with the severity of HIV/AIDS, these results underscore the importance of maintaining a broad perspective when analyzing the costs and benefits of ARV treatment. The social benefits from treatment are likely to exceed the private benefits, but valuing them is a non-trivial challenge. As a result, one purpose of the rough cost-benefit calculations presented above is to show that the private benefits from treatment alone can cover the costs of treatment. Indeed, the large labor supply responses we find here are not the only socio-economic outcomes likely to be

affected by ARV therapy. Both HIV/AIDS and treatment can be expected to influence many other aspects of life within patients' households. Additional analysis of our data suggests important effects on the nutritional status of children living with ARV recipients. Schooling and other forms of investment may also be affected, especially since we find that the incidence of child labor decreases due to treatment. All of these responses will contribute to an understanding of the comprehensive welfare consequences of ARV therapy. A detailed analysis of these other non-health outcomes is part of our future research agenda.

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Table 1. Comparison of Random Sample and HIV Sample

	Random Sample		HIV Sample		
	Mean	Std. Error	Mean	Std. Dev.	P-value
Number of households	503		266		
Household Structure (includes members entering between round 1 and round 2)					
Household size	6.04	0.13	5.45	0.15	0.0038
Average age of household members	24.93	0.57	23.78	0.56	0.1794
Number of under-18 children	3.32	0.10	3.02	0.11	0.0597
Percent of under-18 children who are orphans	6.9%		29.4%		0.0000
Number of extended family members in household	0.92	0.06	1.14	0.09	0.0432
Number of children living outside household	1.92	0.12	1.58	0.15	0.0949
Household Head Characteristics					
Male household head	81%		54%		0.0000
Single household head	22%		50%		0.0000
Age of household head	47.94	0.69	44.84	0.850	0.0062
Asset Ownership (round 1)					
Quantity of land owned (acres)	6.82	0.47	4.72	0.55	0.0054
Percent landless	13.2%		27.2%		0.0000
Value of land owned (shillings)	650,237	44,416	571,555	73,285	0.3316
Value of livestock owned (shillings)	61,401	4,194	36,571	4,148	0.0001

Notes: P-value from t-test for equality of means for Random sample and HIV sample.

Table 2. Impact of ARV therapy on CD4 count and BMI

	(1)	(2)
Dependent variable:	CD4	BMI
	F.E.	F.E.
On ARVs at least 1 month		0.38
		(2.65)***
On ARVs at least 2 months		0.18
		(1.18)
On ARVs at least 3 months	126.72	-0.10
	(10.60)***	(0.61)
On ARVs at least 4 months		0.21
		(1.29)
On ARVs at least 5 months		0.06
		(0.43)
On ARVs at least 6 months	-9.11	0.45
	(0.55)	(3.25)***
On ARVs at least 7 months		0.29
		(2.46)**
On ARVs at least 8 months		0.30
		(2.14)**
On ARVs at least 9 months	41.34	0.53
	(2.31)**	(3.71)***
On ARVs at least 10 months		0.14
		(0.93)
On ARVs at least 11 months		0.22
		(1.45)
On ARVs at least 12 months	7.45	0.27
	(0.37)	(1.79)*
On ARVs at least 15 months	38.71	0.08
	(1.31)	(0.50)
On ARVs at least 18 months	0.42	0.09
	(0.01)	(0.52)
Constant	87.48	19.53
	(12.56)***	(275.93)***
Observations	458	2678
Number of patients	183	164
R-squared	0.52	0.34

Individual fixed effects (F.E.) regressions for ARV patients in our sample.

CD4 is the CD4+ T-cell count

BMI is the body mass index

Data Source: AMPATH Medical Records System

Notes: Absolute value of t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variables are the CD4+ T cell count (column 1) and body mass index (column 2). Regressions include patient fixed effects (F.E.).

Table 3. CD4 and BMI Data for Patients in ARV Sample

	Round 1			Round 2			
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	P-value
CD4+ T-cell count	N=132			N=93			
	174.0	147.5	137.6	244.6	217	148.0	0.0003
Body mass index (BMI)	N=161			N=161			
	20.5	20.1	3.4	21.7	21.3	3.4	0.0015

	Mean	Median	Std. Dev.	5 %-tile	95 %-tile
CD4 count at ARV initiation	N=144				
	95.1	67	110.7	6	206
Days on ARVs (at Round 1)	N=191				
	171.5	126	207.7	-51	707

Number of days patients were on ARVs at Round 1 interview		
True baseline (<=0 days)	36	19%
0-100 days	50	26%
>100 days	105	54%

Notes: P-value from t-test for equality of means for round 1 and round 2.

Table 4. Summary Statistics for Adult Labor Supply in Round 1

Adults (ages 18-65 years)	Random sample		ARV Recipients		
(appearing in both rounds)	Mean	Std Dev	Mean	Std Dev	P-value
	N=1286		N=191		
Age	33.1	12.8	36.8	8.7	0.00
Female	49%		76%		0.00
Years of School Completed	8.1	3.3	7.8	3.2	0.21
Completed Primary	57%		49%		0.05
Activities in past 7 days					
Worked for a wage	17%		18%		0.56
Worked on own farm	84%		60%		0.00
Worked in own business	16%		17%		0.56
No work done in the past week	11%		24%		0.00
Total hours worked in past 7 days					
Unconditional on working	35.3	26.2	24.3	23.0	0.00
Conditional on working	39.6	24.6	32.0	21.2	0.00
Total income in past month	1996	4547	1761	4265	0.51

Notes: P-value from t-test for equality of means for random sample and ARV recipients.

Table 5. Reported Reasons for Not Working in the Past Week (Round 1 only)

	Random sample	ARV patients
Sample size (adults 18-65 years)	1286	191
Did no work in past week	10.8%	24.1%
Reported reason for not working in past week	(N=138)	(N=46)
Sick	**8%**	**85%**
Student	54%	0%
Housework	12%	0%
No work available	7%	7%
Other	18%	9%

Table 6. Labor Force Participation in Round 1 and 2

	(1)	(2)	(3)	(4)
Dependent variable:	**Labor Force Participation in Past Week**			
	Round 1		Round 2	
Age	0.033	0.033	0.035	0.035
	(7.44)***	(7.59)***	(8.35)***	(8.38)***
Age-squared / 100	-0.040	-0.040	-0.040	-0.040
	(6.86)***	(7.02)***	(7.37)***	(7.41)***
Female	-0.066	-0.067	-0.041	-0.042
	(3.88)***	(3.96)***	(2.58)**	(2.59)***
Completed Primary School	-0.039	-0.041	-0.056	-0.057
	(2.22)**	(2.34)**	(3.37)***	(3.40)***
HIV+ patients not on ARVs	-0.132	-0.133	-0.095	-0.096
	(2.90)***	(2.94)***	(2.24)**	(2.26)**
Patients on ARVs	-0.170		-0.096	
	(5.81)***		(3.74)***	
Patients on ARVs < 100 days in Round 1		-0.282		-0.128
		(7.26)***		(3.61)***
Patients on ARVs > 100 days in Round 1		-0.079		-0.071
		(2.21)**		(2.18)**
Constant	0.364	0.359	0.274	0.273
	(4.70)***	(4.66)***	(3.54)***	(3.53)***
Observations	1535	1535	1535	1535
R-squared	0.08	0.09	0.09	0.09

Notes: Absolute value of t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variable indicates whether the individual was engaged in any income-generating activity in the past week. OLS regression results are reported and month-of-interview indicator variables are included.

Table 7. Hours Worked in Past week, in Round 1 and 2

	(1)	(2)	(3)	(4)
Dependent variable:	**Total Hours worked in past week**			
	Round 1		Round 2	
Age	3.431	3.450	3.427	3.431
	(10.55)***	(10.62)***	(11.68)***	(11.69)***
Age-squared / 100	-4.056	-4.082	-4.020	-4.026
	(9.54)***	(9.61)***	(10.62)***	(10.62)***
Female	-13.672	-13.712	-11.586	-11.594
	(10.90)***	(10.94)***	(10.35)***	(10.36)***
Completed Primary School	-0.579	-0.646	1.137	1.121
	(0.44)	(0.49)	(0.97)	(0.96)
HIV+ patients not on ARVs	-10.246	-10.284	-7.830	-7.846
	(3.05)***	(3.07)***	(2.65)***	(2.66)***
Patients on ARVs	-11.596		-8.928	
	(5.36)***		(4.98)***	
Patients on ARVs < 100 days in Round 1		-15.785		-9.916
		(5.47)***		(4.00)***
Patients on ARVs > 100 days in Round 1		-8.200		-8.133
		(3.08)***		(3.60)***
Constant	-19.579	-19.782	-31.448	-31.487
	(3.42)***	(3.46)***	(5.84)***	(5.85)***
Observations	1535	1535	1535	1535
R-squared	0.18	0.18	0.16	0.17

Notes: Absolute value of t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variable is total number of hours devoted to income-generating activities in the past week. OLS regression results are reported and month-of-interview indicator variables are included.

Table 8. Impact of ARV Therapy on Labor Supply, with Individual Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	LFP	Hours	LFP	Hours	Hours
	Individual F.E.				
Round 2 * Patient on ARVs	0.082	3.651			
	(2.58)***	(1.65)*			
Round 2 * Patient on ARVs < 100 days in Round 1			0.167	6.934	3.328
			(3.89)***	(2.31)**	(0.93)
Round 2 * Patient on ARVs > 100 days in Round 1			0.013	0.992	-0.025
			(0.33)	(0.36)	(0.01)
Constant	0.878	35.863	0.878	35.871	41.971
	(35.90)***	(21.05)***	(36.00)***	(21.07)***	(23.25)***
Observations	3070	3070	3070	3070	2668
Number of adults	1535	1535	1535	1535	1334
R-squared	0.03	0.05	0.03	0.06	0.10

Notes: Absolute value of t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variable *LFP* indicates whether the individual was engaged in any income-generating activity in the past week and *Hours* is total number of hours devoted to income-generating activities in the past week. Regressions include individual fixed effects (F.E.), round 2 indicator variable, and month-of-interview indicator variables. Sample includes observations for 70 HIV-positive patients not receiving ARV therapy. There is a separate explanatory variable for this group (interacted with round 2).

Table 9. Estimating the Timepath of Labor Supply after Initiation of ARVs

	(1)	(2)
Dependent Variable:	LFP	Hours
	Individual F.E.	
3 months prior to ARV initiation	0.082	-1.746
	(0.45)	(0.14)
On ARVs at least 3 mths ago	0.123	6.867
	(2.16)**	(1.72)*
On ARVs at least 6 mths ago	0.087	0.047
	(1.34)	(0.01)
On ARVs at least 9 mths ago	-0.022	-0.630
	(0.30)	(0.13)
On ARVs at least 12 mths ago	-0.078	-3.411
	(0.92)	(0.58)
On ARVs at least 15 mths ago	0.107	3.820
	(1.16)	(0.59)
Constant	0.870	35.574
	(35.07)***	(20.52)***
Observations	3070	3070
Number of adults	1535	1535
R-squared	0.04	0.06

Notes: Absolute value of t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variable *LFP* indicates whether the individual was engaged in any income-generating activity in the past week and *Hours* is total number of hours devoted to income-generating activities in the past week. Regressions include individual fixed effects (F.E.), round 2 indicator variable, and month-of-interview indicator variables. Sample includes observations for 70 HIV-positive patients not receiving ARV therapy. There is a separate explanatory variable for this group (interacted with round 2).

Table 10a. First stage regression: effect of ARVs on health status

	(1)	(2)
Dependent variable:	CD4	BMI
	F.E.	
On ARVs at least 3 mths ago	71.4	2.085
	(1.96)*	(4.72)***
On ARVs at least 6 mths ago	17.8	0.611
	(0.56)	(1.43)
On ARVs at least 9 mths ago	-61.0	0.306
	(1.36)	(0.62)
On ARVs at least 12 mths ago	47.3	0.174
	(0.94)	(0.31)
On ARVs at least 15 mths ago	33.7	0.252
	(0.70)	(0.38)
Constant	193.8	18.873
	(2.28)**	(14.61)***
Observations	225	323
Number of patients	156	164
R-squared	0.63	0.42

Notes: Absolute value of t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variables are the CD4 count and body mass index (BMI). All regressions include patient fixed effects (F.E.), round 2 indicator variable and month-of-interview indicator variables. Sample is restricted to ARV recipients in the sample for whom a CD4 count or BMI is available in the AMRS at the time of the round 1 or round 2 interview.

Table 10b. Effect of CD4 and BMI on labor force participation for ARV Recipients

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Labor force participation in past week					
	F.E.	IV, F.E.	Pred, F.E.	F.E.	IV, F.E.	Pred, F.E.
CD4/100	0.002	0.225	0.220			
	(0.03)	(1.57)	(2.59)**			
BMI				0.062	0.097	0.157
				(3.75)***	(2.61)***	(2.79)***
Constant	0.871	0.463	0.426	-0.384	-1.074	-2.373
	(1.84)*	(0.82)	(1.55)	(0.89)	(1.36)	(2.04)**
Observations	225	225	382	323	323	382
Number of patients	156	156	191	164	164	191
R-squared	0.16	.05	0.12	0.18	.05	0.12

Notes: Absolute value of t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variable indicates whether the individual was engaged in any income-generating activity in the past week. CD4 represents the CD4 count and BMI is the body mass index. All regressions include round 2 indicator variable and month-of-interview indicator variables. Columns 1 and 4 include individual fixed effects (F.E.). Columns 2 and 4 estimate instrumental variables specification with individual fixed effects (IV, FE) in which first stage regression estimates impact of ARV therapy on CD4 and BMI (Table 10a) for patients with available CD4 and BMI. Columns 3 and 4 based on CD4 and BMI that is constructed for *all* ARV recipients in the sample using the coefficients from estimating first stage regression (Pred, FE).

Table 11. Impact of ARV Therapy on Components of Labor Supply

	(1)	(2)	(3)	(1)	(2)	(3)
Dependent variable:	Labor force participation (past wk.)			Income earned (past mth.)		
	Wage	Farm	Business	Wage	Farm	Business
	Individual F.E.			Individual F.E.		
Round 2 * Patient on ARVs < 100 days in Round 1	0.050	0.061	0.178	-137.520	-1,249.349	663.071
	(1.24)	(1.14)	(3.88)***	(0.32)	(0.68)	(2.00)**
Round 2 * Patient on ARVs > 100 days in Round 1	0.006	-0.004	-0.007	-145.807	82.836	166.732
	(0.15)	(0.07)	(0.17)	(0.37)	(0.05)	(0.53)
Constant	0.161	0.833	0.189	906.534	-1,085.488	583.004
	(6.94)***	(26.76)***	(7.14)***	(3.69)***	(1.03)	(3.04)***
Observations	2959	2959	2959	2959	2959	2959
Number of adults	1528	1528	1528	1528	1528	1528
R-squared	0.02	0.02	0.03	0.01	0.01	0.02

Notes: Absolute value of t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variable *Labor force participation* indicates whether the individual was engaged in specific income-generating activity (wage, farm, or business) in the past week and *Income earned* is total income earned from specific income income-generating activity (wage, farm, or business) in the past month. Regressions include individual fixed effects (F.E.), round 2 indicator variable, and month-of-interview indicator variables. Sample includes observations for 70 HIV-positive patients not receiving ARV therapy. There is a separate explanatory variable for this group (interacted with round 2)

Table 12. Impact of ARV Therapy for Men and Women

	(1)	(2)	(3)	(4)
Dependent variable:	LFP	Hours	LFP	Hours
	Men		Women	
	Individual F.E.			
Round 2 * Patient on ARVs < 100 days in Round 1	0.049	12.795	0.208	3.927
	(0.69)	(2.11)**	(3.66)***	(1.15)
Round 2 * Patient on ARVs > 100 days in Round 1	0.030	3.978	0.010	-1.378
	(0.42)	(0.66)	(0.20)	(0.45)
Constant	0.901	44.109	0.851	29.338
	(27.56)***	(16.04)***	(23.08)***	(13.30)***
Observations	1430	1430	1640	1640
Number of adults	715	715	820	820
R-squared	0.02	0.08	0.06	0.04

Notes: Absolute value of t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variable *LFP* indicates whether the individual was engaged in any income-generating activity in the past week and *Hours* is total number of hours devoted to income-generating activities in the past week. Regressions include individual fixed effects (F.E.), round 2 indicator variable, and month-of-interview indicator variables. Sample includes observations for 70 HIV-positive patients not receiving ARV therapy. There is a separate explanatory variable for this group (interacted with round 2).

Table 13. Impact of ARV Therapy With Attritors in the ARV Sample

	(1)	(2)	(3)	(4)
Dependent variable:	LFP	Hours	LFP	Hours
	Individual F.E.			
Sample includes:	deceased		deceased & lost to FUP	
Round 2 * Patient on ARVs < 100 days in Round 1	0.146	6.487	0.117	5.891
	(3.38)***	(2.20)**	(2.76)***	(2.05)**
Round 2 * Patient on ARVs > 100 days in Round 1	-0.007	0.687	-0.005	0.759
	(0.19)	(0.25)	(0.12)	(0.28)
Constant	0.875	35.675	0.871	35.489
	(35.01)***	(20.87)***	(34.26)***	(20.69)***
Observations	3096	3096	3120	3120
Number of adults	1548	1548	1560	1560
R-squared	0.03	0.05	0.02	0.05

Notes: Absolute value of t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variable *LFP* indicates whether the individual was engaged in any income-generating activity in the past week and *Hours* is total number of hours devoted to income-generating activities in the past week. Regressions include individual fixed effects (F.E.), round 2 indicator variable, and month-of-interview indicator variables. Sample includes observations for 70 HIV-positive patients not receiving ARV therapy. There is a separate explanatory variable for this group (interacted with round 2).

Table 14. Summary Statistics for Labor Supply of Non-Patient Children and Adults

	Random Sample		ARV households		
	Mean	Std Dev	Mean	Std Dev	P-value
Boys (8-18 years)	433		152		
Worked in past week	78%		74%		0.24
Total hours worked in past 7 days	14.8	15.9	12.3	13.1	0.09
Girls (8-18 years)	347		143		
Worked in past week	74%		63%		0.02
Total hours worked in past 7 days	11.5	11.7	9.0	13.1	0.04
Men (18-65 years)	649		108		
Worked in past week	92%		85%		0.01
Total hours worked in past 7 days	41.9	27.7	26.8	27.1	0.00
Women (18-65 years)	622		125		
Worked in past week	86%		82%		0.17
Total hours worked in past 7 days	29.0	22.9	20.7	18.5	0.00

Notes: P-value from t-test for equality of means for random sample and ARV recipients. Statistics for ARV households exclude ARV recipients and other HIV-positive patients at the Mosoriot HIV clinic.

Table 15. Impact of ARV Therapy on Family Labor Supply

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Adults						
Dependent variable:	LFP			Hours		
	All adults	Men	Women	All adults	Men	Women
ARV hh (<100 days) * Rd. 2	-0.087	-0.030	-0.146	2.020	5.498	-1.117
	(1.25)	(0.34)	(1.59)	(0.57)	(1.09)	(0.26)
ARV hh (>100 days) * Rd. 2	0.013	-0.082	0.085	2.405	0.708	3.584
	(0.25)	(1.27)	(1.07)	(0.70)	(0.13)	(0.91)
Constant	0.924	0.990	0.855	37.234	43.530	30.653
	(31.21)***	(25.83)***	(22.31)***	(16.57)***	(14.12)***	(11.94)***
Observations	3107	1589	1518	3107	1589	1518
R-squared	0.67	0.69	0.67	0.75	0.75	0.71
Panel B. Boys						
Dependent variable:	LFP			Hours		
	All boys	8-12 years	12-18 years	All boys	8-12 years	12-18 years
ARV hh (<100 days) * Rd. 2	-0.142	-0.159	-0.167	-3.762	-3.785	-4.066
	(1.46)	(1.13)	(1.40)	(1.41)	(1.36)	(1.05)
ARV hh (>100 days) * Rd. 2	-0.108	-0.227	-0.056	-3.458	-8.644	-0.484
	(1.22)	(2.08)**	(0.49)	(1.47)	(3.16)***	(0.16)
Constant	0.852	0.819	0.877	20.080	16.705	22.301
	(14.99)***	(8.11)***	(15.44)***	(9.59)***	(5.09)***	(9.17)***
Observations	1226	488	738	1226	488	738
R-squared	0.65	0.67	0.65	0.69	0.70	0.69
Panel C. Girls						
Dependent variable:	LFP			Hours		
	All girls	8-12 years	12-18 years	All girls	8-12 years	12-18 years
ARV hh (<100 days) * Rd. 2	0.005	0.103	-0.019	-0.988	0.105	-1.737
	(0.05)	(0.75)	(0.17)	(0.39)	(0.03)	(0.54)
ARV hh (>100 days) * Rd. 2	0.020	-0.091	0.074	1.466	1.701	1.342
	(0.18)	(0.53)	(0.61)	(0.59)	(0.58)	(0.43)
Constant	0.829	0.711	0.883	17.448	14.738	19.353
	(10.96)***	(6.33)***	(10.12)***	(9.16)***	(4.51)***	(8.89)***
Observations	1068	386	682	1068	386	682
R-squared	0.64	0.70	0.64	0.63	0.62	0.64

Notes: Errors clustered at the household level for each round and robust t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variable *LFP* indicates whether the individual was engaged in any income-generating activity in the past week and *Hours* is total number of hours devoted to income-generating activities in the past week. Regressions include individual fixed effects (F.E.), round 2 indicator variable, and month-of-interview indicator variables. ARV recipients are excluded from analysis. ARV household indicators equal 1 if there is an adult ARV recipient who received ARV therapy for <100 days or >100 in round 1.

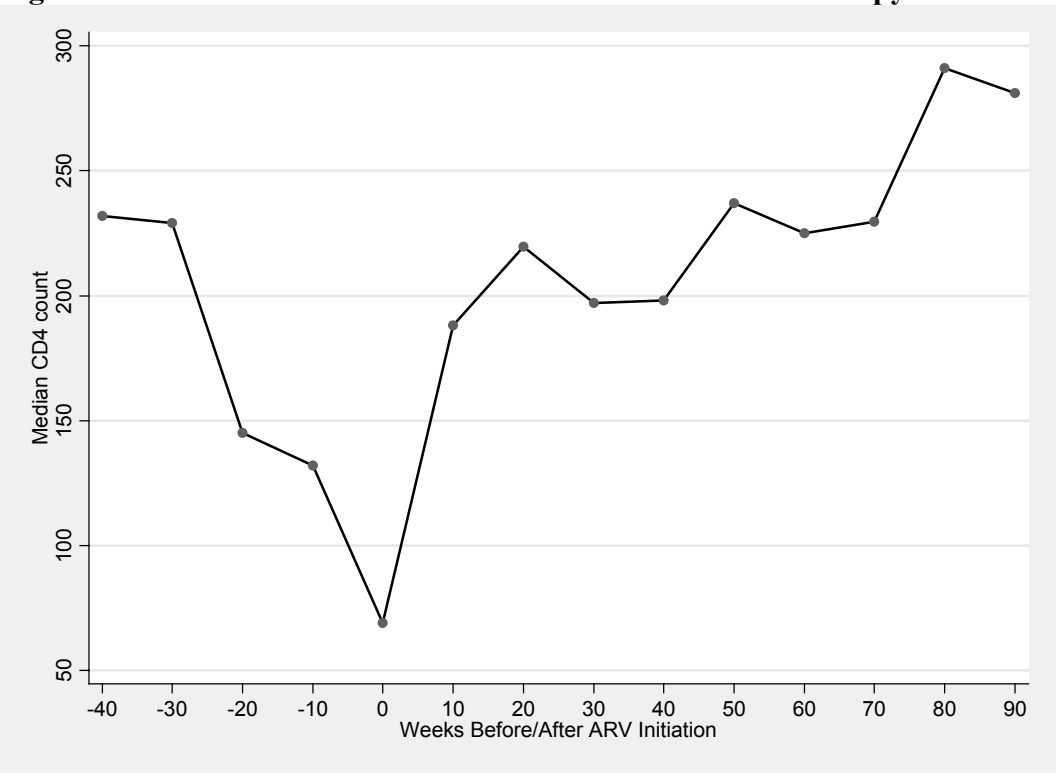
Table 16. Impact of ARV Therapy on Family Labor Supply According to Disease Burden

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Adults						
Dependent variable:	LFP			Hours		
	All adults	Men	Women	All adults	Men	Women
HH with 2 ARV patients * Rd. 2	-0.037	-0.006	-0.092	-21.090	-20.140	-22.999
	(1.30)	(0.21)	(1.63)	(2.86)***	(1.88)*	(5.45)***
HH with 1 ARV patient * Rd. 2	-0.020	-0.064	0.007	2.869	3.969	1.760
	(0.42)	(1.12)	(0.10)	(1.01)	(0.93)	(0.53)
Constant	0.923	0.990	0.848	37.122	43.383	30.474
	(30.60)***	(25.99)***	(21.85)***	(16.48)***	(14.05)***	(11.84)***
Observations	3107	1589	1518	3107	1589	1518
R-squared	0.67	0.69	0.66	0.75	0.75	0.71
Panel B. Boys						
Dependent variable:	LFP			Hours		
	All boys	8-12 years	12-18 years	All boys	8-12 years	12-18 years
HH with 2 ARV patients * Rd. 2	-0.404	-0.792	-0.267	-15.488	-12.448	-16.717
	(2.77)***	(3.44)***	(1.82)*	(3.55)***	(2.84)***	(3.19)***
HH with 1 ARV patient * Rd. 2	-0.082	-0.143	-0.075	-2.481	-6.573	0.128
	(1.10)	(1.54)	(0.78)	(1.24)	(2.71)***	(0.05)
Constant	0.850	0.833	0.877	20.092	16.989	22.136
	(15.04)***	(8.36)***	(15.21)***	(9.65)***	(5.08)***	(9.32)***
Observations	1226	488	738	1226	488	738
R-squared	0.65	0.68	0.65	0.70	0.70	0.70
Panel C. Girls						
Dependent variable:	LFP			Hours		
	All girls	8-12 years	12-18 years	All girls	8-12 years	12-18 years
HH with 2 ARV patients * Rd. 2	0.000	0.338	-0.085	-3.405	5.255	-5.393
	(0.00)	(0.72)	(0.57)	(0.69)	(0.68)	(1.03)
HH with 1 ARV patient * Rd. 2	0.060	0.027	0.096	0.622	0.660	0.591
	(0.75)	(0.21)	(1.09)	(0.29)	(0.25)	(0.22)
Constant	0.822	0.714	0.877	17.422	14.714	19.400
	(10.88)***	(6.25)***	(10.02)***	(9.09)***	(4.49)***	(8.79)***
Observations	1068	386	682	1068	386	682
R-squared	0.64	0.70	0.64	0.63	0.62	0.65

Notes: Errors clustered at the household level for each round and robust t-statistics in parentheses (* significant at 10%; ** significant at 5%; *** significant at 1%). Dependent variable *LFP* indicates whether the individual was engaged in any income-generating activity in the past week and *Hours* is total number of hours devoted to income-generating activities in the past week. Regressions include individual fixed effects (F.E.), round 2 indicator variable, and month-of-interview indicator variables. ARV recipients are excluded from analysis.

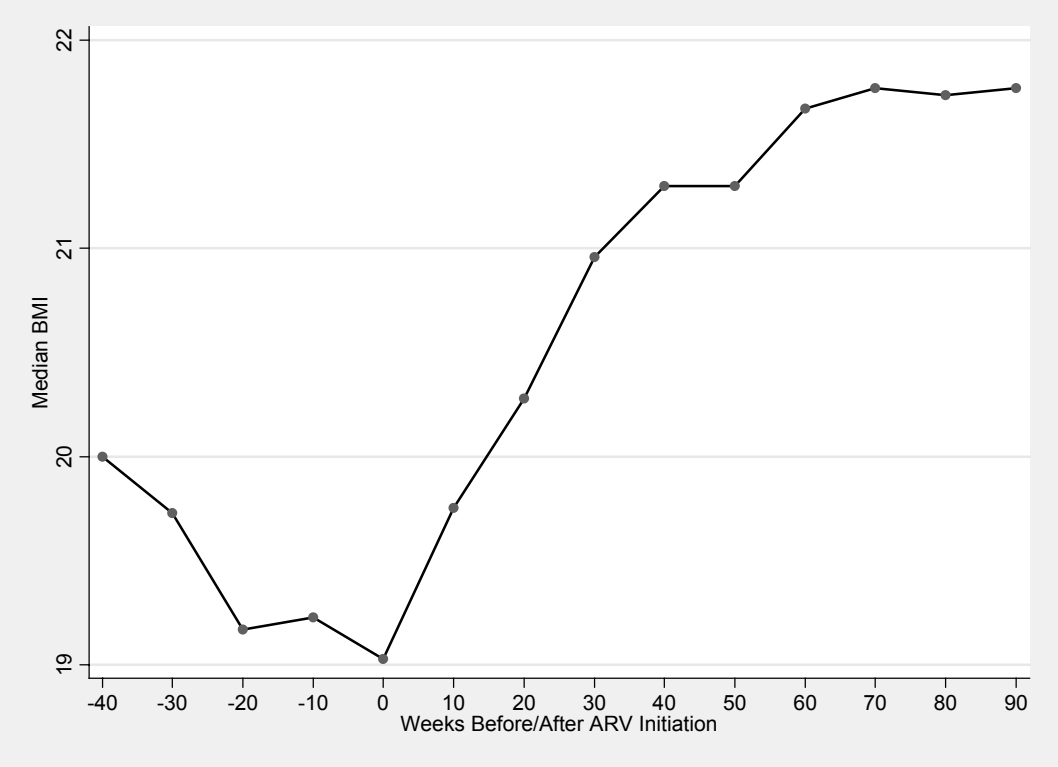
Figure 1. Map of Kenya

Figure 2. CD4 Count Before and After Initiation of ARV Therapy



Source: AMPATH Medical Records System for Mosoriot HIV Clinic.

Figure 3. BMI Before and After Initiation of ARV Therapy



Source: AMPATH Medical Records System for Mosoriot HIV Clinic.

Figure 4. Labor Force Participation Rates Before and After ARV Therapy

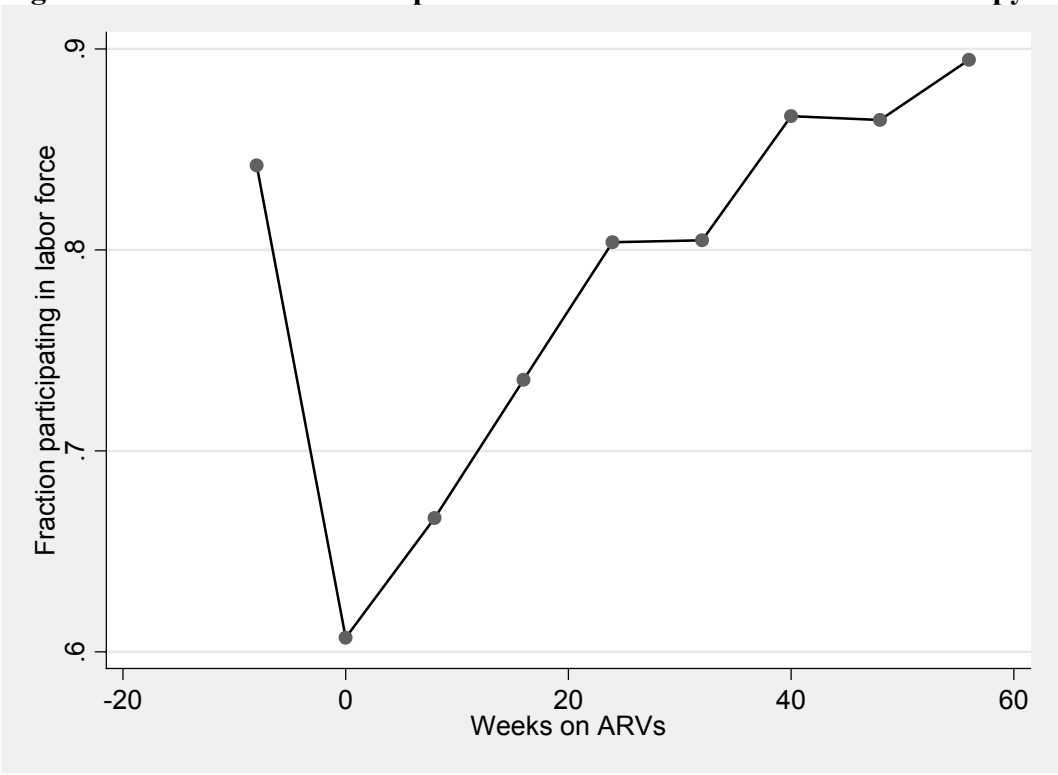


Figure 5. Weekly Hours Worked Before and After ARV Therapy

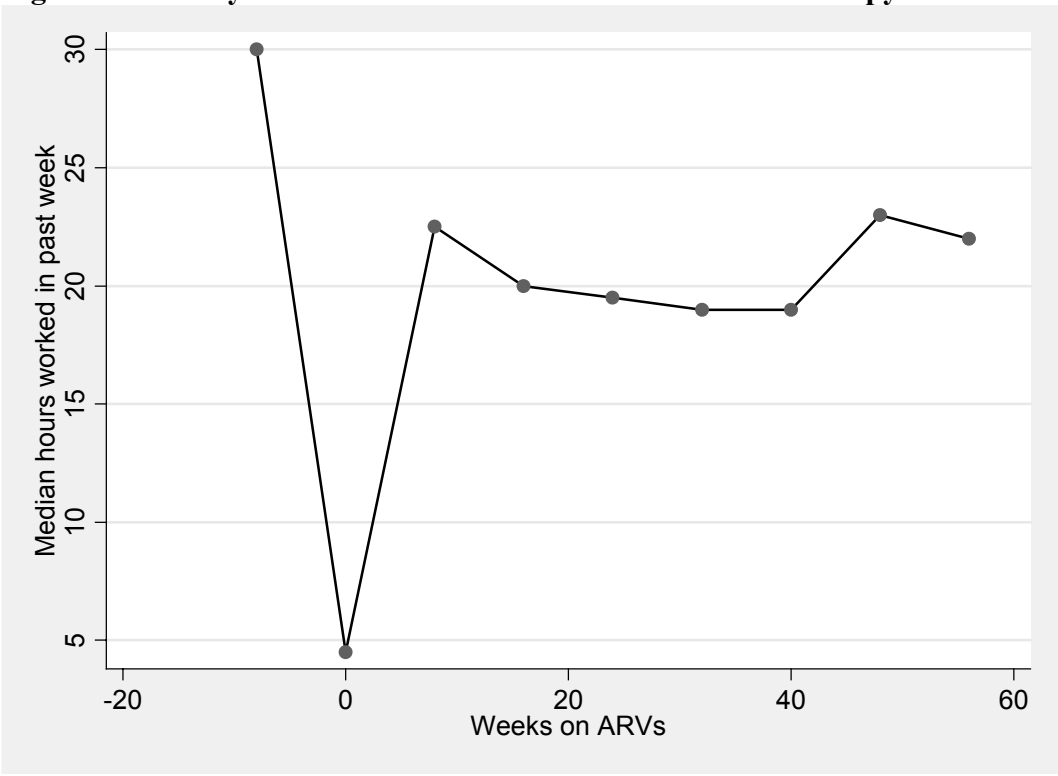


Figure 6. Hours Worked in Past Week by Month of Interview (Men and Women)