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HIV/AIDS, ARV Treatment and Worker Absenteeism: Evidence from a Large African Firm *

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Abstract

In 2001, the Debswana Diamond Company started the first firm-based program in Africa to provide free ARV treatment to its workforce affected by HIV/AIDS. We link individual health information from the firm's treatment program to a unique panel dataset of all the medical and non-medical episodes of absenteeism at the firm's two main mines between the period 1998-2006. This unique dataset allows us to characterize *medium* and *long-run* impacts of the disease and ARV treatment that existing data cannot address. Compared to workers that never enroll in the treatment program, there is no statistically significant difference in the absenteeism rate of enrolled workers in the period 1-5 years *prior* to treatment start. Next we present robust evidence of an inverse-V pattern in worker absenteeism around the time of ARV treatment inception. Enrolled workers miss about 20 days in the year leading up to treatment initiation with a peak of 5 days in the last month. This is about five times the annual absence duration due to illness among non-enrolled workers. The introduction of ARV treatment is followed by a large reduction in absenteeism 6-12 months following treatment inception. Absenteeism 1 to 4 years *after* treatment start is low and similar to non-enrolled workers at the firm.

Finally, we present a simple model to understand the conditions under which it is optimal for profit-maximizing firms to finance/provide ARV treatment to their workers. Under plausible assumptions, our results suggest that for the typical manufacturing firm across East and Southern Africa, the benefits of treatment to the firm cover between 10-33% of the cost of treatment.

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1 Introduction

Over 40 million people worldwide are infected with the HIV virus. More than 60% of these individuals reside in Africa. One of the challenges of characterizing the impact of the disease on a variety of socio-economic outcomes is the slow progression of the disease. Shortly after an individual is infected, a long latency period follows that can last 8-10 years in which the individual is asymptomatic despite a gradual weakening of the immune system.[1] Eventually the individual develops full-blown AIDS and presents a wide variety of opportunistic infections which in the absence of treatment lead to death within less than 1 year.[2]

Over the last five years, numerous international organizations as well as national governments have committed significant resources for the provision of antiretroviral drugs (ARV's) for the treatment of HIV/AIDS infected individuals in the developing world. And although the ambitious goal of providing ARVs to 3 million patients around the world by 2005 has not been achieved, the rate of increase has been large, even in Africa where the number of patients on ARVs increased from 100,000 in 2003 to 810,000 in 2005 (UNAIDS, 2006).

The health benefits of ARVs are by now well established in the developed world (Hammer et al. (1997), Duggan and Evans (2005), Floridia et al. (2002)) and recently a number of papers have also shown large reductions in morbidity and mortality in the first years after treatment start in poor country settings (Koenig et al. (2004), Wools-Kaloustian et al (2006).[3] Despite these positive health effects, there is little evidence on the socio-economic effects of HIV/AIDS and ARVs on individuals, households and firms. Two notable exceptions are Thirumurthy et al (2005) who find sizable increases in labor supply in patients in the first six to nine months after initiation of treatment in a sample of rural households in Kenya, and Fox et al (2004) who document decreases in worker productivity among rural Kenyan tea pickers in the last two years prior to leaving the firm for AIDS related

[1] In the US, the median latency period is 10 years (NIH, 2005) and evidence from Uganda suggests that this is similar in an African setting (Morgan et al. 2002).

[2] The median time from AIDS to deaths in the absence of treatment in the Ugandan study was 9.2 months (Morgan et al. 2002).

[3] Marins et al.(2003) using a longitudinal data from Brazil find that median survival time increased to 58 months for patients on ARVs.

sickness or death.[4] Apart from the intrinsic interest of elucidating the relationship between health and socio-economic behavior (Strauss and Thomas (1998), Case and Deaton (2006), Thomas et al. (2005)),[5] understanding the additional socio-economic benefits of ARV treatment can shed light on the cost-effectiveness of antiretroviral drugs (ARVs) in comparison with available HIV/AIDS prevention interventions. Despite the documented health benefits and the recent reduction of the cost of treatment, the cost-effectiveness of ARV treatment in the context of the developing world has recently been questioned (Canning (2006)).

While the aforementioned studies have shown significant changes in the labor supply of infected workers in the late stages of the disease as well as patients who have just started ARV therapy, little is known about how morbidity affects socio-economic behavior in the longer term. In this paper we focus on the *medium and long term* economic impacts of HIV/AIDS and benefits of ARV treatment. More specifically we analyze the pattern of labor market absenteeism of workers with HIV/AIDS in the years prior to and following the start of ARV treatment, using detailed human resource data spanning a period of almost 10 years from a major private mining firm in Botswana. In 2001, the Debswana Diamond Company, Botswana's main diamond mining enterprise, with a workforce of over 6500,[6] started one of the first free firm-based ARV treatment programs to extend the productive lives of its workers. The decision to provide treatment came as a response to an HIV/AIDS prevalence rate among its workforce of 28% in 1999 and increases in HIV/AIDS related deaths, early retirement and absenteeism (UNAIDS, 2006).

We carry out our analysis by linking a database of the entire universe of regular and sickness related spells of absenteeism at the firm's two main mining sites with information about the health status and timing of ARV treatment start for a group of almost 500 workers enrolled in the company's treatment program. The absenteeism data covers the

[4] A number of macro-economic studies of the impact of the epidemic on economic growth reach conflicting conclusions. Young (2005) posits positive effects via changes in fertility while Bell, Devarajan and Gersbach (2003) and Kalemli-Ozcan (2006) posit negative effects.

[5] In addition to the micro based studies on the relationship between health and socio-economic outcomes, a number of cross country studies have focussed on the relationship between health and growth (Sachs (2003), Acemoglu and Johnson (2006)).

[6] Debswana is an unusually large African firm. The average firm size in the manufacturing sector of many African countries is about 120 employees and the median is about 40-50 employees (Investment Climate Assessment Reports (Kenya (2004), Uganda (2003) and Tanzania (2003)).

period 1998-2006 for the Jwaneng mine and the period 2001-2006 for the Orapa mine. Since the Debswana treatment program was one of the first to be started in Africa and the absenteeism data covers such a long time span, we are in a unique position to observe the labor market behavior of workers with HIV/AIDS up to 5 years prior to and following the initiation of ARV therapy.

We first provide evidence on the link between the health status of a worker (measured by his/her CD4 count) and worker absenteeism in a given month, using measurements of the CD4 count at 0, 6 and 12 months after treatment start.[7] We propose to address the potential endogeneity of health in the worker absenteeism equation by using the length of time between the date of ARV treatment inception and the date of the CD4 count measurement as an instrumental variable for a person's health. Our instrumental variables estimate implies that within the first year of treatment, an increase equal to 100 cells/mL of the CD4 count (the average improvement in health after 6 months of therapy) causes illness-related absenteeism to decrease by roughly 3.5 days per month.

Secondly, we use the staggered timing of worker treatment initiation between 2001 and April 2006 to estimate the patterns of absenteeism around the start of ARV treatment inception. The four main results of our empirical analysis are the following: (1) compared to non-enrolled workers in the firm, we find no difference in the rate of absenteeism of workers with HIV/AIDS in the period of 1-5 years prior to the start of treatment; (2) about 12-15 month prior to the start of treatment we observe a sharp increase in absenteeism equivalent to about 20 days in the year prior to the start of treatment and with a peak of 5 days in the month of treatment initiation; (3) the recovery after the beginning of treatment happens quickly within the first year and (4) 1-4 years after treatment start, treated workers display very low rates of absenteeism, similar to the other workers at the mining company.

Next we develop a framework to predict the conditions under which firms will provide ARV treatment to their workers. The framework, which builds on the literature on the provision of firm-specific human capital (Becker (1964), Acemoglu and Pischke (1999)),

[7]The CD4 count is a measure of the density of CD4 cells – cells that are crucial in the body's immune response mechanism. While there is no reference normal range, CD4 counts >500 cells/ml are considered healthy (Kaufmann et. al. 2002). This is a suitable measure of underlying health as it provides direct measure of the susceptibility of the body to infection.

shows that when the productivity differences between healthy experienced workers and new recruits is small, firms prefer to hire new workers rather than provide treatment to infected workers. Conversely when the productivity gains associated with treatment (keeping experienced workers) are large, firms are more likely to provide treatment. We provide a rationale for when, where and how much firms in Sub-Saharan Africa are willing to pay towards the cost of treatment. We show that given the current costs of provision of ARV's and a number of plausible assumptions about the labor market, the turnover of sick and treated workers, the benefits to the firm cover about 10-33% of the cost of ARV treatment. We conclude that the provision of public subsidies to ARV treatment programs administered by private companies has the potential to become an important mechanism to provide treatment to people affected by HIV/AIDS in a resource constrained setting like Africa.

Our analysis proceeds as follows. We describe Debswana's company based treatment program in Section 2. In Section 3, we introduce our data, empirical strategy and regression framework. Section 4 presents the results of the main analysis. Section 5 presents a simple model to understand the impact of HIV/AIDS and ARV treatment for the company and provides a rationale for firm-based treatment provision. Section 6 concludes.

2 The ARV treatment program at the Debswana Diamond Company[8]

Our analysis evaluates the impact of ARV treatment on labor market outcomes of workers with HIV/AIDS at the Debswana Diamond Company in Botswana. Located in Southern Africa, Botswana is considered an African success story given its political stability and continued economic growth since independence. Despite these economic and political achievements, the country has been hard hit by the HIV/AIDS epidemic with an adult HIV prevalence rate of 24% in 2005 (UNAIDS, 2006) and a life expectancy at birth of only 36 years.

[8]**Unless otherwise noted, this section draws heavily on UNAIDS (2002)**

The country's economic success is closely linked to the fact that Botswana is the largest producer of diamonds in the world. The company that is responsible for the diamond mining activities is the Debswana Diamond Company, a 50-50 joint venture between the Government of Botswana and the DeBeers Company. Employing more than 6,500 workers, it plays an important role in Botswana's economy and is by far the country's largest private employer. From its four major mining sites at Letlhakane, Jwaneng, Damtshaa and Orapa, the company provides about 60% of the government's revenue, accounts for approximately 33% of Botswana's GDP and over 80% of the country's export earnings.

Relative to other large firms in Africa, Debswana has been a pioneer in sustained and effective firm-based responses to the HIV/AIDS epidemic. Following the report of the first AIDS case at the Jwaneng Mine Hospital in 1987, the company started an HIV/AIDS education and awareness program in 1988. Starting in the mid 1990's, the effect of the epidemic on the morbidity and mortality of the company's workforce became increasingly conspicuous as the percentage of ill-health retirements due to HIV/AIDS rose to 75% in 1999 and the number of deaths due to AIDS increased to 59% in the same year. In 1999, the HIV prevalence rate based on the first voluntary anonymous prevalence survey conducted by the company was 28%. The prevalence rate from a similar survey in 2003 continued to be high (19.9%) and was higher among workers aged 30-39 (26%) and among the unskilled and semi skilled workforce (23%).[9]

In May 2001, Debswana Diamond Company started an ambitious treatment program that provides free antiretroviral therapy (ARVs) to the company's workforce and their spouses. The program has been extremely successful and enrolled 158 patients in the first year of operation and that number has increased to over 700 by April 2006. According to recent data from the company, the treatment program has contributed significantly to the productivity and health of the workforce in the period 2003-2005, with reductions in death rates, absenteeism, and the number of sick day leaves (Mbakile, 2005).

[9]Worker bands are analogous to occupation categories. The five worker bands are Band A through E, with band A corresponding to unskilled production/non-production workers, and E to highly skilled managerial positions.

3 Data and empirical strategy

3.1 Data

We use two main sources of data for this research. The first is a dataset containing the complete records of all the worker leaves from Debswana's two main mines. The Jwaneng data covers the period April 1998 to March 2006, while the data from the Orapa mine (covering data from Orapa, Damtshaa and Letlhakane) only starts from January 1st 2001. The human resource records also provide information on gender, age, worker bands as well as the date and reason for discharge in case of job separation. The leave data distinguishes between two different types of leaves: medical (sick) leaves and ordinary leaves. Overall the dataset contains almost 200,000 absenteeism spells for 7661 workers, of which 21% are illness-related leaves and 79% are ordinary leaves.

We aggregate all leave information by employee and month. On average, a worker is absent just a little over a day (1.12) from work and the breakdown by leave-type is .32 days for sick leaves and .8 days per month for ordinary leave. The level of absenteeism at Debswana is comparable to survey evidence from manufacturing firms in South Africa (World Bank (2005)), where the average reported number of sick days is .3 days per month.[10]

The second source of data is a medical database of the ARV treatment program described in the previous section. We have information from 721 workers and spouses who enrolled in the program in the period May 2001 - April 2006. This dataset has information on the timing of enrolment in the program and the start of ARV therapy. In addition we have information about the status of the patient at the end in April 2006: 81% are still in the program, 11% are deceased, and the rest have either left the program or the company.[11] Finally CD4 counts at 0, 6 and 12 months after ARV treatment initiation are collected for all patients on treatment.

Of the 538 workers (excluding their spouses) enrolled at some point in the program,

[10] One reason for the very low levels of absenteeism are the relatively high wages that these private manufacturing and mining firms in Southern Africa pay and more favorable disease (aside from HIV) environment. Monthly absences in less dynamic private sectors range between 2-3 days per month (Investment Climate Assessment Reports (Kenya (2004), Uganda (2003) and Tanzania (2003)).

[11] For those workers who left the company, the treatment program provides medication for another 3 months and also helps with the transition to other treatment programs available in the country.

only 17% did not take any ARV's at some point since program start. While the program has been a success in terms of enrollment levels compared to other company based treatment programs in Africa (Rosen et al. 2006), the high proportion of workers on ARVs among those enrolled in the treatment program suggests that workers are enrolling in the treatment program and starting ARV treatment much later than the medical profession recommends. According to the treatment program, about 60% of workers are diagnosed with stage 4 HIV at the time of enrollment. Appendix Table 1, which provides summary statistics for the variables used in the study, shows that the average CD4 count at ARV treatment start is only 163 cells/mL and almost 70% of patients have a CD4 count at treatment that is lower than the WHO (and Botswana's) guideline of 200 CD4 cells.[12] Moreover, about 25% of patients have a CD4 count of under 50 at treatment start and are very close to death. For this group of workers with very low CD4 counts, the patterns of absenteeism prior to ARV treatment start represents a close description of absenteeism for people infected with HIV/AIDS until very close to death.

3.2 Empirical strategy:

In our analysis we use two approaches to understand the relationship between HIV/AIDS, ARV treatment and worker absenteeism. Our first approach, which studies the effect of health on labor market outcomes, estimates a regression of the form:

$$outcome_{pt} = \beta_0 + \beta_1 health_{pt} + \beta_2 \delta_p + \beta_3 \tau_t + \epsilon_{pt}\,, \tag{1}$$

where $health_{pt}$ is measured by the CD4 count of person p at time t , and our outcome variable is a measure of labor market supply (usually the number of days absent due to sickness or duration of absence due to all absences) in the month that the CD4 count was taken. While this sample contains a limited number of observations (845) it has the advantage of offering a direct measure of the health status of the workers enrolled in the ARV treatment program.

[12]Enrollment and ARV theraphy start at very advanced stages of the disease is common in other ARV treatment programs based in Africa (Wools-Kaloustian (2006)).

The challenge in estimating this effect is common in the literature since as mentioned before one might be worried that causality runs in both directions or that both health and labor supply are driven by unobserved factors. We propose to address this issue by using the length of time between the date of ARV treatment inception and the date of the CD4 count measurement as an instrumental variable for a person's health. More specifically our instruments will be two dummy variables that indicate whether the CD4 measurement was taken 6 months and 12 months after the start of ARV therapy rather than at the start of therapy. Distance from start of treatment is used to instrument for the CD4 count in the first stage which also includes controls for age, gender, worker band (occupational category), calendar month and year and mining site. All specifications include month fixed effects (τ_t) and in some of the specifications we also include person fixed effects (δ_p) since we observe up to three observations per patient in the data. Distance from the start of treatment is a plausible instrument given that there is a large medical literature that shows the positive effects of ARV therapy on patient health within the first year of treatment. Furthermore, the concern that mean reversion could explain improved health outcomes after the onset of ARV therapy is diminished since the natural progression of the disease in the absence of treatment is one of continuous decrease of the CD4 count. Nevertheless, it is possibly that the timing of ARV treatment start is influenced by the interaction of a person's immune system condition and a possibly random episode of illness.

The second approach we employ characterizes monthly worker absenteeism due to sickness around the time of ARV treatment onset. We use information provided by the treatment program to define the month and year of treatment initiation of each enrolled worker. Of the 449 workers (see Appendix Table 1) who were at some point on ARV's, 94 enrolled in 2001, 84 in 2002, 51 in 2003, 64 in 2004, 115 in 2005 and 41 in 2006. Thus, there is substantial variation in the timing of the initiation of ARV treatment.[13]

Our empirical strategy uses the variation resulting from the staggered timing of the start of treatment as a way to estimate the patterns of absenteeism of HIV infected workers around the time of ARV therapy inception. In our main specification we control for month and person fixed effects and moreover we also include as controls a large sample

[13]We were able to match 441 of the 449 (98%) patients on ARVs to the HR database.

of workers from the company who are not associated with the program, which should help us better account for other unobservable factors that might be slowly changing at the firm level over time.

We estimate OLS regressions of the following form:

$$outcome_{pt} = \beta_0 + \sum_i \alpha_i dist\_from\_treatment^i_{pt} + \beta_1 \delta_p + \beta_2 \tau_t + \epsilon_{pt}\,, \tag{2}$$

where $outcome_{pt}$ is one of our dependent variables of interest (usually, duration of absences due to sickness and/or ordinary leaves), measured in days for each month and person cell. The variables $dist\_from\_treatment^i$ are a set of dummy variables equal to one if a person had started ARV therapy i months ago. We restrict i to be +/- 12 months in the main specification but we also show graphical results that extend the time interval to +/- 24 and +/- 36 months. We usually also control for person effects (δ_p) and month effects (τ_t).

The two empirical strategies are similar given that in both cases the source of variation used comes from the timing of when people enroll in the ARV program. The fixed effects model in the first strategy which only uses workers on ARV treatment, compares the same person at up to three points in time (0, 6 and 12 months) and rescales the effect by changes in the CD4 count from the first stage regression. The fixed effects model in the second strategy estimates the reduced form patterns of absenteeism over a much longer time window, but includes also absenteeism for healthy/never treated workers who only help identify time effects.

There are two main reasons that these strategies do not identify the impact of ARV treatment on absenteeism. Firstly, the decision to start treatment is certainly affected by health (and potentially absenteeism) trends in the period immediately prior to treatment start. In the program-evaluation literature, this source of bias is usually addressed by modelling the selection process (e.g. Ashenfelter and Card, 1985). We have decided against this approach since the estimation of the selection process generally requires an exclusion restriction and in our particular case there are no plausible exclusion restrictions across the selection into treatment and labor market outcome equations.

Secondly we do not have a reliable *control* group. In our model, the "no treatment" comparison group are esentially other HIV workers infected at a different time and workers who were never enrolled in the program. As a result, our estimated effects are almost certainly smaller than the "treatment effect of receiving ARV therapy", given that in the absence of treatment, many of the workers would have died. As previously mentioned, in the absence of treatment, the median time between the development of AIDS and death is 9.2 months (Morgan et al. 2002).

We run a number of alternative specifications in order to test the validity of our results. We present figures based on non-parametric Fan locally weighted regressions to show the pattern of absences before and after the introduction of ARV treatment. Since some of our workers exit the sample due to death or separation from the company, in our main unbalanced sample not all persons have data available for each month relative to the starting date of treatment. Thus the number of persons identifying a particular $dist\_from\_treatment^i$ coefficient is not constant and these compositional changes could give rise to possible trends in the data around the starting date. Therefore, we also include results using a "balanced" panel of workers that have at least 12 (or 24, or 36) months of post treatment data. Since the data from one of the mines (Jwaneng) extends over a much longer time period, we can additionally use intervals that are 5 years before and 4 years after the onset of ARV treatment. We also performed a number of additional robustness checks: we re-ran our specification by splitting the sample by early vs. late adopters, gender, worker band and mine. Except in the specifications that include person fixed effects (where we use Huber-White standard errors), we cluster our standard errors at the person level (Bertrand, Duflo and Mullainathan (2004)).

3.3 Accounting for Attrition

In this section we discuss the patterns of attrition in our data and describe the approach that we take to correct for the potentially selective attrition of participants in the ARV program. While selective attrition is a concern in all longitudinal datasets, it can be particularly important in the present analysis since we are dealing with a population in which death related attrition is expected to be important in light of the nature of the disease that we study. In Figure 2 in the appendix we plot monthly attrition rates for

the first three years after the start of ARV therapy. The increase in overall attrition is relatively linear over time and averages below 10% per year. The same graph also breaks down the distribution of attrition due to death at the time of exit or regular separation from the company. Roughly 60% of separations are due to death while working at the company, although we cannot accurately measure mortality since the company does not track former workers after they separate from the company.

We use three different sampling strategies in this analysis. The *balanced* sample includes only those individuals for whom we have labor supply information for all the months between treatment start and sample window. The sample windows are 6 and 12 months for the health/CD4 sample and 12, 24 or 36 months for the regressions that measure the pattern of absenteeism around ARV treatment start.[14] The second sample is *unbalanced* and includes all available monthly absenteeism observations for as long as the individual is observed in the HR database. If selective attrition is severe, we expect the results from the balanced and unbalanced sample to be different. The third approach applies the inverse probability weights (IPW) technique (Fitzgerald, Gottschalk and Moffitt (1998) and Wooldridge (2002)) to adjust for selection bias due to observable characteristics. Our approach will be to use background as well as absenteeism information at the time of ARV treatment start to predict the probability (p_i) that an individual i will still be observed at the end of the sample period. This individual receives a weight equal to $1/p_i$ in the regression analysis, therefore giving more weight in the regression to those individuals whose observable characteristics predict higher attrition rates. The observable characteristics used for this exercise are gender, age, worker band, date of treatment start and absenteeism in the month prior to treatment start.[15] This method, while useful, cannot account for possible differential attrition due to unobserved characteristics. In the absence of an exclusion restriction that would predict attrition due to health without a direct impact on worker absenteeism, we will assume that attrition does not depend on unobservables.[16]

[14] Additionally, we balance the data from the Jwaneng mine using a sample window of 5 years prior and 4 years after ARV treatment start.

[15] While the background characteristics have little explanatory power, higher abseenteeism in the month prior to treatment start has a positive impact on atrition (results not reported).

[16] The concept of selection on observables in the context of attrittion is due to Fitzgerald, Gottschalk and Moffitt (1998) and and is similar to the "ignorability condition" (Wooldridge (2002)) or the concept

4 Results

4.1 CD4 counts and Worker Absenteeism

The relationship between CD4 count and worker absenteeism in the first year of ARV treatment can be easily captured graphically. Figure 1 shows the pattern of the two variables using non-parametric Fan locally weighted regressions with bootstrapped standard errors clustered at the person level for both balanced and unbalanced samples. For CD4 counts over 400 (employee is relatively healthy) there is little evidence of a health-absenteeism link, although due to the limited amount of data, the estimates are relatively imprecise. In the CD4 count range of 100-400, one can observe a clear increase in absenteeism with deteriorating health and this effect is particularly strong for the sickest employees with CD4 counts below 100. An employee with a CD4 count of 50 is absent from work due to illness about a week a month.

Regression results of the effect of health measured by the CD4 count on worker absenteeism is provided in Table 1. Column (1) presents a simple OLS regression that shows the existence of a correlation between health and labor market supply after we control for a number of observable characteristics, such as age, gender, worker band and time effects. These results are robust to the choice of sample (columns 3 and 4) or the inclusion of person fixed effects (column 2), which can only partly alleviate our concerns about reverse causality or omitted variable bias. Next we turn to the analysis of our preferred instrumental variable results. In Panel B of Table 1 we start by showing that our two instrumental variables that indicate that the CD4 count was measured at 6 and 12 months after the start of therapy have a strong and statistically significant effect. On average a person who gets on treatment has an increase in her/his CD4 count of 102 after 6 months and 127 after one year and this result is robust to the inclusion of person fixed effects (column 6 of Panel B) or to different samples (columns 7 and 8 of Panel B). The estimates using instrumental variables across specifications are large and highly significant and vary between -.034 (standard error .004) and -.041 (standards error .005). These estimates suggest that being on ARV therapy for 6 months, the average improvements in health are equal to a CD4 count gain of 100 points and this causes illness-related

of "missing at random" (Little and Rubin (1987)).

absenteeism to decrease by roughly 3.5 days per month, which is equivalent to a decrease in the absenteeism rate by 16%. Two main conclusions can be drawn from an analysis of Figure 1 and Table 1: (1) the overall impact of the health of an HIV infected individual on worker absenteeism is economically large and (2) the effect is particularly strong for those who are extremely sick (CD4 counts below 100).

4.2 Pattern of Absenteeism around ARV Treatment Start

A simpler way to depict the main results of the paper is to demonstrate the effect graphically. Figure 2 plots the relationship between the average number of sickdays taken per month and the distance from treatment start measured in months for a one year window. Panel A uses a non-parametric Fan local regression model while the remaining three panels come from regressions that contain worker and month fixed effects for the three sampling strategies used. In all panels, one can observe a gradual increase in absenteeism in the year before treatment starts. The increase in absenteeism is particularly steep in the six months prior to therapy onset and peaks in the final month at roughly 5 days, which is equivalent to an absenteeism rate of roughly 22%. The positive effects of treatment on labor market outcomes is equally stark in the first months after the start of ARV therapy, so that the shape of absences around treatment implementation is almost symmetric.

The corresponding regression results of illness-related worker absenteeism in the basic equation (2) are in Table 2. Column (1), which uses an unbalanced sample and includes only month fixed effects, presents estimates of α_i, the coefficients for the treatment dummies corresponding to a twelve month window around the onset of treatment. Compared to workers who are not enrolled in the treatment program, workers with HIV/AIDS have a higher duration of illness-related absenteeism (.484 days per month) even a year prior to the start of treatment. The coefficients from this regression display the familiar inverse-V patterns seen in the graphs, peaking at 5.13 days and then declining to less than a day twelve months afterwards. Column (2) in the same table shows similar patterns from a regression that also includes person fixed effects, where the omitted category (-11 month) corresponds to one year prior to treatment start. The remaining columns show the same regressions using the balanced and the inverse probability weight samples and the size and significance of the results is very similar across specifications. In Table 3 we repeat

the analysis from Table 2 but we measure overall absenteeism, which includes sick and regular leave spells. The same patterns emerge as previously and they suggest that enrolled (infected) workers do not use additional regular leave days during episodes of poor health.

Next, we extend our analysis to wider intervals. Figure 3 and 4 repeat the graphs in Figure 2 using two and three year windows, while Figure 5 which uses the longer data series available from the Jwaneng mine plots illness-related absences 5 years prior and 4 years after ARV treatment start. These graphs confirm that most of the changes in absenteeism occur within a one year window. The figures seem to suggest that workers who are on treatment recover remarkably quickly and display very low rates of absenteeism in the medium and long term (1-4 years post treatment initiation). Similarly, an HIV-infected worker displays a pattern of labor supply that is similar to other "non-infected" workers throughout a large part of the post-infection period, a finding that challenges recent estimates in the literature (Fox et al. 2004).[17] In Appendix Figure 3, we have re-run our analysis with the longer intervals and data from the Jwaneng mine without any person fixed effects: the coefficients outside the one year window are all small and usually statistically indistinguishable from zero, suggesting that outside the short one year window around treatment initiation, infected workers display similar labor market outcomes (measured by absenteeism) to the other workers at the company who are not enrolled in the treatment program.

Figure 6 shows how the patterns of absenteeism vary across different groups. In panel A one observes that workers whose enrollment in the treatment program coincided with the start of ARV treatment have higher absenteeism rates than workers who started treatment after program enrollment. Similar patterns are evident in the next two panels, where we observe that workers who are sicker at the time of ARV start, display higher absenteeism rates in the year prior to treatment start. Panel B shows that ARV patients who enrolled closer to the time of program start (2001-2002) have higher absenteeism than those enrolling later (2003-2004). Also, in panel C we plot patients with low (<150) and high (>150) CD4 counts at treatment start and not surprisingly, those with better

[17] One possible explanation for this finding is that stigma (in the absence of effective treatment) discourages workers from revealing their status so that infected workers are only observed very late in their post-infection period.

health are less likely to be absent. The last panel of Figure 6 shows no differences in absenteeism between women and men.

In sum, given the unusual length of the absenteeism panel of almost 10 years and the fact that Debswana's ARV program was one of the first on the African continent, we were able to map out the short, medium and long run patterns of absenteeism of HIV/AIDS infected workers who receive ARV treatment. Our main conclusions are as follows: (1) infected workers are as productive in terms of absenteeism for most of the period when they are HIV positive, (2) about one year around the time of ARV treatment start, we see a steep inverse-V pattern of absenteeism that peaks at about 5 days of absence a month, and (3) in the period 1-3 years after treatment start, patterns of absenteeism are similar to non-enrolled workers suggesting that ARV's are extremely effective in improving workers health and ability to work.

5 Is it Cost Effective for Firms to Provide ARVs?

Our discussion so far has established that to the extent that worker absenteeism is a good proxy for productivity, ARVs are a successful way to restore the productivity of infected workers. In this section, we present a simple model to analyze the cost and benefits of treatment to firms. First, we show the conditions under which treatment of workers with HIV/AIDS is preferred to non-treatment (without early termination) and secondly we show the conditions under which a firm prefers to hire an inexperienced new worker instead of providing treatment to an infected (and experienced) worker. In particular, this framework models the recruitment problem facing a large number of firms in Sub Saharan Africa that have to choose between providing/financing treatment of infected workers with 5-15 years of experience or recruiting novices. Our model builds on the rich literature, started by Becker (1964) and extended most recently by Acemoglu and Pischke (1999), that has explored the rationale for why firms might provide a number of human-capital enhancing investments to their workforce.

To motivate the firm's choice we assume that firms are infinitely lived. There are three types of workers: healthy workers, sick workers and inexperienced workers. The healthy and sick workers are assumed to have considerably more experience than new recruits.

Using asset equations we can write down the value of each type of worker to the firm taking into account the probability of separation between the worker and the firm.[18]

The value to the firm of a healthy experienced worker V_g is given by

$$rV_g = (MPL_g - w_g) + \rho(V_d - V_g) + b(V_n - V_g) \tag{4.3.1}$$

where r is the interest rate, MPL_g and w_g is the marginal product of labor and wage of a healthy worker. We assume that the firm earns rents on a worker as a result of frictions in the labor market that make the firm a wage setter (Burdett and Mortensen (1978), Manning (2003), Postel-Vinay and Robin (2002)).[19] A healthy worker has a probability ρ of contracting a fatal, but treatable disease. If the worker becomes ill, the firm has a choice of whether to keep the ill worker with no treatment, whether to provide treatment to the worker or whether to replace the ill worker with a new worker. More formally, we define $V_d = \max\{V_s^t, V_s^u, V_n\}$, where V_s^t is the value to the firm of an ill worker receiving treatment, V_s^u is the value to the firm of an untreated infected worker and V_n is the value to the firm of a new recruit. We also include the possibility of non-illness related worker turnover; with probability b per unit of time, a healthy worker will separate from the firm in which case a firm hires a new worker.

To solve the firm's problem, we start by establishing the conditions under which firms will provide treatment conditional on worker infection. In particular, we compare the value (to the firm) of providing treatment (or not) to a sick worker. We assume further that firms bear the cost of treatment. In addition, we assume that treatment increases the expected duration of employment with the firm. In particular the probability of illness-related separation is lower under treatment $q < \delta$.[20] Following separation, the firm hires a new worker of value V_n. Given these assumptions, the value to the firm of a sick worker

[18] We borrow the modelling of the firm's problem from Shapiro and Stiglitz (1984). We abstract from other human-capital enhancements that the firm might choose to provide such as training. In our simple framework, productivity increases through the process of learning-by-doing.

[19] Labor market imperfections are likely to be more relevant in developing country settings (see Agenor, 1995 for a detailed review)

[20] This assumption follows from the fact that the treatment is effective and reduces mortality/morbidity risk and that treatment can only be obtained while in employment. The latter is typical of most firm-based treatment programs.

with treatment V_s^t, and without treatment V_s^u is given by[21]:

$$rV_s^t = (MPL_s^t - w_s - c) + q(V_n - V_s^t) \tag{4.3.2}$$
$$rV_s^u = (MPL_s^u - w_s) + \delta(V_n - V_s^u)$$

The firm decides to provide treatment if $V_s^t - V_s^u > 0$. It is convenient to write the net instantaneous payoff to the firm $(MPL_s^t - w_s)$, and $(MPL_s^u - w_s)$ as θ_s^t and θ_s^t. The treatment condition can be stated as follows:

$$(q + r)(\theta_s^t - \theta_s^u) + (\delta - q)(\theta_s^t - rV_n) > (\delta + r)c \tag{4.3.3}$$

There are two parts to the left hand side of the treatment condition. Firstly, the net benefit of treatment includes a productivity difference captured by $\theta_s^t - \theta_s^u > 0$.[22] Secondly, providing treatment keeps a more productive worker longer and obviates the need for a new worker. The sum of these two terms is compared to the cost of treatment c.

This treatment condition illustrates that firms will have larger incentives to offer treatment to some types of workers over others. In particular, workers for whom the costs of illness (in terms of foregone productivity) are very high relative to treatment or workers for whom the returns to tenure are very high are more likely to satisfy the treatment condition. Alternatively, if separation rates of sick workers, captured by δ, is very high, firms are more likely to provide treatment if and only if $(\theta_s^t - rV_n)$ is greater than the cost of treatment, c.

To complete the model we need to determine the firm's choice between hiring a new worker or providing treatment when treatment is preferred to non-treatment. In this direction, we compare the value to the firm of a new worker relative to a treated worker.

We assume that firms do not have any information regarding the health status of

[21] We assume that the wage paid to a treated and untreated ill worker is the same w_s.

[22] We assume that healthy and unhealthy workers with the same characteristics earn the same wages. Differences in $\theta_s^t - \theta_s^u$ are therefore driven by differences in productivity induced by treatment efficacy.

potential employees, but know the underlying incidence rates of the illness.[23] In addition, we assume that the likelihood that a new worker becomes ill is the same as the likelihood of an experienced worker contracting the disease.[24] If a worker reveals he/herself to be ill, then the firm chooses whether they should provide treatment or wait and go back to the labor market. Learning by doing is the primary channel of productivity increases: with probability μ per unit of time the novice becomes a healthy experienced worker with value to the firm V_g. Given these parameters, the choice between treated and novice workers is given by the solution to the following system of equations:

$$\begin{aligned} rV_n &= \theta_n + \rho(V_d - V_n) + \mu(V_g - V_n) \\ rV_g &= \theta_g + \rho(V_d - V_g) + b(V_n - V_g) \\ rV_s^t &= (\theta_s^t - c) + q(V_n - V_s^t) \\ V_d &= \max\{V_n, V_s^t\} \end{aligned} \tag{4.3.4}$$

If $V_n > V_s^t$, then $V_d = V_n$, otherwise $V_d = V_s^t$.

Solving the three simultaneous equations above, firms provide treatment rather than hire a new worker if:

$$(r + \rho + \mu + b)(\theta_s^t - \theta_n) > \mu(\theta_g - \theta_n) + (r + \rho + \mu + b)c \tag{4.3.5}$$

Increasing the interest, infection or separation rates increases the likelihood of treatment when $\theta_s^t - \theta_n > c$,

Assuming that the productivity of a treated worker is restored to pre-illness levels ($\theta_s^t \approx \theta_g$), we can re-write the treatment condition as:

[23] While most firms have a pre-employment examination of some kind (Ramachandran et al. (2006)), it usually does not include an HIV-test. Note that a one-time test would not be sufficient to establish the health status of an individual since he/she can be infected after the pre-employment check.

[24] This might not be a realistic assumption given that new workers are generally younger than older workers and prevalence rates are lower amongst younger (particularly *male*) workers.

$$c^* = \frac{r+b+\rho}{r+b+\rho+\mu}(\theta_s^t - \theta_n) \tag{4.3.6}$$

The treatment condition above provides useful intuition: firms compare the net benefit of treatment against the cost of treatment and the foregone opportunity of a new worker becoming a healthy and productive worker. The magnitude of $(\theta_s^t - \theta_n)$ depends on the differential slopes of the marginal product of labor and wage profiles for a given worker over his/her tenure in the firm. In order for firm-based provision of ARVs to be optimal, two conditions need to be satisfied. Firstly, we require that there is a wedge between the marginal product of labor and worker wages. Theoretically this wedge has been posited in different types of models, such as the presence of labor market imperfections (Burdett and Mortensen (1998), in competitive implicit contract models such as (Lazear, 1979) or in models with symmetric imperfect information (Harris and Holmstrom, 1982). The second condition needed for the provision of ARVs by the firm is driven by the size of differential rents to the firm of "experienced" but ill workers relative to "novice" workers of unknown health status. In order for the right hand side of equation 4.3.6 to be positive, we require that the marginal product-wage gap be larger for workers with longer tenure.

The empirical literature on the profile of productivity and wages with tenure is inconclusive. A number of microeconomic studies have examined the tenure-productivity and tenure-wage relationship.[25] Two recent contributions, Hellerstein, Neumark and Troske (1999) and Crepon, Deniau and Perez-Duarte (2003), attempt to estimate the relative marginal productivity of different types of labor. Hellerstein et. al. (1999) using US data conclude that the marginal productivity of middle aged workers rises at the same rate as earnings. Conversely Crepon et. al.(2003) using French data find that earnings rise faster than productivity for middle-aged workers, suggesting a declining marginal productivity-wage gap with tenure.[26] The findings in these studies suggest that firms would not provide treatment in equilibrium since $\theta_s^t - \theta_n \leq 0$. Thus hiring a new worker

[25]These include papers by Lazear (1979, 1981), Medoff and Abraham (XXXX), Hutchens (1987, 1989), Carmichael (1983), Jovanovic (1981), Borjas (1981) and Jovanovic and Mincer (1947).

[26]An earlier paper by Kotlikoff and Gokhale (1992) using earnings data from a Fortune 500 company arrives at the same conclusion.

dominates treating a long-tenure infected worker, a result consistent with a conjecture by Rosen (2006) that the economic basis for firm-based treatment provision is thin.

However, two recent cross-country studies show that countries or sectors with a high proportion of long tenure workers have higher productivity (Auer, Berg and Coulibaly (2004)) and that economies with a larger share of 40-49 year olds have higher growth rates (Feyrer 2007). While omitted variables are likely to compromise the validity of these conclusions, these results suggest an alternative production function with stronger complementarities than those assumed by the micro-studies. In particular, firms might care about maintaining a substantial share of long tenure workers, since the marginal productivity of any worker is likely to depend on the average tenure of the workforce. In a world of stronger complementarities, firm-based treatment provision to experienced workers could be optimal.

Assuming that $\theta_s^t - \theta_n \geq 0$, we turn to the data to find reasonable measures of each of the parameters above to establish the conditions under which firms will offer their workers treatment. We assume a discount rate $r = 0.08$. Firm data from the South Africa Manufacturing survey yields an average tenure of 7 years which implies that $b = 0.14$ (South Africa Investment Climate Report (2004)). Our HIV incidence data comes from Shelton (2006). We take as our estimate of ρ, the high end of his estimates of HIV incidence rates over a duration of one year: $\rho = 0.06$. Our estimate of μ depends on the share of individuals who would be revealed to be high-productivity types in time interval t. We assume that 12% of new workers reach high productivity levels in their first year. This implies that $\mu = (1-\rho)(1-b) * 0.12 = 0.1$.[27]

Generating estimates for the magnitude of $(\theta_g - \theta_n)$ is not straightforward given the discrepancies in the literature and limited empirical estimates. Postel-Vinay and Robin (2002) is the only paper with usable estimates for this calibration. We make the following assumptions regarding the size of $\theta_s^t - \theta_n$: a new worker is analogous to the typical worker in the 25th percentile and an experienced worker is in the 75th percentile in

[27]Substituting for these parameters in our treatment condition

$$c^* = 0.736 * (\theta_g - \theta_n)$$

The slope parameter 0.736 is sensitive to the size of μ. For $\mu = 0.3$, the slope is now 0.48 and 0.36 when $\mu = 0.5$.

the distribution of firm quality. Using results from Postel-Vinay and Robin (2002) for unskilled workers suggests that, $(\theta_g - \theta_n) \approx 0.43w$. Assuming that the experienced worker comes from the median firm reduces this magnitude to $0.33w$.[28] Using these estimates, together with median wages from recent manufacturing surveys, we calculate the percentage of treatment costs that firms are willing to pay. We assume that the cost of treating a worker is uniform across the central and eastern African countries at \$360/year or \$30/month. The monthly cost of treatment in Botswana, Namibia and Swaziland is estimated at \$100 and \$141 in South Africa.[29] The results of this calibration are shown in figure 7. We show the results for two levels of the productivity-wage gap and two assumptions about the efficacy of treatment. The first bar shows the percent the typical firm is willing to pay when we assume that the productivity wedge $(\theta_g - \theta_n) = 0.1w$ and the effect of treatment fully restores productivity. The second column maintains the size of the wedge but assumes that treatment only partially restores worker productivity so that the wedge gap is $0.7 * (\theta_g - \theta_n)$. The third and fourth bars show corresponding numbers when the size of the productivity-wage gap is $0.4w$. Median monthly wages of an unskilled worker range between \$79/month in Eritrea to \$136 in Nigeria. For the Southern African economies, wage estimates are only available for production workers (both skilled and unskilled). The median monthly estimates range from \$156 in Botswana to \$702 in South Africa (various publications, World Bank).

Assuming that $(\theta_g - \theta_n) \approx 0.1w$ and that treatment fully restores productivity, the typical firm in Tanzania can finance 13% of the cost of providing treatment for an *unskilled* worker, while the typical firm in Nigeria can finance about 33% of the cost of treatment. In the Southern African economies where the costs of treatment are higher, the typical firm in Botswana can finance about 11% of treatment costs while the typical firm in South Africa can finance about 36% of treatment costs. [30] Assuming that treatment only

[28]These numbers come from figure 1 in Postel-Vinay and Robin(2002). In order to generate a productivity-wage gap that is a function of a particular wage, we convert wages at the 25th and 75th percentiles as functions of the median wage.

[29]These numbers are based on costs of the AMPATH treatment program in Kenya. The breakdown is about \$150 for first line ARV drugs and \$200 are the remaining treatment related costs (such clinic, medical and lab expenditures). The Botswana estimate is derived from Debswana's per patient costs. The estimate for South Africa comes from Cleary, McIntyre and Boulle (2006).

[30]Note that we assume uniform labor market frictions across economies and even more unrealistically uniform productivity-wage gaps across countries.

restores productivity to 70% of pre-infection productivity, firms in Nigeria and South Africa can finance about 25% of treatment costs. Assuming a productivity-wage gap of $0.4w$ implies that the typical firm in Tanzania could finance 52% of treatment costs, while a corresponding firm in Botswana can finance 46% of treatment costs for all of its workers. Assuming less than perfect efficacy of treatment the typical firm in Nigeria and South Africa can finance 94% and 100% of treatment costs. Taking $(\theta_g - \theta_n) \approx 0.1w$ as the most plausible productivity-wage gap, manufacturing firms in Africa can finance between 10-25% of the costs of ARV treatment when treatment is less than perfect and 13-33% when treatment efficacy fully restores worker productivity. The benefits to firms of providing ARV treatment is large considering that the socio-economic benefits from ARV treatment extend well beyond labor supply. As an example, Graff Zivin et al. (2006) show large gains to the health and schooling of children in households with adults receiving treatment.

6 Conclusion

In this paper we exploit an unusually long panel dataset of worker absenteeism from the Debswana Diamond Company as well as information on one of Africa's first firm-based ARV treatment programs to understand the effect of HIV/AIDS and ARV treatment on worker productivity. We find evidence that compared to other workers at the firm, individuals who are infected with HIV/AIDS display similar patterns of absenteeism until roughly one year prior to treatment start, when absenteeism starts to increase sharply. From an absenteeism peak of 5 days in the month of treatment onset, the workers quickly recover within the first year of treatment and then continue for the next three years to have patterns of absenteeism that are similar to those of healthy workers. Our results suggest that in an African context, ARV's are effective in the short, medium and long run in improving the health and productivity of workers and challenge recent claims that global support of ARV treatment will create health pensioners (The Economist. August 2006).

In the final section of the paper, we build a simple model in order to understand when the free provision of treatment to HIV workers is beneficial to firms. We first show that

the decision to provide treatment to an experienced sick worker depends crucially on the assumption that the marginal product-wage gap be larger for workers with longer tenure than newly hired inexperienced workers. Next we review the empirical literature on the pattern of worker productivity and wages with tenure and conclude that the micro and macro based studies do not yield any conclusive conclusions. Using a plausible *positive* measure of the marginal product-wage gap and data from manufacturing firm surveys in Africa, we show that firms can recover between 10-33% of treatment costs. These results do not account for other possible benefits of ARV treatment to the firm, such as reductions in medical and health insurance costs, death benefits, funeral costs as well as the benefits to the firm's reputation from investing in socially responsible programs.

Since the cost of treatment exceeds the benefits of treatment across a range of economies in Eastern and Southern Africa, widespread firm-based ARV provision is an unlikely policy option. And while relatively recent developments, such as the creation of the Global Business Coalition on HIV/AIDS, foreshadow an increasing involvement of firms in combating HIV/AIDS, the majority of firms in the developing world that have established workplace programs for their employees are very special companies, similar to the case of Debswana in Botswana. However, since our results suggest that the private benefits to firms from treatment can be significant, the provision of public subsidies to ARV treatment programs administered by private companies has the potential to become an important mechanism to provide treatment to people affected by HIV/AIDS in a resource constrained setting like Africa, as exemplified by the success of the public-private partnership between DaimlerCrysler and GTZ in South Africa.

References

Acemoglu, Daron and Simon Johnson, (2006). "Disease and Development: The Effect of Life Expectancy on Economic Growth," NBER Working Papers 12269, National Bureau of Economic Research, Inc.

Acemoglu, Daron., and Jorn-Steffen Pischke (1999) "Beyond Becker: Training in Imperfect Labor Markets" *Economic Journal* 109: 112-142

Auer, Peter and Janine Berg and Ibrahim Coulibaly, 2004. "Is a stable workforce good for the economy? Insights into the tenure-productivity-employment relationship," Employment strategy papers 2004-15, International Labour Office.

Becker, Gary (1964) *Human capital*. Chicago: The University of Chicago Press

Bell, Clive, Shanta Devarajan and Gersbach, H. 2003. "The Long Run Economic Costs of AIDS. Theory and an Application to South Africa." Policy Research Working Paper 3518, World Bank, Washington, D.C.

Bertrand Marianne and Esther Duflo and Sendhil Mullainathan, 2004. "How Much Should We Trust Differences-in-Differences Estimates?," *The Quarterly Journal of Economics*, MIT Press, 119(1) 249-275

Burdett, Kenneth and Mortensen, Dale, 1978. "Labor Supply Under Uncertainty". In *Research in Labor Economics*, ed. Ronald G. Ehrenberg. Greenwhich, CT: JAI Press.

_____. 1998. "Wage Differentials, Employer Size, and Unemployment". *International Economic Review* 39 (2): 257-73.

Canning, David, 2006, "The Economics of HIV/AIDS in Low-Income Countries: The Case for Prevention", *The Journal of Economic Perspectives* 20(3)

Case, Anne and Angus Deaton, (2006) "Health and wellbeing in Udaipur and South Africa", Center for Health and Wellbeing, Princeton University, WP

Cleary S, McIntyre D, Boulle A. 2006. "The cost-effectiveness of Antiretroviral Treatment in Khayelitsha, South Africa – a primary data analysis", *Cost Effectiveness and Resource Allocation*. Vol. 4:20

Crepon, B., Deniau, N., and Perez-Duarte, S. 2002. "Wages, Productivity and Worker Characteristics" Institut National De La Statistique et des Etudes Economiques (INSEE) WP #2003-04.

Duggan, Mark and William N. Evans, 2005. "Estimating the Impact of Medical Innovation: A Case Study of HIV Antiretroviral Treatments," NBER Working Papers 11109, National Bureau of Economic Research, Inc.

Feyrer, James, (2007) "Demographics and Productivity", forthcoming in *Review of Economics and Statistics*

Fitzgerald, John, and Peter Gottschalk and Robert Moffitt, (1998). "An Analysis of the Impact of Sample Attrition on the Second Generation of Respondents in the Michigan Panel Study of Income Dynamics". *Journal of Human Resources*, Spring 1998

Floridia, M., et al., 2002. "HIV-Related Morbidity and Mortality in Patients Starting Protease Inhibitors in Very Advanced HIV Disease", *HIV Medicine*, 3(2): 75-84.

Fox MP and Rosen S and MacLeod WB et al. (2004) "The impact of HIV/AIDS on labour productivity in Kenya". *Tropical Medicine and International Health* 9: 318-324.

Graff Zivin, Joshua and Harsha Thirumurthy and Markus Goldstein, 2006. "AIDS Treatment and Intrahousehold Resource Allocations: Children's Nutrition and Schooling in Kenya," NBER Working Papers 12689, National Bureau of Economic Research, Inc.

Hammer, S.M., et al., 1997. "A Controlled Trial of Two Nucleoside Analogues Plus Indinavir in Persons with Human Immunodeficiency Virus Infection and CD4 Cell Counts of 200 per Cubic Millimeter or Less", *The New England Journal of Medicine* 337(11): 725-33.

Harris, Milton and Holmstrom, Bengt. 1982. "A Theory of Wage Dynamics". *Review of Economic Studies* July 49 : 315-33

Hellerstein, Judith K and Neumark, David and Troske, Kenneth R, 1999. "Wages, Productivity, and Worker Characteristics: Evidence from Plant-Level Production Functions

and Wage Equations," *Journal of Labor Economics*, University of Chicago Press, 17(3): 409-46

Kalemli-Ozcan, Sebnem (2006), "AIDS, Reversal of the Demographic Transition and Economic Development: Evidence from Africa," NBER Working Paper 12181

Kaufmann GR, Bloch M, Finlayson R, et al. (2002). "The extent of HIV-1-relatedimmunodeficiency and age predict the long-term CD4 T lymphocyte response to potent antiretroviral therapy." *AIDS*. 16:367.

Koenig, Serena P., Fernet Leandre, and Paul E. Farmer. 2004. "Scaling-up HIV Treatment Programmes in Resource-limited Settings: The Rural Haiti Experience". *AIDS* 18:S21-S25

Lazear, Edward. 1979. "Why is there Mandatory Retirement?" *Journal of Political Economy* 87(6) : 1261-84.

Little, R and D Rubin. 1987. *Statistical Analysis with Missing Data,* New York, Wiley.

Manning, Alan. 2003. *Monopsony in Motion*. Princeton University Press, Princeton New Jersey.

Marins, Jose Ricardo P. et al. 2003. "Dramatic Improvement in Survival Among Adult Brazilian AIDS patients." *AIDS* 17:1675-1682.

Mbakile, Bekezela (2005). Presentation given at the Center for Global Development, October 2005

Morgan, Dilys et al. 2002. "HIV-1 Infection in Rural Africa: Is There a Difference in Median Time to AIDS and Survival Compared With That in Industrialized Countries?" *AIDS* 16:597-603.

Postel-Vinay, Fabien and Jean-Marc Robin, (2002). "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity," *Econometrica*, Econometric Society, 70(6):2295-2350

Ramachandran. Vijaya and Manju Kedia Shah and Ginger Turner, (2006). "Does the Private Sector Care About AIDS? Evidence from Investment Climate Surveys in East Africa," Working Papers 76, Center for Global Development.

Rosen, Sydney. 2006. quoted in *Financial Times*, December 1 2006.

Rosen, Sydney, Rich Feeley, Patrick Connelly and Jonathan Simon, (2006), "The private Sector and HIV/AIDS in Africa: Taking Stock of Six Years of Applied Research," Center for International Health and Development Discussion Paper No.7, 2006.

Sachs, Jeffrey, (2003). "Institutions Don't Rule: Direct Effects of Geography on Per Capita Income," NBER Working Papers 9490, National Bureau of Economic Research, Inc.

Shapiro, Carl and Joseph E. Stiglitz (1984), "Equilibrium Unemployment as a Worker Discipline Device", *American Economic Review*, (74): 433-444.

Shelton, JD, Halperin DT, and Wilson, D. "Has global HIV incidence peaked?", *Lancet* 367 : 1120–1122.

Strauss, John and Duncan Thomas (1998). "Health, Nutrition, and Economic Development". *Journal of Economic Literature* 36: 766-817

Thirumurthy, Harsha and Johsua Graff-Zivin and Markus Goldstein, 2005. "The Economic Impact of AIDS Treatment: Labor Supply in Western Kenya," NBER Working Papers 11871, National Bureau of Economic Research, Inc.

Thomas, Duncan et al (2006). "Causal Effect of Health on Labor Market Outcomes: Experimental Evidence" UCLA mimeo

UNAIDS. (2002). "The Private Sector Responds to the Epidemic: Debswana -a Global Benchmark. Geneva: Joint United Nations Program on HIV/AIDS (UNAIDS Case Study)

The Economist. "Look to the Future: The War Against AIDS". August 19th 2006. The Economist Newspapers Ltd. London, UK.

UNAIDS. (2006). Report on the global AIDS epidemic 2006. Geneva: Joint United Nations Program on HIV/AIDS (UNAIDS)

Wooldridge, Jeffrey, (2002). "Inverse probability weighted M-estimators for sample selection, attrition and stratification," CeMMAP working papers CWP11/02, Centre for Microdata Methods and Practice, Institute for Fiscal Studies.

Wools-Kaloustian, Kara, et al. 2006. "Viability and Effectiveness of Large-scale HIV Treatment Initiatives in Sub-Saharan Africa: Experience from Western Kenya. AIDS 20(1): 41-48

World Bank. 2003. "Uganda: An Assessment of the Investment Climate". Washington DC: World Bank

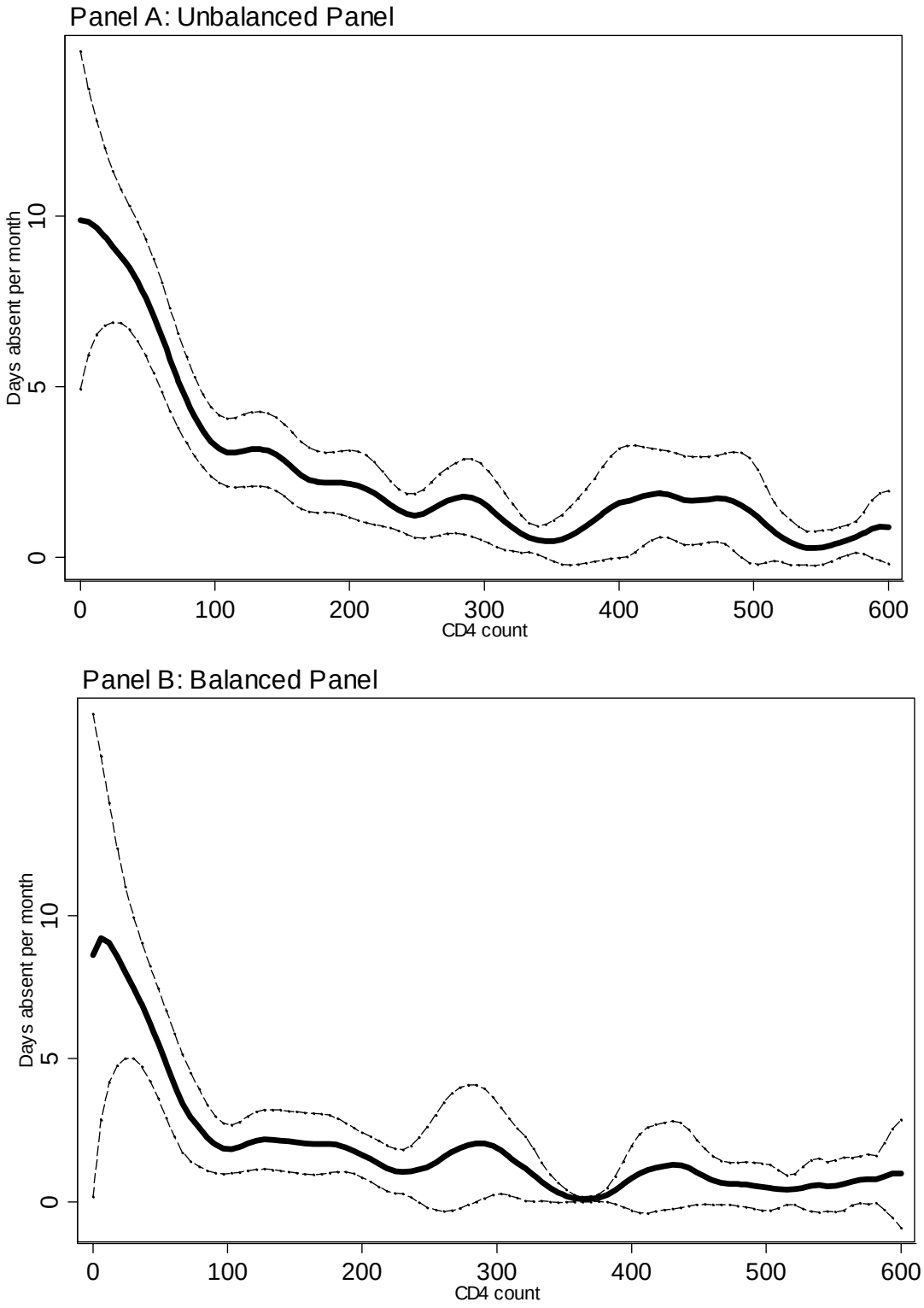
World Bank. 2004. "Tanzania: An Assessment of the Investment Climate". Washington DC: World Bank

World Bank. 2004. "Kenya: An Assessment of the Investment Climate". Washington DC: World Bank.

World Bank. 2005. "South Africa: An Assessment of the Investment Climate". Washington DC: World Bank.

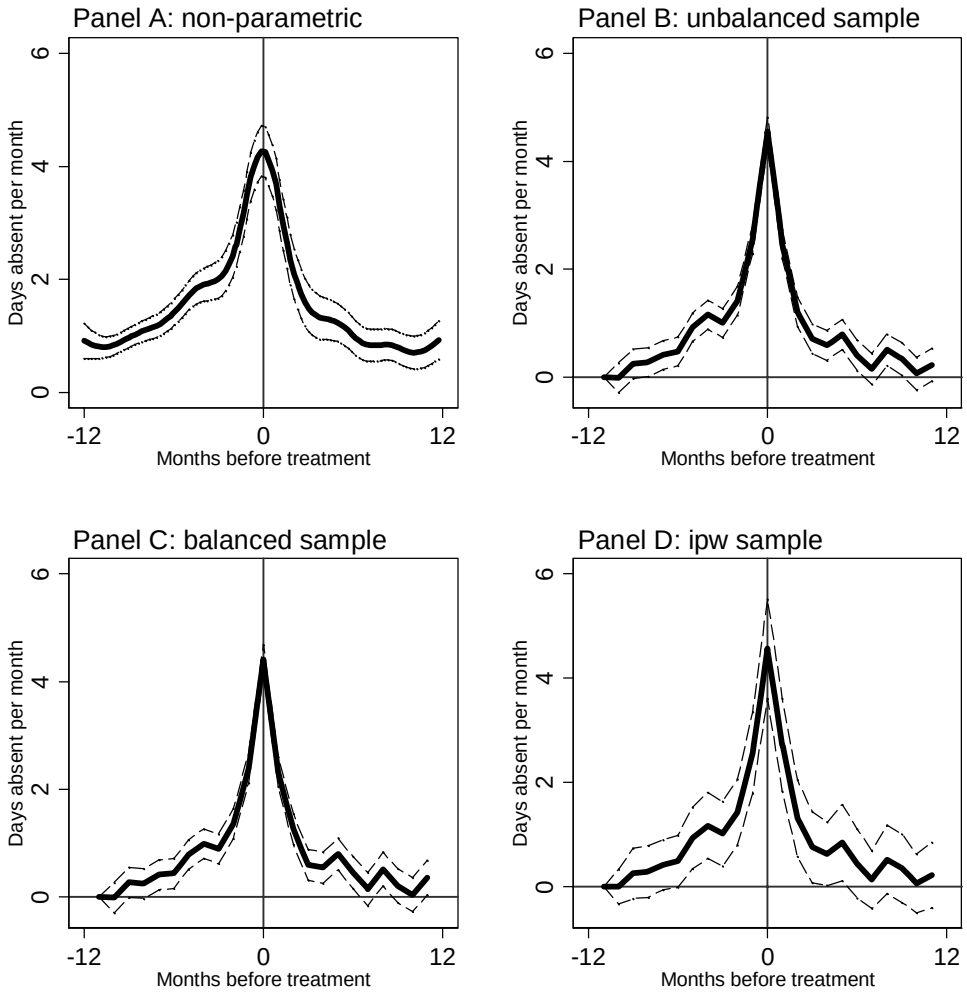
Young, Alwyn, (2005) "The Gift of the Dying: The Tragedy of AIDS and the Welfare of Future African Generations", *Quarterly Journal of Economics* Vol 120 No. 2

Figure 1: Relationship between CD4 Count and Sick Days from Work



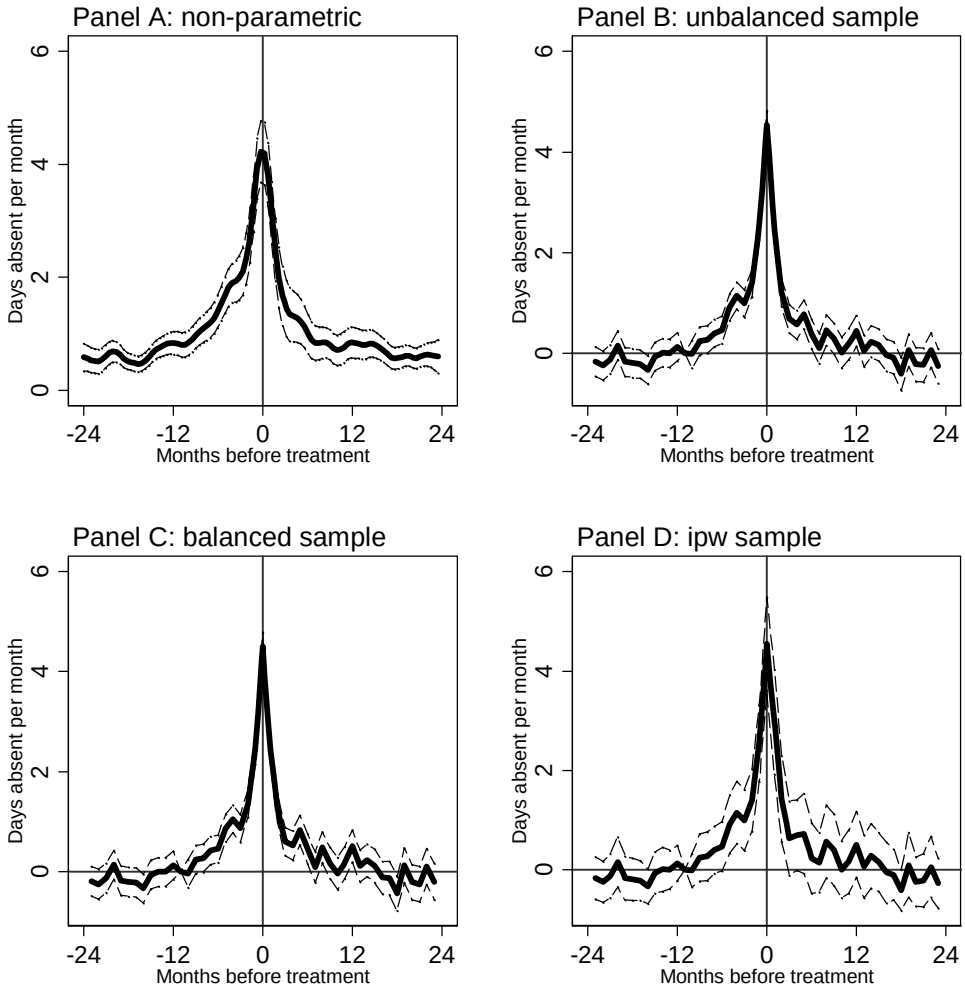
Note: Non-parametric Fan locally weighted regression with bootstrapped standard errors clustered by worker. Sickness-related absence duration data comes from the company's HR database and was linked to the CD4 count measured at the start of ARV treatment as well as 6 and 12 months after treatment start. Panel A uses an unbalanced sample while Panel B uses a balanced sample that includes only patients with three CD4 mesures.

Figure 2 : Effect of ARV treatment - One year window



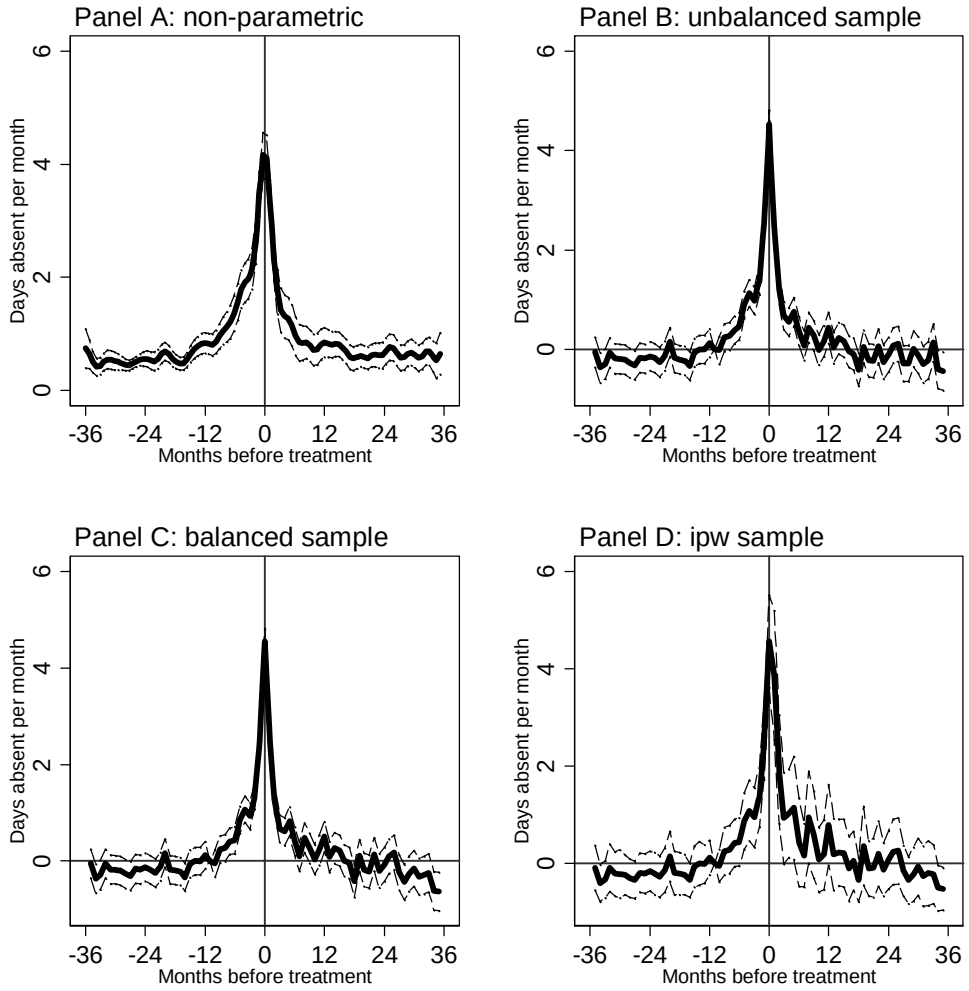
Note: Panels A is from a Non-parametric Fan locally weighted regression with bootstrapped standard errors clustered by worker. Panels B, C and D are from a fixed effect regression that includes worker and month fixed effects and they corresponds to the results in Columns 2, 4 and 6 of Table 2. Sickness-related absence duration data comes from the company's HR database. The interval used is one year before and after the onset of ARV treatment. Panels A and B use an unbalanced sample as defined in Table 2, panel C a balanced sample and panel D a sample with weights based on inverse probability weights (IPW).

Figure 3 : Effect of ARV treatment - Two year window



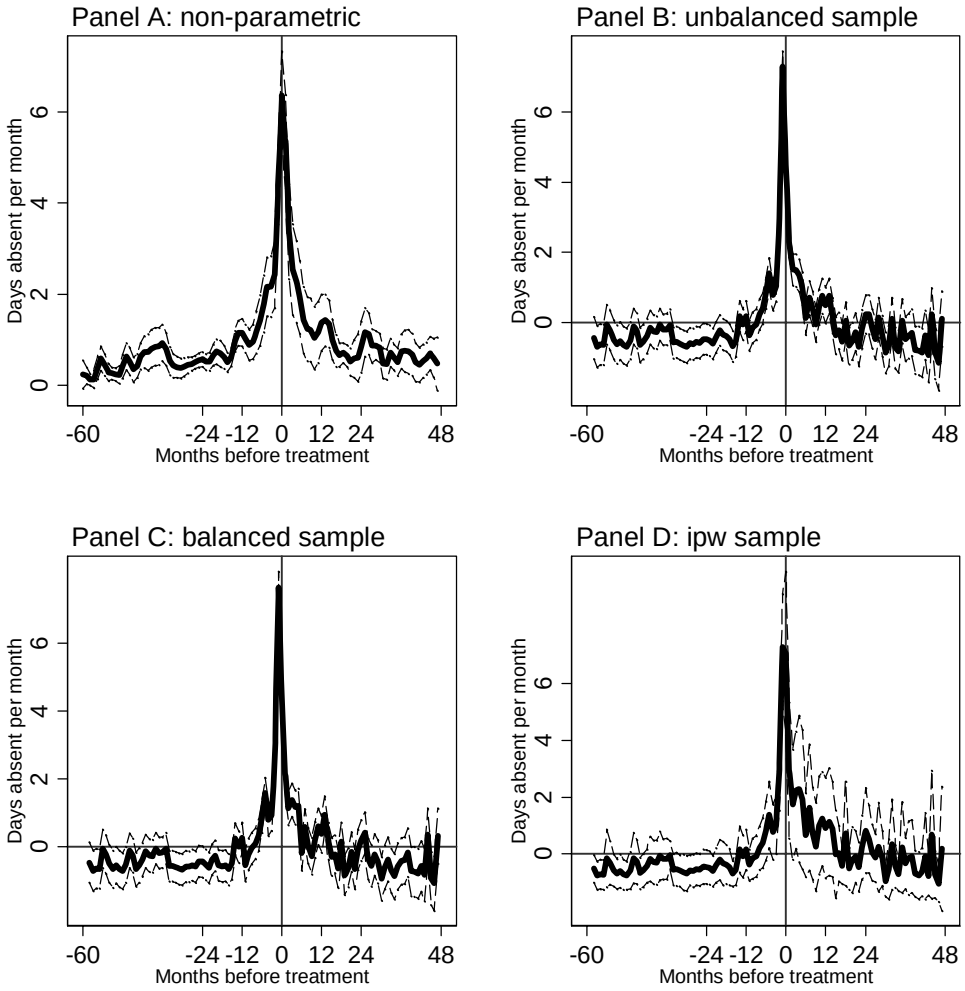
Note: Panels A is from a Non-parametric Fan locally weighted regression with bootstrapped standard errors clustered by worker. Panels B, C and D are from a fixed effect regression that includes worker and month fixed effects and they corresponds to the results in Columns 2, 4 and 6 of Table 2. Sickness related absence duration data comes from the company's HR database. The interval used is two years before and after the onset of ARV treatment. Panels A and B use an unbalanced sample as defined in Table 2, panel C a balanced sample and panel D a sample with weights based on inverse probability weights (IPW).

Figure 4 : Effect of ARV treatment - Three year window



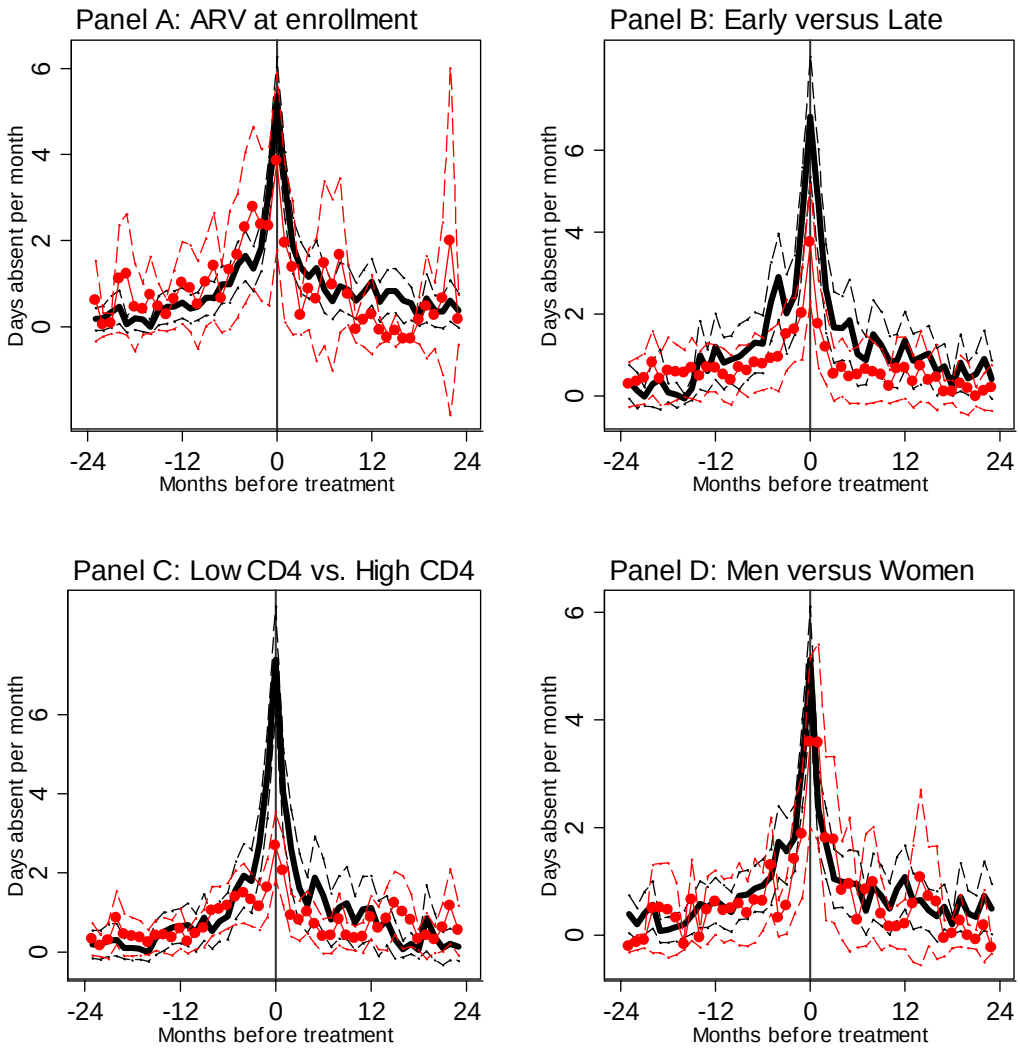
Note: Panels A is from a Non-parametric Fan locally weighted regression with bootstrapped standard errors clustered by worker. Panels B, C and D are from a fixed effect regression that includes worker and month fixed effects and they corresponds to the results in Columns 2, 4 and 6 of Table 2. Sickness-related absence duration data comes from the company's HR database. The interval used is two years before and after the onset of ARV treatment. Panels A and B use an unbalanced sample as defined in Table 2, panel C a balanced sample and panel D a sample with weights based on inverse probability weights (IPW).

Figure 5 : Effect of ARV treatment - Jwaneng mine



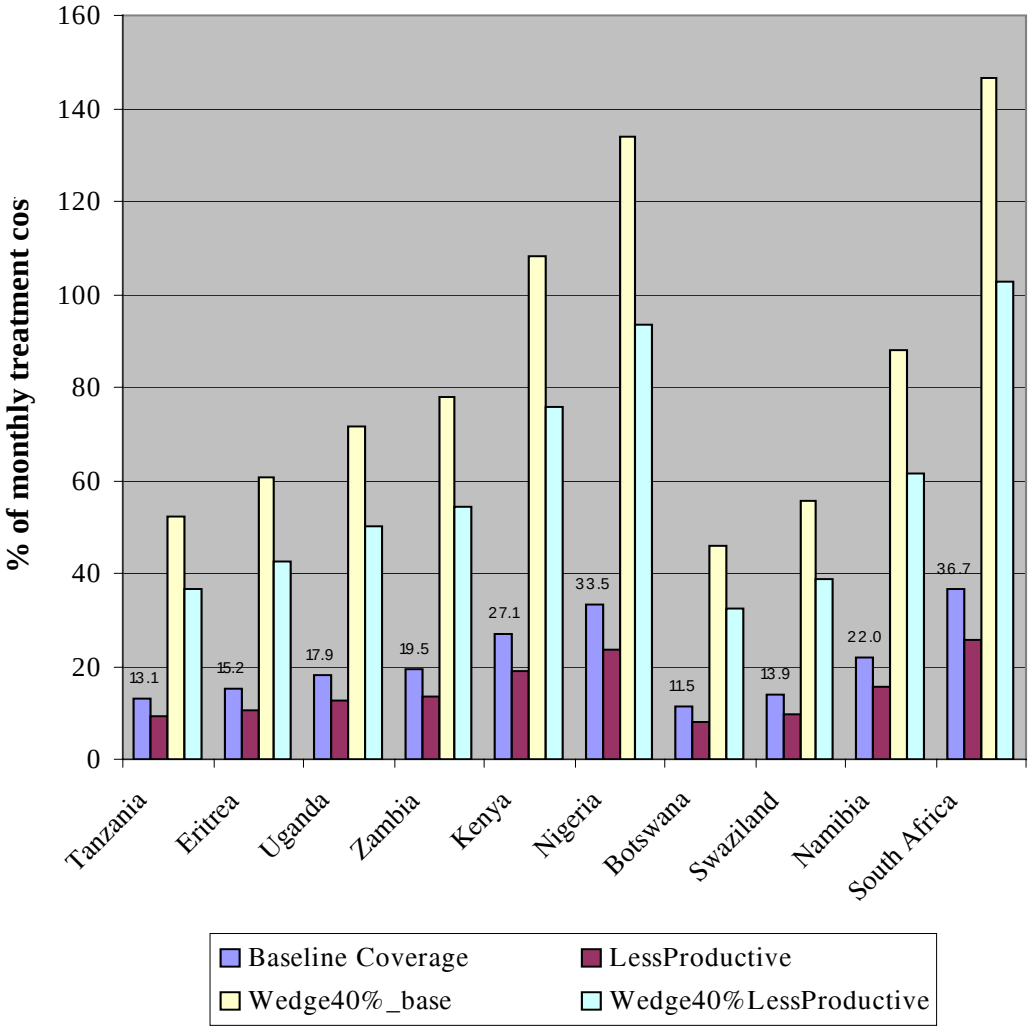
Note: Panels A is from a Non-parametric Fan locally weighted regression with bootstrapped standard errors clustered by worker. Panels B, C and D are from a fixed effect regression that includes worker and month fixed effects and they corresponds to the results in Columns 2, 4 and 6 of Table 2. Sickness related absence duration data comes from the company's HR database for the Jwaneng mine. The intervals used are 5 years before and 4 years after the onset of ARV treatment. Panels A and B use an unbalanced sample as defined in Table 2, panel C a balanced sample and panel D a sample with weights based on inverse probability weights (IPW).

Figure 6 : Effect of ARV treatment across groups



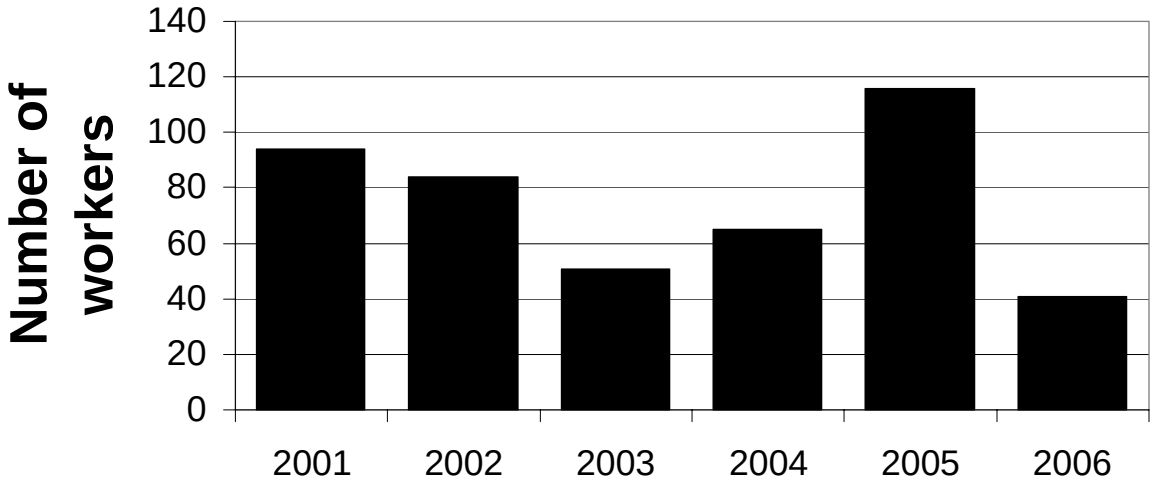
Note: All panels are based on Non-parametric Fan locally weighted regression with bootstrapped standard errors clustered by worker. Sickness-related absence duration data comes from the company's HR database for. The intervals used are 2 years before and after the onset of ARV treatment and uses a unbalanced sample as defined in Table 2. Panel A plots outcomes for individuals who started on ARVs when they enrolled in the program (black, continuous line) versus those who started ARVs after enrollment (red, dotted line). Panel B plot those who enrolled early (2001-2002) in the program (black, continuous line) versus late (2003-2004) (red, dotted line). Panel C plots those with low CD4 at ARV start (<150) (black, continuous line) versus high CD4 count (>150)(red, dotted line). Panel D plots outcomes for men (black, continuous line) versus women (red, dotted line).

Figure 7: % Firm Coverage of Patient Treatment Cost



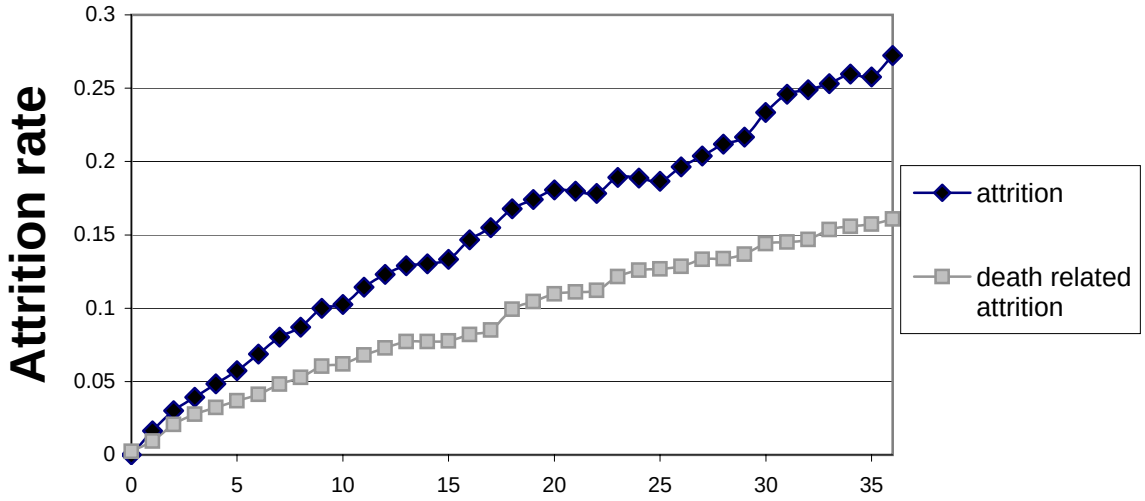
Notes: See Section 5 for a discussion of the assumptions made for the present calculations.

Appendix Figure 1: Timing of ARV enrollment



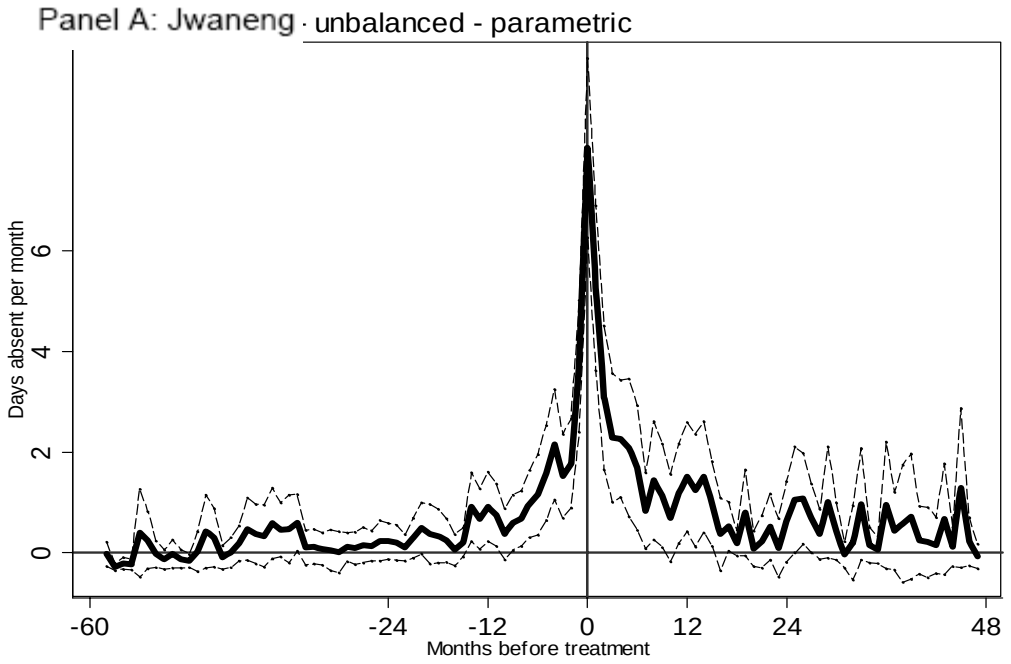
Source: Author's calculations based on HR and ART program data.

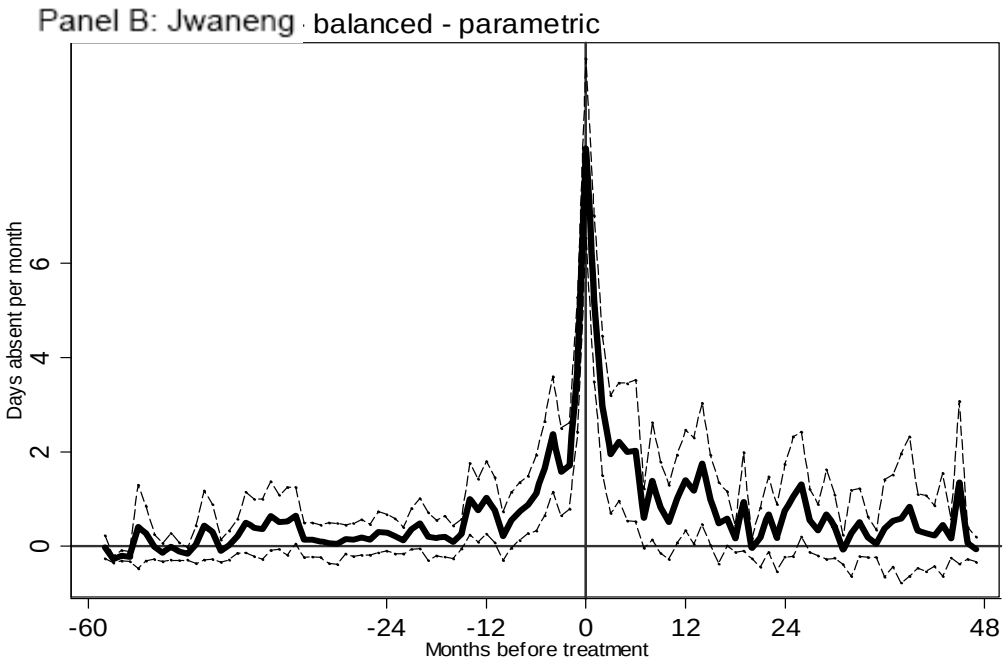
Appendix Figure 2: Attrition since start of ARV's



Source: Author's calculations based on HR and ART program data.

Appendix Fig 3: Effect of ARVs at Jwaneng mine, robustness checks





Note: Both panels are based on OLS regressions that include month fixed effects. Sickness-related absence duration data comes from the company's HR database for the Jwaneng mine. The intervals used are 5 years before and 4 years after the onset of ARV treatment. Panels A uses an unbalanced sample as defined in Table 2, panel B uses a balanced sample.

Table 1: CD4 Counts and Absenteeism from Work

	Panel A: Number of Sick Days per Month							
	OLS unbalanced	*Fixed Effects unbalanced*	*OLS balanced*	*OLS ip-weights*	*IV unbalanced*	*IV-Fixed Effects unbalanced*	*IV balanced*	*IV ip-weights*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
CD4 count	**-0.011*** **	**-0.011*** **	**-0.007*** **	**-0.010*** **	**-0.041*** **	**-0.034*** **	**-0.037*** **	**-0.040*** **
	[0.002]	[0.002]	[0.002]	[0.002]	[0.005]	[0.004]	[0.007]	[0.006]
Mean of dep. variable	**3.22**	**3.22**	**2.16**	**2.39**	**3.22**	**3.22**	**2.16**	**2.39**
	Panel B: First Stage for CD4 Count							
6 month dummy					**101.738*** **	**108.876*** **	**107.674*** **	**89.030*** **
					[10.653]	[9.712]	[12.669]	[10.880]
12 month dummy					**126.925*** **	**127.155*** **	**130.188*** **	**113.538*** **
					[12.224]	[10.834]	[13.945]	[12.412]
Mean of dep. variable					**220.89**	**220.89**	**245.58**	**234.68**
F-test					**70.91**	**95.62**	**50.94**	**52.36**
Observations	845	845	414	844	845	845	414	844

Notes: Sick days from work data comes from the company's HR database and was linked to the CD4 count measured at the start of ARV treatment as well as 6 and 12 months after treatment start. All regressions except in columns (2) and (6) include controls for age, worker band, gender and month and year of treatment start and the standard errors are clustered at the person level. Results in columns (2) and (6) are based person fixed effects regressions. The instruments used in column (5)-(8) are two dummy variable indicators that indicate that the CD4 count was measured at 6 and 12 months after the start of ARV theraphy. The regressions in columns (3) and (7) use a balanced sample that includes only patients with three CD4 mesures. The regressions in columns (4) and (8) use inverse probability weights (IPW), and the remaining columns use an unbalanced sample.*** significant at 1% level. ** significant at 5% level. * significant at 10% level.

Table 2: Sick Related Absenteeism around the Start of ARV treatment
(Dependent variable: Number of days absent from work due to sickness in a month)

	Unbalanced Panel		***Balanced Panel***		***IPW Panel***	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Months since ARV treatment						
-11 months	**0.484*** **	**----**	**0.484*** **	**----**	**0.485*** **	**----**
	[0.161]	----	[0.172]	----	[0.161]	----
-10 months	**0.474*** **	**-0.009**	**0.466*** **	**-0.017**	**0.475*** **	**-0.008**
	[0.160]	[0.138]	[0.170]	[0.144]	[0.160]	[0.283]
-9 months	**0.745*** **	**0.250***	**0.750*** **	**0.269***	**0.746*** **	**0.251**
	[0.195]	[0.138]	[0.211]	[0.143]	[0.195]	[0.298]
-8 months	**0.775*** **	**0.283** **	**0.716*** **	**0.248***	**0.775*** **	**0.284**
	[0.193]	[0.137]	[0.204]	[0.143]	[0.193]	[0.288]
-7 months	**0.920*** **	**0.412*** **	**0.891*** **	**0.411*** **	**0.920*** **	**0.417**
	[0.197]	[0.137]	[0.198]	[0.142]	[0.197]	[0.289]
-6 months	**1.034*** **	**0.477*** **	**0.979*** **	**0.435*** **	**1.034*** **	**0.481***
	[0.210]	[0.136]	[0.213]	[0.141]	[0.210]	[0.288]
-5 months	**1.481*** **	**0.927*** **	**1.321*** **	**0.782*** **	**1.481*** **	**0.933*** **
	[0.255]	[0.135]	[0.258]	[0.141]	[0.255]	[0.314]
-4 months	**1.721*** **	**1.159*** **	**1.534*** **	**0.986*** **	**1.721*** **	**1.167*** **
	[0.282]	[0.135]	[0.286]	[0.141]	[0.282]	[0.326]
-3 months	**1.562*** **	**1.004*** **	**1.435*** **	**0.892*** **	**1.562*** **	**1.012*** **
	[0.268]	[0.135]	[0.271]	[0.141]	[0.268]	[0.315]
-2 months	**1.966*** **	**1.416*** **	**1.894*** **	**1.360*** **	**1.966*** **	**1.424*** **
	[0.274]	[0.135]	[0.286]	[0.141]	[0.274]	[0.318]
-1 months	**3.113*** **	**2.561*** **	**2.926*** **	**2.390*** **	**3.113*** **	**2.568*** **
	[0.351]	[0.135]	[0.365]	[0.141]	[0.351]	[0.366]
0 months	**5.132*** **	**4.556*** **	**4.975*** **	**4.413*** **	**5.132*** **	**4.563*** **
	[0.430]	[0.136]	[0.446]	[0.141]	[0.430]	[0.430]
1 months	**3.082*** **	**2.467*** **	**2.921*** **	**2.321*** **	**3.423*** **	**2.716*** **
	[0.366]	[0.137]	[0.379]	[0.143]	[0.415]	[0.400]
2 months	**1.792*** **	**1.215*** **	**1.816*** **	**1.260*** **	**1.957*** **	**1.306*** **
	[0.303]	[0.138]	[0.324]	[0.144]	[0.334]	[0.337]
3 months	**1.226*** **	**0.710*** **	**1.073*** **	**0.591*** **	**1.332*** **	**0.753** **
	[0.267]	[0.140]	[0.275]	[0.146]	[0.293]	[0.314]
4 months	**1.102*** **	**0.593*** **	**1.011*** **	**0.541*** **	**1.197*** **	**0.625** **
	[0.228]	[0.141]	[0.230]	[0.148]	[0.254]	[0.287]
5 months	**1.308*** **	**0.795*** **	**1.266*** **	**0.797*** **	**1.414*** **	**0.840** **
	[0.302]	[0.143]	[0.325]	[0.150]	[0.329]	[0.327]
6 months	**0.919*** **	**0.407*** **	**0.913*** **	**0.453*** **	**1.012*** **	**0.44**
	[0.262]	[0.145]	[0.280]	[0.153]	[0.288]	[0.307]
7 months	**0.616*** **	**0.16**	**0.530** **	**0.14**	**0.636*** **	**0.13**
	[0.209]	[0.148]	[0.213]	[0.156]	[0.219]	[0.292]
8 months	**0.984*** **	**0.506*** **	**0.918*** **	**0.516*** **	**1.043*** **	**0.516***
	[0.266]	[0.150]	[0.280]	[0.159]	[0.289]	[0.304]
9 months	**0.829*** **	**0.340** **	**0.613** **	**0.204**	**0.880*** **	**0.348**
	[0.255]	[0.152]	[0.244]	[0.161]	[0.274]	[0.304]
10 months	**0.543*** **	**0.069**	**0.427** **	**0.04**	**0.570*** **	**0.055**
	[0.195]	[0.153]	[0.213]	[0.163]	[0.209]	[0.273]
11 months	**0.728*** **	**0.229**	**0.772*** **	**0.361** **	**0.753*** **	**0.212**
	[0.240]	[0.154]	[0.283]	[0.164]	[0.249]	[0.306]
12 months	**0.996*** **	**0.485*** **	**0.853*** **	**0.430*** **	**1.039*** **	**0.485***
	[0.252]	[0.155]	[0.257]	[0.165]	[0.269]	[0.291]
Observations	369916	369916	368898	368898	369869	369869
Controls	month fixed effects	person & month fixed effects	month fixed effects	person & month fixed effects	month fixed effects	person & month fixed effects

Notes: The unit of observation is a person month. Huber-White standard errors in parentheses, except for columns (1) (3) and (5) where the standard errors are clustered at the person level. The unbalanced panel uses all available person month observations, the balanced panel includes only those workers on ARV treatment for at least 12 months. Columns (5) and (6) use a sample with weights based on inverse probability weights (IPW). All regressions also add the rest of the workers at the company as controls.*** significant at 1% level. ** significant at 5% level. * significant at 10% level.

Table 3: Overall Absenteeism around the Start of ARV treatment
(Dependent variable: Number of days absent from work in a month)

	Unbalanced Panel		*Balanced Panel*		*IPW Panel*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Months since ARV treatment						
-11 months	**0.509*** **	**----**	**0.477** **	**----**	**0.510*** **	**----**
	[0.177]	----	[0.188]	----	[0.177]	----
-10 months	**0.455*** **	**-0.057**	**0.449** **	**-0.03**	**0.455*** **	**-0.057**
	[0.174]	[0.190]	[0.185]	[0.198]	[0.174]	[0.292]
-9 months	**0.766*** **	**0.239**	**0.725*** **	**0.243**	**0.767*** **	**0.24**
	[0.208]	[0.190]	[0.224]	[0.198]	[0.208]	[0.309]
-8 months	**0.841*** **	**0.313***	**0.796*** **	**0.321**	**0.842*** **	**0.315**
	[0.206]	[0.189]	[0.218]	[0.197]	[0.206]	[0.296]
-7 months	**1.109*** **	**0.560*** **	**1.097*** **	**0.604*** **	**1.109*** **	**0.564***
	[0.217]	[0.188]	[0.221]	[0.196]	[0.217]	[0.305]
-6 months	**0.913*** **	**0.311***	**0.820*** **	**0.26**	**0.913*** **	**0.32**
	[0.217]	[0.187]	[0.220]	[0.195]	[0.217]	[0.298]
-5 months	**1.644*** **	**1.039*** **	**1.511*** **	**0.955*** **	**1.644*** **	**1.045*** **
	[0.264]	[0.186]	[0.271]	[0.195]	[0.265]	[0.326]
-4 months	**1.661*** **	**1.048*** **	**1.475*** **	**0.910*** **	**1.661*** **	**1.054*** **
	[0.285]	[0.186]	[0.290]	[0.194]	[0.285]	[0.333]
-3 months	**1.629*** **	**1.011*** **	**1.531*** **	**0.961*** **	**1.629*** **	**1.018*** **
	[0.273]	[0.186]	[0.279]	[0.194]	[0.273]	[0.323]
-2 months	**2.176*** **	**1.565*** **	**2.077*** **	**1.514*** **	**2.176*** **	**1.571*** **
	[0.297]	[0.186]	[0.311]	[0.195]	[0.297]	[0.342]
-1 months	**3.150*** **	**2.536*** **	**2.931*** **	**2.365*** **	**3.150*** **	**2.542*** **
	[0.357]	[0.186]	[0.372]	[0.195]	[0.357]	[0.377]
0 months	**5.101*** **	**4.467*** **	**4.910*** **	**4.325*** **	**5.101*** **	**4.473*** **
	[0.433]	[0.187]	[0.450]	[0.195]	[0.433]	[0.437]
1 months	**2.926*** **	**2.240*** **	**2.750*** **	**2.110*** **	**3.263*** **	**2.469*** **
	[0.364]	[0.188]	[0.377]	[0.197]	[0.411]	[0.403]
2 months	**1.822*** **	**1.165*** **	**1.771*** **	**1.167*** **	**2.001*** **	**1.260*** **
	[0.307]	[0.190]	[0.328]	[0.199]	[0.336]	[0.348]
3 months	**1.419*** **	**0.812*** **	**1.251*** **	**0.710*** **	**1.546*** **	**0.875*** **
	[0.281]	[0.192]	[0.292]	[0.202]	[0.305]	[0.331]
4 months	**1.187*** **	**0.570*** **	**1.161*** **	**0.614*** **	**1.257*** **	**0.576***
	[0.253]	[0.194]	[0.261]	[0.204]	[0.274]	[0.313]
5 months	**1.246*** **	**0.630*** **	**1.213*** **	**0.674*** **	**1.354*** **	**0.675** **
	[0.310]	[0.196]	[0.335]	[0.207]	[0.335]	[0.338]
6 months	**1.044*** **	**0.433** **	**0.979*** **	**0.452** **	**1.131*** **	**0.456**
	[0.288]	[0.199]	[0.308]	[0.211]	[0.311]	[0.334]
7 months	**0.601*** **	**0.05**	**0.505** **	**0.06**	**0.609*** **	**0.01**
	[0.224]	[0.204]	[0.231]	[0.216]	[0.232]	[0.308]
8 months	**0.900*** **	**0.326**	**0.775*** **	**0.313**	**0.961*** **	**0.335**
	[0.274]	[0.206]	[0.292]	[0.220]	[0.295]	[0.314]
9 months	**0.948*** **	**0.358***	**0.685** **	**0.211**	**0.994*** **	**0.357**
	[0.276]	[0.209]	[0.274]	[0.222]	[0.293]	[0.328]
10 months	**0.498** **	**-0.078**	**0.328**	**-0.124**	**0.529** **	**-0.093**
	[0.213]	[0.210]	[0.231]	[0.225]	[0.225]	[0.289]
11 months	**0.842*** **	**0.233**	**0.817*** **	**0.332**	**0.862*** **	**0.208**
	[0.260]	[0.212]	[0.300]	[0.227]	[0.268]	[0.327]
12 months	**1.162*** **	**0.537** **	**1.033*** **	**0.532** **	**1.196*** **	**0.525***
	[0.270]	[0.213]	[0.278]	[0.228]	[0.284]	[0.314]
Observations	369916	369916	368898	368898	369869	369869
Controls	month fixed effects	person & month fixed effects	month fixed effects	person & month fixed effects	month fixed effects	person & month fixed effects

Notes: The unit of observation is a person month. Huber-White standard errors in parentheses, except for columns (1) (3) and (5) where the standard errors are clustered at the person level. The unbalanced panel uses all available person month observations, the balanced panel includes only those workers on ARV treatment for at least 12 months. Columns (5) and (6) use a sample with weights based on inverse probability weights (IPW). All regressions also add the rest of the workers at the company as controls.*** significant at 1% level. ** significant at 5% level. * significant at 10% level.

Appendix Table 1: Descriptive Statistics

	Mean	SD	N
Information for those receiving ARV treatment			
CD4 at treatment start	163	136	427
CD4 after 6 months	268	183	237
CD4 after 12 months	296	192	181
Age	42.65	8.28	441
Percent Male	0.82	0.39	441
Absenteeism Information (everyone)			
Monthly sickdays	0.32	2.07	369916
Monthly ordinary leave	0.80	2.02	369916

Notes: SD is the standard deviation and N is the sample size. The information on absences are based on the sample included in Table 2.