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

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October 2005

Abstract

Antiretroviral (ARV) therapy has been shown to reduce morbidity and mortality among people living with AIDS. In sub-Saharan Africa, the region most affected by HIV/AIDS, little is known about the extent to which ARV therapy affects socio-economic outcomes. Using longitudinal data from a household survey conducted in collaboration with a treatment program in western Kenya, this paper estimates the impact of ARV therapy on two outcomes: (1) the labor supply of adult AIDS patients receiving treatment; and (2) the labor supply of children and adults living in the patients' households. These impacts are identified by examining changes in the treatment group's labor supply over time and using data from a random sample of adults in the survey area to control for time-varying factors (such as seasonality) that also influence labor supply. We find that the provision of ARV therapy results in a large and relatively immediate increase in the labor supply of AIDS patients. Within six months after the initiation of treatment, there is a 20 percent increase in the likelihood of participating in the labor force and a 35 percent increase in weekly hours worked. The impacts of ARV therapy on the labor supply of individuals residing with the treated patients are heterogeneous. In particular, boys and women in treated patients' households work significantly less after initiation of treatment, while girls and men do not change their labor supply. These results show that ARV therapy influences intrahousehold time allocation decisions and that the benefits of treatment accrue to patients and their family members.

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* This project would not have been possible without support and assistance from the Academic Model for Prevention and Treatment of HIV/AIDS (AMPATH) and members of the IU-Kenya partnership. We are also grateful to Michael Boozer, T. Paul Schultz, and Christopher Udry for many comments and suggestions. We have benefited from discussions with Richard Akresh, Joseph Altonji, Amit Khandelwal, Christopher Ksoll, Tavneet Suri, and participants in seminars at Yale and the Center for Interdisciplinary Research on AIDS. We thank Kara Wools-Kaloustian and especially, Beverly Musick, for guidance in using the AMPATH medical records. Many individuals contributed to the implementation of the household survey under the direction of the authors and Mabel Nangami. Giovanna d'Adda assisted in managing the second round of the survey and the data collection was facilitated by the excellent field supervision of Irene Muhunzu. We also acknowledge the tremendous contributions of Andrew Anyembe, Caroline Amuyunzu, Jayne Chaina, Norbert Ketter, James Mungai, June Ochanda, and Jacklyne Tetee for administering questionnaires; and Chelimo Cherono, David Marende, Maurice Mungai, Florence Oduor, and Martha Simiyu for computer entry of questionnaires. Finally, we are indebted to the clinical officers and staff of the Mosoriot Rural Health Training Center, the HAART and Harvest Initiative farm, and the many individuals in Nandi District who participated in the survey. Financial support for this project was received from the Economic and Social Research Council (UK), Pfizer, Inc., The World Bank, Yale University's Center for Interdisciplinary Research on AIDS (CIRA) through a grant from the National Institute of Mental Health to Michael Merson, M.D. (No. P30 MH 62294), the Social Science Research Council, and the Calderone Program at Columbia University. All errors and opinions are our own.

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1. Introduction

Sub-Saharan Africa is home to 25 million of the nearly 40 million people living with HIV/AIDS (UNAIDS 2004). AIDS-related mortality among adults has created nearly 12 million orphans in the region, and some countries have seen life expectancy plummet to below 35 years. Following increases in donor support and substantial reductions in the prices of medicines, antiretroviral (ARV) therapy has become an important part of the policy response to combat AIDS.[4] 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 is currently a major challenge in many countries.[5] At the same time, 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).[6]

Numerous studies have shown that highly active antiretroviral therapy[7] reduces morbidity and mortality among HIV-infected individuals, in both industrialized countries (Hogg et al. 1998; Palella et al. 1998; Hogg et al. 2001) and developing countries (Laurent et al. 2002; Marins et al. 2003; Koenig, Leandre, and Farmer 2004; Coetzee et al. 2004; Wools-Kaloustian et al. 2005). Particularly in low-income settings, these health impacts can result in large improvements in socio-economic outcomes and influence a range of intrahousehold decisions and welfare measures.[8] For example, if treatment increases the likelihood that children attend or remain in school, the resulting accumulation of human capital have long-term implications. Given the enormous scope of non-health impacts from ARV therapy, proper assessment of the value of treatment programs and efficient allocation of resources depend critically on estimates of these non-health impacts. These estimates can also contribute to a better understanding of the long-term welfare consequences of AIDS, building upon recent studies by Bell, Devarajan, and Gersbach (2003) and Young (2005).

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[4] 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)

[5] As explained below, not all HIV-positive individuals are currently in need of ARV therapy.

[6] Furthermore, as many have pointed out, the belief that funding treatment is not economically worthwhile has been a key obstacle to obtaining greater donor support (Binswanger 2003; Clinton 2003).

[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.

[8] See Strauss and Thomas (1998) for a survey of the large literature on health and income in developing countries.

In this paper, we estimate the short-term impact of ARV therapy on the labor supply of adult AIDS patients and their family members in western Kenya. In many developing country settings, labor is an essential input in agricultural production and correlates strongly with income from other economic activities. Hence the labor supply of adults in the household will influence household welfare more generally. Several studies examining the impact of mortality in areas with high HIV prevalence have also placed an emphasis on labor supply (Yamano and Jayne 2004; Beegle 2004).[9] Fox et al. (2004) have estimated the impacts of AIDS-related morbidity. Using retrospective data from a Kenyan tea estate, they find significant decreases in the productivity of HIV-positive workers prior to their death or medical retirement. This study is the first to examine the extent to which ARV therapy can stop or reverse such declines in labor supply.

Our analysis is based on data from a household survey we conducted in collaboration with a growing ARV treatment program in western Kenya. Over the course of one year, longitudinal socio-economic and health data were collected from over 750 rural households, including many with AIDS patients who receive treatment at a rural HIV clinic. These data have been linked to longitudinal medical data containing clinical and laboratory measures of AIDS patients' health status. The presence of individuals whose HIV status is known status, the ARV treatment program, and the linked medical data are innovative features of this survey.

To identify the impact of treatment, we examine changes over time in the labor supply of treated patients and their household members. 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 patients in the sample 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 treatment—it improves dramatically soon after the initiation of treatment but improves more slowly thereafter. We exploit this nonlinearity to test for heterogeneous treatment impacts on labor supply.

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, we find a 20 percent increase in the likelihood of participating in the

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

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 greatly shortened life expectancy, our estimated labor supply impacts are an underestimate of the true impact of treatment on the treated.[10]

An analysis of ARV therapy on the labor supply of treated patients' household members is more complicated, as the impacts are theoretically ambiguous. On the one hand, the increase in a patient's labor supply increases family income, allowing other household members to work less. On the other hand, the improvement in a patient's health reduces the caretaker and housework burden on family members, thereby expanding their time endowment for work and leisure. We find that the labor supply of boys and women in patients' households declines after initiation of ARV therapy. This suggests that intrahousehold decisions about time allocation are influenced by the provision of treatment, and that as a result the welfare of some household members may increase considerably. The results for child labor are particularly important, as they allow for potential schooling impacts from treatment.

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 the medical data from the HIV clinic where this study was conducted to examine the medical outcomes of patients. We show that patients receiving ARV therapy have large improvements in medical outcomes. In Section 5, we discuss our strategy for estimating the impact on labor supply of patients. Section 6 presents the main results of the paper. In Section 7, we examine the labor supply of children and adults living with the 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 the virus destroys the white blood cells that are essential to the immune system. In sub-Saharan Africa, most HIV transmission among adults occurs through sexual intercourse between men and women. Soon after transmission, infected individuals enter a clinical latent period of many years during which

[10] Given the clinical effectiveness and life saving nature of ARV therapy, randomized evaluations of treatment interventions are not feasible on ethical grounds.

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).[11] 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, death usually occurs within one year after progression to AIDS. Indeed, one study in Uganda reports a median survival time of 9.2 months (Morgan et al. 2002) and another study in Brazil finds a median survival time of 5.1 months (Chequer et al. 1992). Opportunistic infections are generally the cause of death in AIDS cases.

ARV therapy has been proven to reduce the likelihood of opportunistic infections and prolong the life of HIV-infected individuals.[12] Numerous studies in various countries and patient populations have reported positive results (see, among many, Palella et al. 1998; Hogg et al. 2001). 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 the onset of 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 is an important issue in discussions about the provision of treatment. First-line ARV regimens used to cost more than $10,000 per patient per year. The widespread generic production of drugs in developing countries, has reduced these prices significantly—to $152 in June 2005 (Campaign for Access to Essential Medicines 2005). Further declines may be possible with greater generic competition and bulk purchasing agreements.

[11] Conversion to HIV-positive serology normally occurs within 4-10 weeks after transmission. The duration of the clinical latent period can be shorter. In developed countries, the duration has been found to vary from 7 to 15 years, depending on age, mode of transmission, and quality of care, among other factors.

[12] Highly active antiretroviral therapy always consists of three antiretroviral medications, with a common first-line regimen of nevirapine, stavudine, and lamivudine. Generic medications which combine 3 medications in 1 pill (such as Triomune) have recently become available.

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).[13] The Division has an area of 76 square miles and a population of 35,383 individuals that comprise 6,643 households (Central Bureau of Statistics 1999). Households are scattered across more than 100 villages where animal and crop farming is the primary economic activity and maize is the major crop.

The main health care provider in the survey area is the Mosoriot Rural Health Training Center, a government health center that mainly provides primary care services. The health center also contains a clinic which provides free medical care (including ARV therapy) to HIV-positive patients. This clinic was opened in November 2001 and was the first rural HIV clinic of the Academic Model for the Prevention and Treatment of HIV/AIDS (AMPATH).[14] 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.[15] During this period, adequate funding has been available to treat all patients who need ARV therapy (according to standard WHO criteria discussed in Section 4).[16,17]

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.[18] The survey sample contains two different groups of households: 503 households selected randomly from a census of all households in Kosirai Division without an AMPATH patient (random sample

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

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

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

[16] 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.

[17] As of June 2005, ARV therapy was being provided to 38,000 of nearly 250,000 Kenyans needing treatment (World Health Organization 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 AMPATH patients receiving ARVs).

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

households) and 266 households with at least one AMPATH patient (HIV households).[19] 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 and resided outside Kosirai Division but 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.

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.[20] 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.[21] The remaining HIV-positive patients in our sample had not progressed to AIDS and thus did not receive ARV therapy before round 2. Attrition between rounds due to mortality is minimal in the random sample (7 out of 3,097 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.[22] Height and weight measurements were made for children under the age of 5 years. Relevant outcomes such as asset sales and purchases, child anthropometrics, income, employment, and food consumption were recorded in each round to obtain longitudinal data.

Table 1 summarizes the main demographic characteristics of the random sample and HIV households in the sample during round 1. On average, households in the survey area have 6

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[19] 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.

[20] 274 of these 320 HIV-positive individuals were interviewed; HIV-positive spouses of in-clinic respondents were not interviewed, and neither were any HIV-positive children. 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.

[21] 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.

[22] 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.

members. HIV households tend to be smaller, with 5.4 members on average. There is a significant difference between households in the sex and marital status of the household head and the orphan status of children: HIV households are far 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 also own significantly less land and livestock, which is one of several indicators from the survey that they are worse off than other households in the community.[23]

4. Impact of ARV Therapy on Patient Health

The AMRS contains longitudinal information on the health status of patients at AMPATH's eight HIV clinics in western Kenya. Before estimating the impact of treatment on labor supply, in this section we discuss evidence from the AMRS on the health response to ARV therapy. 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.[24] 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. According to WHO guidelines, it is at this stage when functional capacity deteriorates and patients should begin ARV therapy (WHO 2002).[25]

Although most AMPATH patients receiving treatment come to the HIV clinics every month, their CD4 count is monitored at intervals of roughly six months.[26] 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

[23] For further details on the household survey and the first round data, see Goldstein, Graff Zivin, Nangami, and Thirumurthy (2005).
[24] Most uninfected individuals have a CD4+ T cell count of 800 to 1050 per mm^3 of blood.
[25] 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).
[26] The CD4 count was obtained less frequently and at unspecified intervals prior to 2004, when funding was more limited.

weeks of ARV therapy followed by slower increases thereafter.[27] In addition, the CD4 count at the time of initiation of treatment (baseline) is found to be a significant predictor of subsequent 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 all 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.[28] 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 not considered to have AIDS. Subsequent changes are smaller and less consistent. Figure 3 shows a similar non-linear relationship for the BMI.

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 impacts should be relatively accurate. This is more of a concern for long-term trends. Since most patients that die at the Mosoriot HIV clinic are those that presented with advanced disease and baseline CD4 counts well below 100/mm^3 (Wools-Kaloustian et al. 2005), the long-term trends displayed here will be more applicable to patients who begin treatment before becoming very sick.

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 post-treatment outcomes for the 191 adult ARV recipients who appear in both rounds of the survey, the following equation is estimated using patient fixed effects:

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

where α_i is a patient fixed effect, H_{it} is a measure of patient i's health status (CD4 count or BMI), and $ARV_{i,t-\tau}$ indicates whether or not patient i was receiving ARV therapy τ months prior to the appointment (at time t) when health status is measured.[29,30] The omitted group consists of all

[27] 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).

[28] 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.

[29] 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

patients who have received treatment for less than three months or are within three months of beginning 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, we are able to report estimates 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.[31]

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.[32] 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. Due to the non-linear temporal response of health status to ARV therapy, ARV recipients 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 impacts on labor supply.

5. Estimation Strategy

We use longitudinal information on three outcomes which measure an individual's labor supply: an indicator of participation in any economic activities during the past week, total hours worked in the past week, and total income earned in the past month. For each household member older than 8 years, the survey recorded this information 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 has an impact on labor supply is provided by Figures 4 and 5, which plot the relationship between adult ARV patients' labor supply outcomes

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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).

[30] 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.

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

[32] 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.

and time on treatment. The temporal response to treatment of labor force participation rates (Figure 4) and weekly hours worked (Figure 5) closely resembles the non-linear temporal 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.

5.1 Reduced Form Estimation of the Treatment Impact

We identify the impact of ARV therapy by examining changes in the treatment group's labor supply between rounds, using data from the random sample to correct for time-varying factors that might bias the estimates. These include important factors that determine labor supply, such as seasonality in agriculture or aggregate health shocks (greater malaria burden in specific months, for example). As we show below, labor supply in the survey area displays considerable seasonality. It is worth nothing that 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.[33] The first equation estimated is:

$$Y_{it} = \alpha_i + \beta_1 (ARV_i * ROUND2_t) + \beta_2 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{it}, \qquad (2)$$

where Y_{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, 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.[34] 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. The coefficient of interest, β_1, indicates whether ARV recipients have a different change in labor supply between rounds than adults in the random sample.

Equation 2 assumes that treatment effects will be identical for all patients. 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

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[33] 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 which can cause changes in workers' earnings.

[34] This equation could also be approximated as:

$$Y_{it} = \alpha + \beta_1 ARV_i + \beta_2 (ARV_i * ROUND2_t) + \beta_3 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{it} \qquad (2')$$

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

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 2 is thus estimated:

$$Y_{it} = \alpha_i + \beta_1 (ARV_{<100,i} * ROUND2_t) + \beta_2 (ARV_{>100,i} * ROUND2_t) \\ + \beta_3 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{it}. \tag{3}$$

While the division of ARV recipients into two samples will indicate whether there are heterogeneous impacts 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:

$$Y_{it} = \alpha_i + \beta_1 ARV_{i,t-3} + \beta_2 ARV_{i,t-6} + \beta_3 ARV_{i,t-9} + \beta_4 ARV_{i,t-12} + \beta_5 ARV_{i,t-15} \\ + \beta_6 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{it}. \tag{4}$$

$ARV_{i,t-\tau}$ 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 who have received treatment for three months or longer are compared to "baseline" outcomes of patients who have received treatment for fewer than three months (or are about to begin treatment).[35] Data from adults in the random sample again control for monthly fluctuations in labor supply.

5.2 Instrumental Variables Estimation

The specifications above provide reduced form estimates of the treatment impact. To show that treatment influences labor supply through the mechanism of improvements in health status, we take advantage of AMRS data on patients' medical outcomes. Restricting the analysis to only ARV recipients, we estimate:

$$Y_{it} = \alpha_i + \beta_1 H_{it} + \beta_2 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{it}, \tag{5}$$

[35] 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 $\beta_1+\beta_2$.

where α_i is a fixed effect for individual *i* and H_{it} is the health status (CD4 count or BMI) of patient *i* at time *t* (round 1 or round 2).[36]

The endogeneity of health and omitted variables can both result in biased estimates of the effect of health on labor supply, even with individual fixed effects. To estimate the effect of health status based only on variation driven by the availability of ARV therapy, we first employ an instrumental variables (IV) estimation strategy. We instrument for health status using indicator variables of treatment duration (i.e., equation 1).

One shortcoming of this IV approach is that the number of observations is limited by the availability of CD4 counts and BMI measures.[37] Thus we use the point estimates of the coefficients in equation 1 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 5 for a larger sample than is possible under the IV strategy.

The next section presents the results from estimating the reduced form and instrumental variables strategies.

6. Results for Adult Patients' Labor Supply

We restrict the analysis of labor supply to individuals between the ages of 18 and 65 who appear in both rounds.[38] Table 4 presents summary statistics from the first round for 191 adult ARV recipients and 1,286 adults in the random sample.[39] Crop farming is the primary economic activity of households in the survey area, as illustrated by the high fraction of individuals working on their own farm. A non-trivial fraction of adults also report working off-farm for a wage or in a household enterprise.

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

[36] One drawback of this strategy is that it does not use information from the random sample.

[37] 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.

[38] 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.

[39] 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.

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 the 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 the unemployed adult ARV recipients.

The data on labor supply also show it is important that our analysis control for seasonality. 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.[40]

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 that women have significantly lower levels of labor supply. We find that ARV recipients are significantly less likely to be engaged in economic activities than adults in the random sample (column 1). Also noteworthy, however, is that the 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

[40] 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.

identification problems, we estimate labor supply regressions with individuals fixed effects, as discussed in Section 5.1. Table 8 reports results from estimating equations 2 and 3. We find that the impact of ARV therapy on labor supply is large and statistically significant. Adults receiving treatment are 8.2 percentage points more likely to be working in round 2 (column 1), controlling for time-varying factors that are evident in 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 percentage 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.

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 impact of treatment on labor supply is also applicable to those 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 primary impact of treatment on labor supply occurs by allowing previously sick patients 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 also at the time of the round 1 interview. As discussed earlier, in the absence of treatment these patients have a small probability of surviving another six months, until the round 2 interview date. In this sense, the estimated labor supply impacts are likely to be *underestimates* of the true impact of treatment on the treated.[41]

Table 9 reports the results from estimating equation 4, with a more complete set of indicators to identify temporal impacts. 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 smaller and not statistically significant. The point estimates show that three to six months after initiation of 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 the 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.[42]

6.2 Effects of Health Status on Labor Supply

To show that ARV therapy influences labor supply through improvements in health status, we estimate equation 5 using the instrumental variables strategy outlined in Section 5.2. Table 10 shows that both CD4 count and BMI are positively associated with the likelihood of having worked in the past week. The insignificance of CD4 count in columns 1 and 2 are likely due to our limited sample size. Expanding our sample size by using CD4 count predictions (column 3) yields significant results that are similar in magnitude to the instrumental variables model 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 treatment impact, where patients experience a since the CD4 response in the first three to six months of treatment is estimated to be $127/mm^3$ increase in CD4 counts and a 20 percent increase in labor force participation in the first three to six months of treatment. 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

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[41] The typical problem of mean reversion, which results in an overestimate of the treatment impact, is therefore not applicable here.

[42] 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.

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 3 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 separately 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 potential 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. We also find gender differences for some components of labor supply: women are much less likely to have worked for a wage, but equally likely to have worked in a non-farm business. As a result, 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 3 separately for men and women.

As Table 12 shows, the labor supply increases for male patients are found in weekly hours worked but not participation rates. This suggests that patients already working prior to initiation of treatment are primarily the ones who increase their labor supply after treatment. For women, there is an increase in the fraction of patients who supply labor, but no average 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, 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 attrite between rounds, the estimated labor supply impacts apply only to those ARV patients who survived or continued to come to the clinic until round 2. The average impact of 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 attrited patients who were interviewed at the HIV clinic in round 1, we were unable to obtain any information on their households 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.

A conservative approach to estimating the average impact of ARV therapy is to analyze the panel data while treating all attrited patients as individuals with *zero* labor supply in round 2.[43] Since it is unlikely that all attrited patients are dead, this strategy provides us with a lower bound on the labor supply impact.[44] As Table 13 shows, we find that even with the inclusion of 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. This influences how to interpret the role of mortality in our analysis. In fact, for the 9 patients in our sample who died between

[43] This strategy will also give us a lower bound on the labor supply impact because some of attrited patients may still be alive and getting treatment at some other AMPATH clinic, or they might have missed several appointments and therefore not have been in the round 2 sample.

[44] 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.

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). Our earlier results, therefore, should be recognized as being valid for patients who survive. Additionally, the broader relevance of these results is heightened if HIV-positive patients begin receiving treatment before 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 Upper Bound of Treatment Impacts

As noted earlier, there is strong evidence that individuals who have developed AIDS will survive for very little time without treatment. Since the CD4 counts of patients in our sample are well below 200/mm^3 (the level associated with developing AIDS), it can be assumed that very few of the patients would survive until round 2 without treatment. While this counterfactual case is not observed by us, we can create an upper bound of the treatment impact by assuming that, without treatment, all patients in the sample would not be participating in the labor force in round 2. Comparing the observed treated group to this constructed control group, we can obtain difference-in-difference estimates of the impact of ARV therapy. For patients who are just beginning treatment in round 1, the impact of ARV therapy on labor supply is very large: an increase in 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 analysis (in Table 8) and suggests that our earlier results are considerable underestimates of the true impact of treatment on the treated.

7. Impact of ARV Therapy on Family Labor Supply

Intrahousehold reallocation of time to activities is known to be an important consumption smoothing mechanism in low-income countries. Particularly 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. Jacoby and Skoufias (1997) find that children's school attendance rural India is responsive to seasonal fluctuations in income. Others have examined the time allocation of children and adults in response to income and health shocks, finding that responses depend on the gender of household members (Pitt and Rosenzweig 1986; Kochar 1995). Such intrahousehold decisions about time allocation suggests that ARV therapy can also influence the labor supply of treated patients' labor supply. Having estimated a large increase in patients' labor supply following the "positive health shock" from 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 determinants of family labor supply (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 which allows other household members to work less. Second, as the treated patient's health improves, the time demanded for taking care of the patient or doing additional housework is diminished, thereby expanding other household members' available time endowment for work and leisure. The net effect on labor supply of family members is therefore theoretically ambiguous.

To estimate the net impact of treatment on child labor 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:

$$\begin{aligned} Y_{iht} = \alpha_i + \beta_1 (ARVHH_{<100,h} * ROUND2_t) + \beta_2 (ARVHH_{>100,h} * ROUND2_t) \\ + \beta_3 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{iht}. \end{aligned} \tag{6}$$

Y_{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 before round 1. We estimate the equation separately for men, women, and young and old boys and girls.

Table 14 presents summary statistics for children and adults in the random sample and in ARV 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), although the mean number of hours is considerably lower than for adults.[45] 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 using the longitudinal data and estimating equation 6. Panel A reports results for 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 labor supply of boys and girls, respectively. We test for heterogeneous responses among young and old boys and girls (8-12 years and 12-18 years, respectively). The results indicate that there is a large decline in labor supply of boys after an adult household member begins to receive ARV therapy. In contrast, there is no change in the labor supply of girls. Column 2 of the Panel B shows that for younger boys in ARV households, there is a gradual decline in labor supply between rounds. 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; in households with adults who began receiving treatment more than 100 days before round 1, labor force participation rates decline significantly, by 22.7 percentage points. For older boys (column 3), however, we find a large but insignificant decline in labor supply soon after the initiation of treatment, followed by a small decline thereafter. Hours worked also declines significantly for younger boys, there is reduction of 8.6 hours between round 1 and round 2 which occurs 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

[45] The mean levels for children are low enough to be consistent with regular school attendance, which will be examined in subsequent work.

extremely large declines in labor supply between round 1 and round 2. Finally, Panel C of Table 15 shows that ARV therapy results in no significant change in the labor supply of girls.

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 can 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.[46] Given that girls generally allocate fewer hours to income-generating activities, ARV therapy might influence the time allocation of girls in the domain of housework (not measured in labor supply), especially since adult women's labor supply is being affected by treatment.

Another way of examining the impact of ARV therapy on the family members' labor supply is to take advantage of variation in the number of treated adults in ARV households. In 9 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 patient. Thus, we examine whether there are larger changes in labor supply in these ARV household by estimating the following equation:

$$\begin{aligned} Y_{iht} = \alpha_i + \beta_1(ARVHH_{2patient,h} * ROUND2_t) + \beta_2(ARVHH_{1patient,h} * ROUND2_t) \\ + \beta_3 ROUND2_t + \sum_{\tau=1}^{10} \gamma_\tau MONTH_t^\tau + \varepsilon_{iht}\,. \qquad (7) \end{aligned}$$

The indicator variable $ARVHH_{2patient,h}$ equals 1 if household h has two ore more 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 7 are presented in Table 16. In panel B, we find that for boys of all ages, there is a much larger decline in labor supply between rounds in the double-patient households than the single-patient households. For young boys in double-patient households, there is a large and significant decline in labor force participation rates of 79.2 percentage points. In single-patient households, the decline is considerably smaller (14.3 percentage points) and almost significant at the 10 percent level. Likewise, there is a significant

[46] The next step in this research is to examine whether there are corresponding changes in school enrollment or attendance for boys.

decline in labor force participation rates of older boys in double-patient households but not in single-patient households. For hours worked, there are significant declines for young boys in all ARV households (column 5). In contrast, older boys experience a significant decline in double-patient households alone. Among all other household members, the only other change in labor supply occurs among adults in double-patient households, with substantial declines in hours worked for men and women. The changes in hours worked for adults and boys are extremely large compared to mean levels in round 1.

These results suggest that in households with multiple adults who have developed AIDS, certain other household members are forced to work considerably more before treatment is initiated. As before, we find that boys and women in particular are adjusting their labor supply after adult patients are treated. More generally, in contrast to the large positive impacts of ARV therapy on the labor supply of treated patients, the results in this section always show zero or negative changes in the labor supply of the patients' family members. These results suggest there is an income effect from ARV therapy that allows treated patients' family members to decrease labor supply.

8. Conclusion

This paper provides the first evidence to date on the impact of ARV therapy on labor supply of AIDS patients and their household members. Using data from our household survey, we find that patients receiving ARV therapy have significantly higher labor supply within three to six months after the initiation of treatment. These results suggest that with treatment, the labor supply of AIDS patients can indeed recover from periods of severe illness. We also find evidence that the labor supply of patients' family members (particularly women and boys) declines after initiation of treatment, suggesting that these members may have been compensating for the previously sick patients' low labor supply. Importantly, this implies that the benefits of treatment accrue to not only the patient, but also to others in the household.

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 socio-economic outcomes. Given ethical constraints on implementing such an evaluation, our strategy represents the best available method of controlling for certain confounding factors (such as seasonality in labor supply and nutrition) while estimating the impact of treatment. Moreover, especially for the case of patients' labor supply, we argue that the absence of a randomized control group is likely to result in underestimates of the impact of treatment. There is considerable medical evidence that life expectancy among untreated individuals with AIDS is extremely low (between 6-12 months). Given that we find a large increase in labor supply after the initiation of ARV therapy, our conclusion that treatment results in significantly higher labor supply would only be strengthened by the presence of a true counterfactual group.

The number of people requiring ARV therapy in developing countries will continue to grow in the next decade. For evaluating an important intervention that has yet to be scaled-up in sub-Saharan Africa, the results presented here are highly relevant. The increases in treated patients' labor supply that are estimate here can serve as important inputs for studies of cost-effectiveness and macroeconomic impacts. Perhaps more importantly, the results on family labor supply underscore the relevance of accounting for possible spillover effects within the household when evaluating ARV therapy.

Given the results for labor supply, a number of household outcomes can also be expected to improve upon initiation of treatment. Using a similar methodology that again takes advantage of data from the random sample, other research analyzes longitudinal information on household food consumption levels, children's nutrition and schooling, and exchange of money and goods between individuals. Preliminary results suggest, for example, that there is considerable improvement in the short-term nutritional status (as measured by weight-for-height) of children living with adult ARV recipients. Thus, in addition to making AIDS patients more productive, ARV therapy may also be increasing welfare through the intrahousehold allocation of resources.

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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	0.52	0.34
R-squared	183	164

Absolute value of t statistics in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%
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

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	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 random sample and HIV sample.

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)***
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 regressions include month-of-interview indicator variables. The sample includes observations for 70 HIV-positive patients not receiving ARV therapy and a separate explanatory variable for this group.

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)
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 regressions include month-of-interview indicator variables. The sample includes observations for 70 HIV-positive patients not receiving ARV therapy and a separate explanatory variable for this group.

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.				F.E.
Round 2 * HIV+ Patient not on ARVs	0.042	3.522	0.044	3.577	4.370
	(0.84)	(1.00)	(0.87)	(1.01)	(1.11)
Round 2 * Patient on ARVs	0.082	3.651			
	(2.58)***	(1.65)*			
Round 2 * Patients on ARVs < 100 days in Round 1			0.167	6.934	3.328
			(3.89)***	(2.31)**	(0.93)
Round 2 * Patients 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 10. 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 (using equation 1) 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)	(4)	(5)	(6)
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 * Patients 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 * Patients 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 * Patients 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 * Patients 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 * Patients 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 * Patients 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
ROUND 2					
Worked in past week	84%		72%		0.00
Total hours worked in past 7 days	11.0	11.3	8.7	11.1	0.03
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
ROUND 2					
Worked in past week	74%		68%		0.16
Total hours worked in past 7 days	7.7	8.3	8.2	11.3	0.61
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
ROUND 2					
Worked in past week	91%		81%		0.00
Total hours worked in past 7 days	35.6	25.0	25.8	24.9	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.

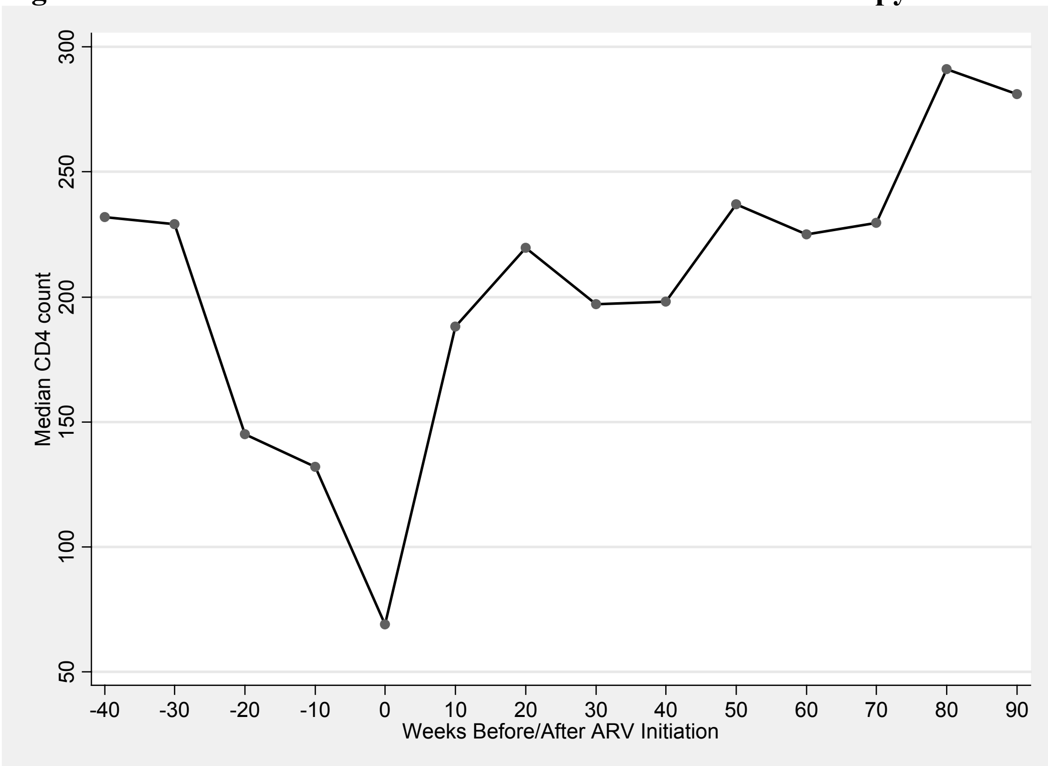
Table 16. Impact of ARV Therapy on Family Labor Supply According to Disease Burden

	(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.

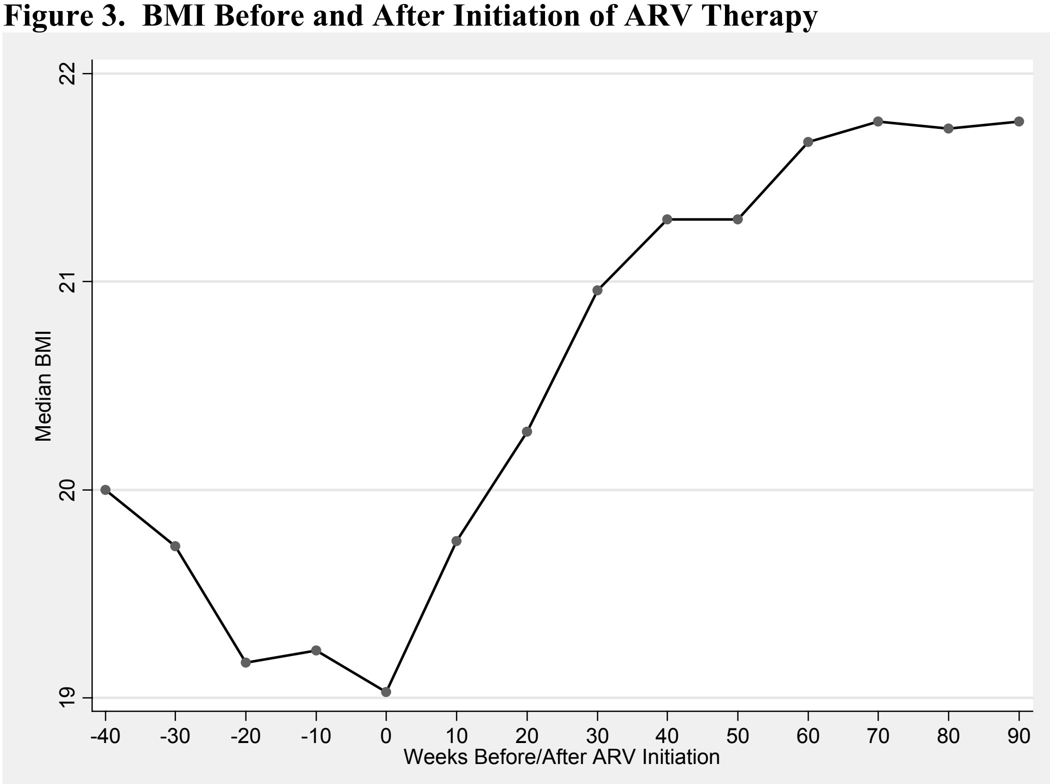
Figure 1. Map of Kenya

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

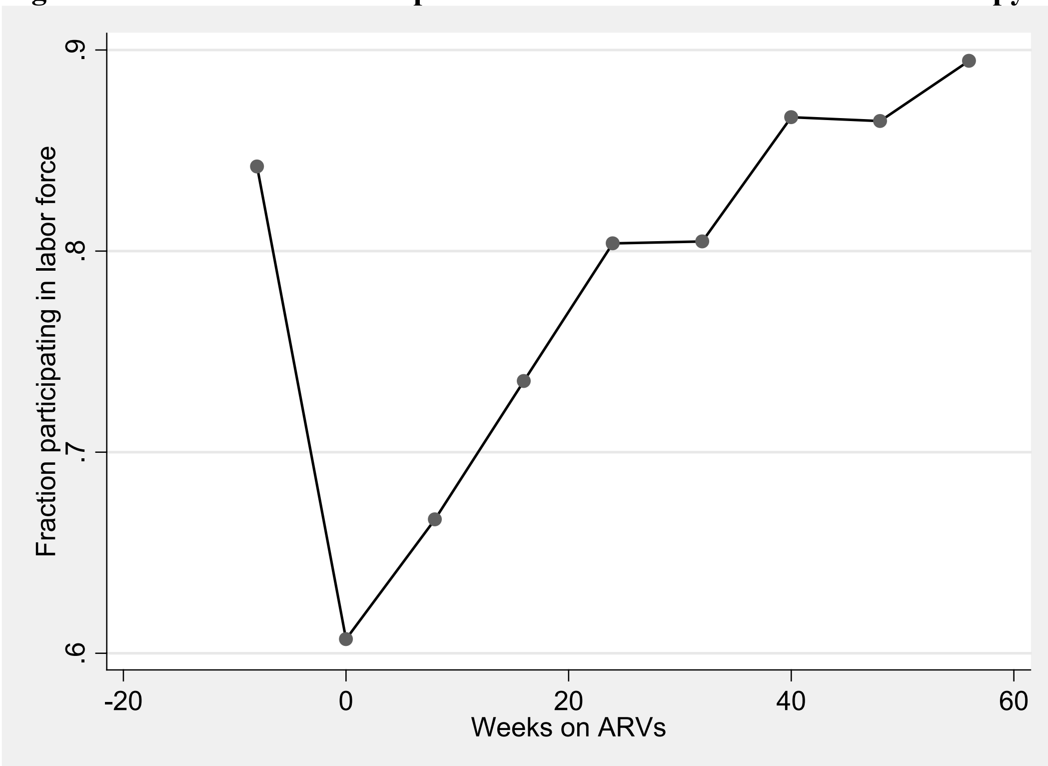


Figure 5. Weekly Hours Worked Before and After ARV Therapy

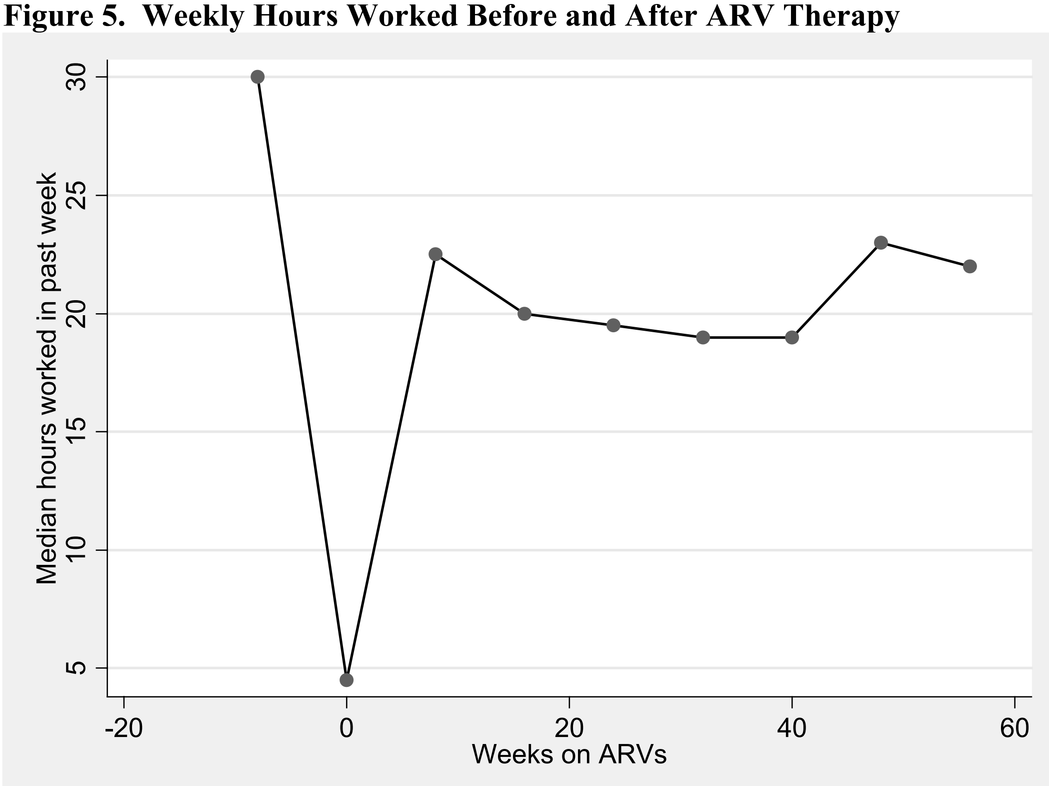


Figure 6. Hours Worked in Past Week by Month of Interview (Men and Women)