The Impact of HIV/AIDS and ARV Treatment on Worker Absenteeism: Implications for African Firms*

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Abstract

In 2001, the Debswana Diamond Company started the first firm-based program in Africa to provide free anti-retroviral treatment (ARVs) to HIV+ employees. We link individual health information from the firm's treatment program to a unique panel dataset of all the doctor sanctioned and non-medical episodes of absenteeism at the firm's two main mines between the period 1998-2006. This 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 15 months to 5 years *prior* to treatment start. Next we present robust evidence of an inverse-V shaped pattern in worker absenteeism around the time of ARV treatment inception. Enrolled workers are absent 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.

Next we present a simple model to understand the conditions under which it is optimal for profit-maximizing firms to establish workplace treatment programs for HIV positive workers. Under plausible assumptions about the labor market and the efficacy of treatment, our results suggest that for the typical manufacturing firm across East and Southern Africa, the benefits of treatment to the firm cover 8-22% of the cost of treatment. Without large increases in worker productivity, sizeable subsidies or declines in the cost of treatment, workplace treatment programs are not a feasible avenue for addressing the epidemic in high prevalence African economies.

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1 Introduction

In this paper we focus on the effect of HIV/AIDS on firms in the most affected African economies and try to understand whether, in an environment where the costs of the disease are high and treatment using anti-retroviral therapy (ARVs) is available and effective, it is economically beneficial for firms to provide treatment to their workers. Understanding the implications of HIV/AIDS and its treatment is an interesting case study in human resource management given the high prevalence of the disease in the working age population. While the positive health effects of anti-retroviral treatments (ARVs) around the world are by now well established (Hammer et al. (1997), Duggan and Evans (2005), Floridia et al. (2002), Lichtenberg (2006), Koenig et al. (2004), Wools-Kaloustian et al (2006)), the existing evidence has been limited to analyzing only the short run impact of HIV/AIDS and ARV treatment on labor market outcomes (Thirumuthy et al (2005), Fox et al (2004) and Larson et al. (2008)).

We take advantage of a unique dataset that permits a description of the *medium and long term* economic impacts of HIV/AIDS and the benefits of ARV treatment to workers and firms. 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 large private mining firm in Botswana. Secondly, we evaluate the feasibility of workplace programs for ARV treatment in Africa using our empirical results, data from recent manufacturing surveys on compensation and assumptions about worker productivity and wage setting behavior. We develop a framework to predict the conditions under which firms will provide ARV treatment to their workers. We find that although ARV treatment is extremely effective in reducing absenteeism in the medium and long run, firms' willingness to pay for treatment is only a small fraction of treatment costs.

In the first part of our analysis we estimate the impact of HIV/AIDS and ARV treatment

on worker absenteeism using data from the Debswana Diamond Company, an enterprise that employs over 6500 workers, and which started one of the first free firm-based ARV treatment programs in Africa. The decision to provide treatment came as a response to an HIV 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 illness related spells of absenteeism at the firm's two main mining sites with information about the health status and timing of ARV treatment initiation for a group of almost 500 workers enrolled in the company's treatment program. Since the absence 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. A limitation of our data is that we are unable to measure productivity losses due to presenteeism: losses associated with lower effort while on the job or worker re-assignment in response to illness.[1]

Firstly, we use the staggered timing of worker treatment initiation between May 2001 and April 2006 to estimate the patterns of absenteeism around the start of ARV treatment. 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 enrolled in the HIV/AIDS treatment program 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 non-enrolled workers at the mining company.

Our main empirical strategy does not allow us to identify the causal effect of ARV

[1]While the labor market effects of the epidemic include worker turnover due to voluntary and involuntary separation such as early retirements and death, we focus here on worker absence which is much more reliably measured.

treatment on absenteeism since we do not observe labor market outcomes in the absence of treatment. Therefore we develop a strategy for identifying a counterfactual for enrolled workers and present the results of a simple simulation of the health dynamics of untreated late-stage AIDS patients and a productivity-health mapping that draws from our analysis.[2] The results of this strategy suggest large but plausible long term treatment effects.

We also 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.[3] Our estimate suggests that within the first year of treatment, an increase equal to 100 cells/μl of the CD4 count (the average improvement in health after 6 months of therapy in this program) causes illness-related absence to decrease by roughly 1 day per month.

The second part of our analysis develops a framework to provide a rationale for when, where and how much a typical firm in Sub-Saharan Africa is willing to pay towards the cost of treatment. Building on the literature on firm-based skills development (Becker (1964), Acemoglu and Pischke (1999)) and the prevailing cost and efficacy of ARV treatment, we outline the tradeoff firms face in retaining a skilled but infected worker against the cost of treatment and the opportunity cost of not replacing that worker. Our calibration shows that given the current costs of provision of ARVs and a number of plausible assumptions about the labor market, the firm's willingness to pay for treatment covers only 8-22% of the cost of ARV treatment across a number of affected countries. Our results suggest that without the

[2]The World Health Organization has defined a primary infection stage and four clinical stages associated with progression from HIV infection to AIDS. The progression of the disease follows the decline (increase) of crucial immune response CD4 cells (HIV density). Clinical stage 1 is asymptomatic stage which can last a long time. Stage 2 of the disease is characterized by minor weight loss (<10%) and respiratory and fungal infections. Stage 3 is characterized by significant weight loss (>10%), chronic diarrhoea, persistent fever and severe infections. Stage 4 (late stage) is characterized by severe wasting and a wide range of severe bacterial, fungal and viral infections (Revised World Health Organization (WHO) Clinical Staging of HIV/AIDS For Adults and Adolescents (2005)).

[3]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/μl 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.

provision of public subsidies,[4] large increases in worker productivity or sizable reductions in the costs of treatment, ARV treatment programs financed by private companies are not economically beneficial to the typical African firm.

Our analysis proceeds as follows. We describe the treatment program in Section 2. In Section 3, we discuss the data, empirical strategy and regression framework. Section 4 presents the results of the main analysis. Section 5 discusses a plausible strategy to establish a counterfactual for the absenteeism rate of enrolled workers. Section 6 presents the results and limitations of a simple model to understand the impact of HIV/AIDS and ARV treatment and provides a rationale for firm-based treatment provision. Section 7 concludes.

2 The ARV treatment program at the Debswana Diamond Company

Our analysis evaluates the impact of HIV/AIDS and ARV treatment on labor market outcomes of infected workers at the Debswana Diamond Company in Botswana, a country that has been hard hit by the HIV/AIDS epidemic with an adult HIV prevalence rate of 24% and a life expectancy at birth of only 36 years in 2005 (UNAIDS, 2006).

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 De Beers Corporation. Employing more than 6,500 workers, it 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.[5]

Relative to other large firms in Africa, Debswana has been a pioneer in sustained and

[4]Public subsidies could be justified given the child health and schooling benefits to the households of those who receive treatment (see Thirumurthy et. al 2005).

[5]Debswana is unusually large even in the broader African context. The average firm in manufacturing sectors across much of Africa is about 80 employees with a median of 20-50 employees (World Bank 2003, 2004a, 2004b, 2005).

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. 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 retirements due to HIV/AIDS rose to 75% of ill-health retirements in 1999 and the share of deaths due to AIDS increased to 59% in the same year. In 1999, the company conducted the first of a number of voluntary, anonymous prevalence surveys that revealed an HIV prevalence rate of 28%. The prevalence rate in 2003 remained high (19.9%) and was higher among workers aged 30-39 (26%) and among the unskilled and semi-skilled workforce (23%).

In May 2001, Debswana Diamond Company started an ambitious treatment program that provides free anti-retroviral therapy (ARVs) to the company's workforce and their spouses. Enrollment is determined as a consequence of regular health visits in which tests for HIV might be required.[6] The uptake of voluntary counseling and testing has been low and enrollment is largely driven by the timing of an individuals infection, their history of health shocks and the robustness of their immune system. The program has been extremely successful. 158 patients were enrolled in the first year of operation and that number had increased to 721 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, ill-health retirements, and the number of sick day leaves (Mbakile, 2005).[7]

[6]The firm has been careful to maintain strict confidentiality of health status given the high levels of stigma. As such, the enrollment decision is primarily determined by the interaction of the worker and his/her doctor.

[7]These estimates are from a presentation given at the Center for Global Development, Washington DC in October 2005.

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 absence episodes from Debswana's two main mines. The Jwaneng data covers the period April 1998 to March 2006, while the data from the Orapa mine 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.[8] The absence data distinguishes between two different types of leaves: medical (sick) leaves and ordinary leaves. The administrative data used in this paper is of much higher quality than the data cited in other studies of absence in developing countries (see Chaudhry et.al. (2006)). Firstly, a worker must get a note from a doctor at one of the mine hospitals before he can take a *paid* sick leave.[9] Secondly, since a large fraction of full time and contract workers are paid on a daily basis, the human resource records are very reliable. 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 one day a month (1.12) from work and the breakdown by leave-type is .32 days for sick leaves and .8 days 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 self-reported duration of illness-related absence is .3 days per month.

The second source of data is a medical database of the ARV treatment program described in the previous section.[10] We have information from 721 workers and spouses who ever

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

[9]Workers can take up to a maximum of 184 sick days in a three year cycle. Regular or non-paid leave can then be used if a worker exceeds this limit.

[10]Triple therapy with a combination of two Nucleoside Reverse Transcriptase Inhibitors (NRTIs) (either

enrolled in the program in the period May 2001 - April 2006. This dataset has information on the timing of enrollment in the program and the start of ARV therapy.[11] 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.[12] Finally CD4 counts at 0, 6 and 12 months after ARV treatment initiation are collected for all patients on treatment. Appendix Table 1 provides summary statistics for the treatment program: among the 721 patients enrolled, there are 538 workers and 183 spouses. We were able to match 530 of the 538 workers in the program to their human resource records. Among these 530 workers with matched records, 441 (83%) started ARVs at some point during the study period. 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 is medically recommended. About 60% of enrolled workers are diagnosed with WHO clinical stage 4 at the time of enrollment. Appendix Table 1 shows that the average CD4 count at ARV treatment start is only 163 cells/μl and almost 70% of patients have a CD4 count at treatment that is lower than the WHO (and the program's) guideline of 200 CD4 cells/μl.[13] 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, the patterns of absenteeism prior to ARV treatment start represents a close description of absenteeism for workers until very close to death.

Combivir or Duovir) and a Protease Inhibitor (PI) (such as Lopinavir/Ritonavir) is the typical course of treatment in the Debswana treatment program.

[11] These two dates do not necessarily coincide. A worker who enrolls well before becoming symptomatic is likely to start treatment later.

[12] 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.

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

3.2 Empirical strategy

In our analysis we use two approaches to document the relationship between HIV/AIDS, ARV treatment and worker absence. The first approach we employ characterizes monthly worker absence duration 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 441 workers with complete human resource data (see Figure 1A) who were at some point on ARVs, 91 enrolled in 2001, 84 in 2002, 51 in 2003, 63 in 2004, 113 in 2005 and 39 in 2006. Thus, there is substantial variation in the timing of the initiation of ARV treatment.

Our main 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 the large sample of workers from the company who are not enrolled in 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:

$$outcome_{pt} = \beta_0 + \sum_i \alpha_i dist\_from\_treatment^i_{pt} + \beta_1 \delta_p + \beta_2 \tau_t + \epsilon_{pt}\,, \tag{1}$$

where $outcome_{pt}$ is the 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 +/- 36 months. In our preferred specifications, we control for person effects (δ_p) and month effects (τ_t). Note that for workers who are not enrolled in

the treatment program $dist\_from\_treatment^i$ is undefined and observations corresponding to these non-enrolled workers are not used to identify α_i. Rather, enrolled workers i months from treatment onset identify α_i.

The second approach uses a direct measure of health (a person's CD4 count) to better understand the effect of health on labor market outcomes in the first year of treatment. We estimate a regression of the form:

$$outcome_{pt} = \beta_0 + \beta_1 health_{pt} + \beta_2 \delta_p + \beta_3 \tau_t + \epsilon_{pt}\,, \tag{2}$$

where $health_{pt}$ is measured by the CD4 count of person p at time t , and our outcome variable is duration of illness-related absences in the month that the CD4 count was taken. This regression is restricted to those individuals who have started treatment. For the 441 workers on ARVs with matched human resource records we have up to three CD4 counts per worker (at 0, 6 and 12 months after treatment start), resulting in 845 observations.[14] While this sample contains a limited number of observations, it has the advantage of offering a direct measure of the health status of the workers enrolled in the ARV treatment program. 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. In the specifications without person fixed effects we control for age, gender, occupational categories and mining site. One important concern is that mean reversion could explain improved health outcomes after the onset of ARV therapy. This worry 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 possible that the timing of ARV treatment start is influenced by an interaction of the condition of a person's immune system and a

[14]Not all patients have three CD4 measurements. This is due to missing data and the fact that some of the recently enrolled patients had not been scheduled for the second and/or third measurement by the end of the sample period.

random shock to health.

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

There are two main reasons why these strategies do not identify the impact of ARV treatment on absenteeism. Firstly we do not have a reliable *control* group. In our model, the "no treatment" comparison group is composed of 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 "average treatment effect of receiving ARV therapy", given that in the absence of treatment, many of the workers would have died. Morgan et. al. (2002) estimate a median duration of 9.2 months between the development of AIDS and death. We explore an alternative strategy to establish a counterfactual in section 5 below.

Secondly, 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.

As discussed above, we expect that estimates around treatment initiation are biased since workers who start treatment are likely to have an unusually low error term associated with treatment start. The importance of these biases for the estimates further away from the treatment start date depends critically on the time series properties of the error term;

biases will be larger if the correlation of the error terms over time is significant. Heckman and Robb (1985) in a context similar to ours have shown that as long as the error process is stationary[15], the spurious effect is symmetric around the date of treatment. Thus the comparison of the absenteeism rate of a person three years before and after treatment start will not be biased by the possibly endogenous treatment start date. Moreover, since we know from the medical literature that an HIV infected individual is generally asymptomatic three years prior to treatment start, the difference in absences three years before and after treatment will identify the extent to which ARV drugs restore a person's ability to supply labor (on the extensive margin) compared to a healthy person.

We have performed 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 (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 to compare outcomes by early vs. late enrollment, 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)).

[15]In the absence of treatment, the stationarity assumption will not hold. However, given that treatment is effective in restoring a patient's ability to fight health shocks, we are comfortable assuming stationarity of error terms.

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 is particularly important in the context of a terminal disease in which attrition as a result of death is likely considerable. In Figure 1B 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.[16]

We present results that use three different samples to address a number of estimation concerns. The *balanced* sample includes only those individuals for whom we have labor supply information for all the months in the sample window. The sample windows are 12 or 36 months for the regressions that measure the pattern of absenteeism around ARV treatment start and we use a one year interval for the health/CD4 sample.[17] The second is the unrestricted *unbalanced* sample 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 samples to be different. The third sample uses the inverse probability weights (IPW) (Fitzgerald, Gottschalk and Moffitt (1998) and Wooldridge (2002)) to adjust for attrition bias due to observable characteristics. We use background as well as absence duration 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

[16]The average annual attrition rate for non-enrolled workers in the period 2001-2006 is about 5%.

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

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. While the background characteristics have little explanatory power, higher absenteeism in the month prior to treatment start has a positive impact on attrition. 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.[18]

4 Results

4.1 Pattern of Absenteeism around ARV Treatment Start

A simple way to depict the main results of the paper is by graphical illustration. Figure 2 plots the relationship between the average number of sick days taken per month and the distance from treatment start measured in months for a three year window. Panel A uses a non-parametric Fan local regression model while the next three panels come from regressions that contain worker and month fixed effects for the three sampling strategies outlined above. In panels E and F we do not include person fixed effects in order to allow a comparison of workers on treatment to non-enrolled workers. In all panels, one can observe a gradual increase in absenteeism in the 12 months before treatment initiation. 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 absence rate of roughly 22%. The positive effect of treatment on labor market outcomes is equally stark: absenteeism falls sharply in the first six months following ARV therapy initiation, so that the shape of

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

absences around treatment implementation is almost symmetric.

We present regression results of the basic equation (1) in Table 1. 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 enrolled in the treatment program 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 non-parametric graphs, peaking at 5.13 days and then declining to less than a day twelve months afterwards.[19] Column (2) in the same table shows similar patterns from a regression that also includes person fixed effects. Introducing personal fixed effects requires that we drop one more parameter (-11 months) since knowing the month and patient perfectly predicts the time to/since treatment. The remaining columns show the same regressions using the balanced and the inverse probability weight samples.[20] The size and significance of the results is very similar across specifications allaying concerns of attrition bias. The same patterns emerge when we use the sum of regular and illness-related absences and they suggest that enrolled workers do not use additional regular leave days during episodes of poor health.[21]

Next, we present the results of the analysis for the widest interval possible. Figure 3 plots illness-related absences using the longer data series from the Jwaneng mine; 5 years prior to and 4 years after ARV treatment start. As in Figure 2, most of the changes in absenteeism occur within a one year window. Workers who are on treatment recover remarkably quickly and display very low rates of absenteeism in the medium and long term (1-4 years after treatment initiation). Similarly, an enrolled worker displays a pattern of labor supply that

[19]Diagnosis and treatment is carried out in the on-site mine hospitals. According to the treatment program rules, workers who start ARVs do not receive an automatic sick leave and the opening hours of the treatment program allow workers not to miss work on the day they start ARVs.

[20]The small reduction in the inverse probability weight sample is due to the fact that some of the observations have missing observable characteristics.

[21]See Table 2 in working paper version (Habyarimana, Mbakile and Pop-Eleches, 2009). The results are unchanged when we exclude the HIV+ workers enrolled in the program who are not taking ARVs.

is similar to non-enrolled workers throughout a large part of the post-infection period, a finding that challenges recent estimates in the literature (Fox et al. 2004). In panels E and F of Figure 3, we have re-run our analysis 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, enrolled infected workers take similar absence durations as other workers at the company who are not enrolled in the treatment program.[22]

In graphs not reported in the paper we have examined differences in absence patterns across worker types. We find 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. This is consistent with the fact that we find lower absenteeism rates in the year prior to treatment for workers with a higher CD4 count at treatment start. In addition, we find no differences in absenteeism between women and men.[23]

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 in Africa, we were able to map out the short, medium and long run patterns of absenteeism of HIV infected workers who receive ARV treatment. Our main results are as follows: (1) infected workers are as productive in terms of absence from work 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 shaped pattern of absenteeism that peaks at about 5 days of absence a month, and (3) in the period 1-4 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.

[22]In panels E and F of Figure 2 where we use the three year windows with data from both mines, the coefficients become statistically insignificant only about 18 months after treatment start.

[23]These results are presented in detail in an earlier version (Habyarimanam, Mbakile and Pop-Eleches, 2009).

4.2 CD4 counts and Worker Absenteeism

Finally we use the health information of the treated workers to characterize the relationship between underlying health (measured by CD4 counts) and worker absenteeism in the first year of ARV treatment. Figure 4 shows this relationship using non-parametric Fan locally weighted regressions with bootstrapped standard errors clustered at the person level for an unbalanced sample. 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 on worker absenteeism is provided in Table 2. Columns (1)-(3) present simple OLS regressions for the three samples (unbalanced, balanced, ipw-weights) and include controls for a number of observable characteristics, such as age, gender, worker band and time effects. Columns (4)-(6) also use the same samples but include person fixed effects. The results indicate that workers with a higher CD4 count are less likely to be absent from work: the estimates across all six specifications are large and highly significant and vary between -.0072 (standard error .0015) and -.0111 (standard error .0021). These estimates suggest that a difference in CD4 count of 100 points (which is the average improvement in health after 6 months of ARV therapy in this treatment program) is associated with a decrease in illness-related absenteeism of roughly one day per month.[24] Two main conclusions can be drawn from an analysis of Figure 4 and Table 2: (1) we find additional evidence that the overall impact of ARV treatment 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).

[24]Other studies in a similar setting find a similar CD4 response to ARV treatment. See for example Coetzee et. al (2004) and Wools-Kaloustian et. al. (2006)

5 Thinking about a Counterfactual

Figures 2 and 3 present the absence dynamics of workers who enroll in the treatment program between May 2001 and April 2006. As we discuss in the empirical strategy, the point estimates that trace out the inverse-V shaped trajectory around treatment start are identified using other HIV workers who start treatment at different times. This empirical strategy does not identify the effect of treatment on productivity since this requires observing the productivity dynamics of similar workers in the absence of treatment. As with other program evaluations, this exercise faces the same 'missing data' problem that treated units are observed in one state and the counterfactual is never observed. In our case, this problem is made even harder since we do not know the HIV status of any worker who is not enrolled in the treatment program. In this section we explore one approach to construct a counterfactual. We use information on health status at enrollment, the relationship between health and productivity and assumptions about the rate of disease progression in the absence of treatment.[25]

We know that in the absence of treatment, the health of infected workers would deteriorate further culminating in death in a short period. In order to generate the counterfactual trajectory of labor supply, we need to specify a time-path of health in the absence of treatment and predict corresponding productivity from the health-productivity mapping shown in figure 4. We use the results in Morgan et. al. (2002) on the median time to death for untreated late stage HIV patients to specify a very simple linear time path of health:

[25]We also tried a propensity score matching approach (Dehejia and Wahba (1999)) but the results are quite disappointing. While we do a good job in matching pre-treatment absence patterns, our post-treatment absence profile is not consistent with a permanent decline in health. We conjecture three reasons for our inability to generate a counterfactual based on the workers who exit the firm prior to 2001. Firstly, there is a lot of heterogeneity and noise in the absenteeism patterns of workers in the two years prior to treatment start. Therefore it is hard to generate a "typical" profile of absences for a person in the latter stages of HIV/AIDS that can then be matched to workers who retire or exit prior to 2001. Secondly, it is likely that the firm's decision to introduce treatment is optimal with respect to a rising epidemic: that is, the program is introduced at a time when the health of most infected workers has reached a point where treatment is necessary. Finally, it is possible that early victims of the epidemic exit before we can observe their absence profiles in the 'post-treatment' period.

late stage patients lose 12 CD4 cells/μl every month and death occurs at a CD4 count of 30 cells/μl.[26][27] The health-productivity-mapping is drawn from a cross-sectional regression of absence on a quadratic of CD4 count using information of workers at treatment onset ($t = 0$). This relationship tells us the marginal effect on absence of a decline in health of 1 CD4 cell/μl but predictably cannot provide any guidance on how to treat death. We assign 100% absence to all workers at or below our CD4 threshold of 30 cells/μl.[28] The results of this exercise are shown in Figure 5. The dashed line shows the expected trajectory of worker absence durations under the no-treatment condition for the three year window corresponding to the balanced panel of figure 2. Under these assumptions, all enrolled workers would be dead within 26 months of their treatment start dates. The difference between this trajectory and the actual time path (dark line) in Figure 5 confirms the large effect of treatment on productivity.

6 Is it Cost Effective for Firms To Provide ARVs?

Our results suggest that to the extent that worker absenteeism is a good proxy for productivity, the ARV treatment program evaluated here is effective in restoring the productivity of infected workers over a considerable duration. But is this evidence enough to motivate firms to provide ARV treatments? In this section, we present a simple framework that models a representative firm's decision to extend health coverage to include a terminal disease such as HIV/AIDS.[29] This framework captures the human resource management problem facing a

[26] The Morgan et. al (2002) sample from which our estimates of health decline are drawn is very similar to the treatment program sample studied here. Set in rural Uganda, the median CD4 count for those subjects developing AIDS (Stage 4 of the WHO classification) was 126 (Median CD4 count for enrolled workers is 144). Median CD4 count within 6 months of death was 61; 20% of these subjects had a CD4 count <10.

[27] The linearity assumption likely generates the most conservative 'treatment' effects. It is likely that the rate of decline is much higher at lower levels of CD4 count which would reduce working time considerably.

[28] An alternative assumption would be to assign a company absence ceiling beyond which the employment contract is terminated and a new worker is hired. Modeling the productivity implications of this would require further assumptions on the costs (in days worked) of replacing this worker and getting the new worker to the same level of productivity.

[29] In choosing a representative firm approach, we abstract from inter-firm strategic considerations which would require us to consider the full panoply of benefits of extending coverage rather than a narrow focus on the immediate beneficiaries of these treatment programs.

large number of firms in Sub-Saharan Africa that have to choose between providing/financing treatment for infected experienced workers and hiring new recruits.[30]

The details of this exercise are laid out in Appendix A. We begin by showing the conditions under which a representative firm will provide treatment in a context with no alternative sources of ARV treatment. Firstly, we show the conditions under which treatment of workers with HIV/AIDS is preferred to non-treatment and secondly we delineate the conditions under which a firm prefers to hire an inexperienced worker instead of providing treatment to an infected (and experienced) worker. Our main treatment condition (equation 5 in Appendix A) provides useful intuition: firms compare the productivity benefits of treatment against the cost of treatment and the opportunity cost of keeping the infected worker. If the net benefits of retaining a treated worker exceed the expected gains of a novice worker staying healthy and becoming highly productive, then firms prefer to retain the treated worker.

Finally using the willingness-to-pay-for-treatment condition (equation 6), we attempt to estimate the share of actual treatment costs that manufacturing firms in Africa are willing to pay. In doing so, we try to account for the additional benefits of treatment along the intensive margin of labor supply. The best evidence comes from a Kenyan study of tea pluckers (Larson et. al. (2008)) which indicates that conditional on being present at work, the productivity of treated women on treatment is 10-15% lower while the productivity of treated men is similar to a control group. In order to obtain a non-negative willingness-to-pay, two conditions need to be satisfied. Firstly, we require that there is a wedge between the marginal product of labor and wages.[31] Secondly, we require a positive correlation between the size of the marginal product-wage gap and worker tenure. Given the limited empirical evidence on the shape of worker productivity-wage relationship, we use the firm-

[30]This framework builds on the rich literature started by Becker (1964) and extended most recently by Acemoglu and Pischke (1999), that explores the rationale for why firms provide a number of human-capital enhancing investments to their employees.

[31]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).

based estimates in Postel-Vinay and Robin (2002) for our calibration. The description of the parameter values used in the calibration are discussed in Appendix A and the results of this exercise are presented in Appendix Table 2. Our estimates indicate that manufacturing firms in Africa can finance between 7-21% of the costs of ARV treatment when treatment efficacy is low and the productivity-tenure profile is shallow (column (4)) and 13-50% when treatment efficacy is high and we assume a steep productivity-tenure profile (column (1)). Our preferred estimates from column (3) suggest a willingness-to-pay range of 8-22%. In sum, despite the evidence that ARV treatment is able to restore the productivity of workers in the medium and long term, the benefits to firms of providing ARV treatment are too small for most firms in Africa to be economically feasible.[32]

6.1 Limitations of the model

Below we discuss some of the important limitations of our modelling framework. First, our analysis assumes uniformity across and within countries on the labor market frictions that give rise to positive marginal product-wage gaps. Secondly, our model does not fully account for a possible adverse selection effect that might arise if riskier types of workers select to work for a firm that offers ARV treatment. Thirdly, the decision of the firm to provide treatment might also be influenced by the availability of alternative treatment options. Our analysis in the appendix shows that these two latter factors generally would induce firms to be less inclined to offer treatment to their workers.

At the same time, our model and calibration does not account for a number of mechanisms that could make the provision of treatment profitable for the firm. Firstly the production function assumed exhibits no major complementarities between workers. A production function with strong complementarities would likely increase the firm's willingness to pay for

[32]As mentioned earlier, we are not considering the socioeconomic benefits from ARV treatment that extend well beyond labor supply. As Graff Zivin et al. (2006) show large gains to the health and schooling of children in households with adults receiving treatment, gains in worker productivity are likely accompanied by substantial benefits at the household level.

treatment.[33] Secondly our assumption of a representative firm precludes important strategic considerations that would have to incorporate the full range of treatment benefits (such as reciprocity effects on uninfected workers and consumers, (Akerlof and Yellen (1990) and Fehr and Gachter (2002)). Depending on how big these additional benefits are and the relative pay-off to treatment provision, multiple equilibria may exist that include one in which some/all firms finance ARV treatment.

In sum, while we acknowledge some of the limitations of our modelling and calibration exercise, our main finding that the benefits of treatment to African firms is unlikely to cover a large fraction of costs is consistent with the conjecture in Rosen (2006) and projections from recent firm survey data from Sub-Saharan Africa. Using data from the World Bank's Enterprise Survey web-portal, across 17 African countries surveyed in 2005/6, an average of only 12% of manufacturing firms provide HIV-testing services.[34] Less than 1 in 6 firms in South Africa provides HIV-testing and Tanzania and Rwanda are outliers with more than a quarter of firms providing HIV testing. Since the provision of treatment requires HIV testing, these estimates represent an upper bound of the share of firms providing treatment.

7 Discussion and 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 approximately 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

[33] 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).

[34] Reliable firm survey evidence is only limited to HIV prevention activities (http://www.enterprisesurveys.org/).

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, ARVs 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 discuss a simple model in order to understand when the establishment of workplace AIDS treatment programs is optimal for firms in high prevalence economies. 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. Using a plausible *positive* measure of the marginal product-wage gap, data from a range of manufacturing firm surveys in Africa and assumptions on the efficacy of treatment, our preferred estimates suggest that firms are willing to pay 8-22% of current treatment costs. 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. Moreover, it is unlikely that the rationale for treatment by firms would change if other possible benefits of ARV treatment to the firm are taken into consideration, 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.

Our conclusions are consistent with the fact that the majority of firms in Africa that have established ARV treatment workplace programs for their employees are very special companies, similar to Debswana. And while relatively recent developments, such as the creation of the Global Business Coalition on HIV/AIDS, foreshadow an increasing involvement of the private sector in combating HIV/AIDS, some of the recent success stories rely on the provision of significant public subsidies to ARV treatment programs administered by private companies as exemplified by the success of the public-private partnership between DaimlerCrysler and GTZ in South Africa.

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A Appendix

To motivate the representative firm's choice we assume that firms are infinitely lived. Workers differ in two attributes: experience and health status. There are three types of representative workers: healthy workers h, sick workers s, and inexperienced workers n. The healthy and sick workers are assumed to have considerably more firm-specific experience than new recruits. Using asset equations, we can model the firm's problem as solving the following program.[35]

$$rV_n = \theta_n + \rho(V_d - V_n) + \mu(V_h - V_n) \tag{3a}$$
$$rV_h = \theta_g + \rho(V_d - V_h) + b(V_n - V_h) \tag{3b}$$
$$rV_s^t = (\theta_s^t - c) + q(V_n - V_s^t) \tag{3c}$$
$$rV_s^u = \theta_s^u + \delta(V_n - V_s^u) \tag{3d}$$
$$V_d = \max\{V_n, V_s^t, V_s^u\}$$

In writing out this program, we have replaced the net instantaneous payoff to the firm $(MPL_j^i - w_j)$ as θ_j^i.[36] $\theta_j^i \geq 0$ represents the wedge between the marginal product of worker of type $j \in \{h, s, n\}$ and treatment condition $i \in \{u, t\}$, and wage w_j^i.[37] At recruitment, the firm does not know the status of the worker but knows the distribution of disease incidence.[38] A worker has a probability ρ of contracting a potentially terminal, but treatable chronic disease. If the worker becomes ill, the firm has a choice of whether to keep the infected 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 $V_d = \max\{V_s^t, V_s^u, V_n\}$ as the firm's choice problem conditional on a worker revealing her disease status, where V_s^t is the value to the firm of a treated worker, 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. While the provision of treatment is likely to affect separation rates, we assume a constant non-illness related worker turnover rate of b per unit of time.[39] Firms bear the cost of treatment c, and the probability of illness-related separation is lower under treatment $q < \delta$.[40]

We solve this program sequentially. We consider the firms preference over treatment

[35]We borrow the modelling of the firm's problem from Shapiro and Stiglitz (1984). We abstract from other human-capital enhancements such ast training that the firm might choose to provide. In our simple framework, productivity increases through the process of learning-by-doing. Incorporating firm-specific training into the model likely strengthens the case for firm-based treatment.

[36]Implicit in this set up is a simple additive production function with minimal or no complementarities. We discuss the implications of relaxing this implicit assumption in the discussion section.

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

[38]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 even a one-time pre-employment HIV-test would not be sufficient to establish the health status of an individual since he/she can be infected after the pre-employment check.

[39]Using the data from Jwaneng that goes back to 1998, we do not find any statistically significant changes in the pattern of exits after 2001.

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

conditional on infection and then between a treated worker and a novice. Solving equations 3c and 3d above, the firm decides to provide treatment if $V_s^t - V_s^u > 0$. This treatment condition can be stated as follows:

$$(q+r)(\theta_s^t - c - \theta_s^u) + (\delta - q)(\theta_s^t - c - rV_n) > 0 \tag{4}$$

There are two parts to the left hand side of the treatment condition. The first captures the net productivity effects of treatment over the duration that an untreated worker would be in employment.[41] The second captures the benefit associated with keeping a more productive worker longer $(\delta - q)$ per unit of time and delaying the hiring a new worker $[\theta_s^t - c - rV_n]$. This treatment condition illustrates that the firm will face different incentives to offer treatment to different types of workers. In particular, workers for whom the costs of illness (in terms of foregone productivity) are very high relative to treatment costs or workers for whom the returns to tenure are very high are more likely to satisfy the treatment condition.

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. We assume that the likelihood that a new worker becomes ill is the same as the likelihood of an experienced worker contracting the disease.[42] If a worker reveals him/herself to be ill, then the firm chooses whether they should provide treatment or wait and replace. 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_h. Given these parameters, the choice between treated and novice workers is given by the solution to of equations 3a, 3b and 3c: if $V_n > V_s^t$, then $V_d = V_n$, otherwise $V_d = V_s^t$.

Assuming that equation 4 holds and solving the three simultaneous equations above, firms provide treatment rather than hire a new worker if:

$$(r + \rho + b)(\theta_s^t - c - \theta_n) > \mu[\theta_h - (\theta_s^t - c)] \tag{5}$$

Firms compare the net productivity benefits of treatment against the expected gains of replacing the infected worker. In addition to our assumption of positive θ_j^i, the magnitude of $(\theta_s^t - c - \theta_n)$ 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.[43]

Assuming that the productivity of a treated worker is not fully restored to pre-illness levels (so that $\theta_s^t = \alpha\beta\theta_h$), where α represents the relative productivity effect of treatment on attendance and β represents the relative productivity effect conditional on attendance, $(\alpha, \beta \in [0,1])$, we can state the firm's willingness to pay for treatment c^* as:[44]

within-firm deployment responses such as re-assignment which could lower infected worker wages (as in Larson et. al. (2008)).

[41] Since we assume that healthy and unhealthy workers with the same characteristics earn the same wages, differences in $\theta_s^t - \theta_s^u$ are driven by differences in productivity induced by treatment efficacy.

[42] 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.

[43] We abstract from heterogeneity in worker productivity so that the within worker comparison is analogous to the cross-worker comparison.

[44] $\beta < 1$ can represent lower productivity on the regular task the worker is assigned to or re-deployment

$$c^* = \frac{1}{r+b+\rho+\mu}\{[\alpha\beta(r+b+\rho)(\theta_h-\theta_n)] + [(1-\alpha\beta)(\mu\theta_h-(r+b+\rho)\theta_n)]\} \quad (6)$$

Equation 6 provides the basis for thinking about the implications of employee sorting and a public treatment option. Firstly note that if treatment restores attendance and productivity at work sufficiently ($\alpha\beta \to 1$), then the willingness to pay is determined primarily by the productivity-tenure relationship $[\theta_h - \theta_n]$. How does the possibility of adverse selection in vacancy applications affect the firm's willingness to pay? An implicit differentiation of equation 6 with respect to ρ suggests that adverse sorting in vacancy applications reduces the willingness to pay for treatment unless $(2\alpha\beta - 1)\theta_h - \theta_n > 0$. Since the product $\alpha\beta$ represents the efficacy of treatment, low efficacy of treatment combined with a shallow productivity-tenure trajectory will in general, reduce the likelihood of firm-based treatment.

In addition, the existence of an alternative albeit poor public treatment option (in which firms no longer bear the direct cost of treatment c) alters the firm's preference-for-treated workers condition: the firm will prefer to keep a treated worker if

$$(r+\rho+b)(\widehat{\alpha\beta}\theta_h - \theta_n) > (1-\widehat{\alpha\beta})\mu\theta_h \quad (7)$$

Where $\widehat{\alpha\beta}$ represents the efficacy of public treatment programs. In general, if the public treatment option is a close substitute to the firm-based program, then firms will prefer to retain infected workers if condition 5 holds. However, a poor treatment program captured by a large $(\alpha\beta - \widehat{\alpha\beta}) > 0$ can alter the firm's preference for retaining treated workers and/or motivate firm-based provision.

Finally we turn to a calibration of the willingness to pay for ARV treatment using equation 6. A major challenge in this exercise is estimating reliable productivity-wage profiles so as to determine the relative magnitudes of θ_h and θ_n. The empirical evidence on the shape of the productivity-wage profile over a worker's tenure is thin and not very informative for our purposes as it focuses on middle-aged workers.[45][46] If the findings for middle-aged workers extend to the comparison between an experienced worker and a new recruit, then firms would not provide treatment in equilibrium since $\theta_s^t - \theta_n \leq 0$.

Generating estimates for the magnitude of θ_h and θ_n is not straightforward given the limited empirical estimates. Postel-Vinay and Robin (2002) is the only paper with plausibly usable estimates for this calibration. We make the following assumption: a new worker is analogous to the typical worker of a firm at the 25th percentile in the firm productivity dis-

to a less productive task.

[45]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 over some range of tenure.

[46]An older literature includes Lazear (1979, 1981), Medoff and Abraham (1980), Hutchens (1987), Carmichael (1983) and Kotlikoff and Gokhale (1992).

tribution, and an experienced worker is the typical worker of a firm at the 75th percentile. Using their results for unskilled workers and expressing these productivity wedges as a function of the median wage implies that $\theta_h \approx 0.45w$ and $\theta_n \approx 0.13w$.[47] Note that in using the estimates below, we assume uniform labor market frictions across economies and even more unrealistically uniform productivity-wage gaps across countries.

We assume a discount rate $r = 0.08$. Firm data from the South Africa investment climate survey (2003) 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 et. al. (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 $\mu = (1-\rho)(1-b) * 0.12 = 0.1$. Using our empirical results and those from Larson et. al. (2008) we assume that $\alpha = 0.95$ and $\beta = 0.9$.[48]

Using these estimates implies that under our baseline scenario, $c^* = 0.12w$. A firm is willing to contribute just under 1/8 of the workers' wage for ARV treatment. We assume that the cost of treating a worker is uniform across the central and eastern African countries at \$360/year or \$30/month. We use the typical therapy prescribed for the Debswana treatment program to estimate the monthly cost of treatment in Botswana, Namibia and Swaziland at \$100 and \$141 in South Africa.[49] Wages are drawn from the South Africa investment climate report (World Bank, 2005). The results of this calibration are shown in Appendix Table 2.

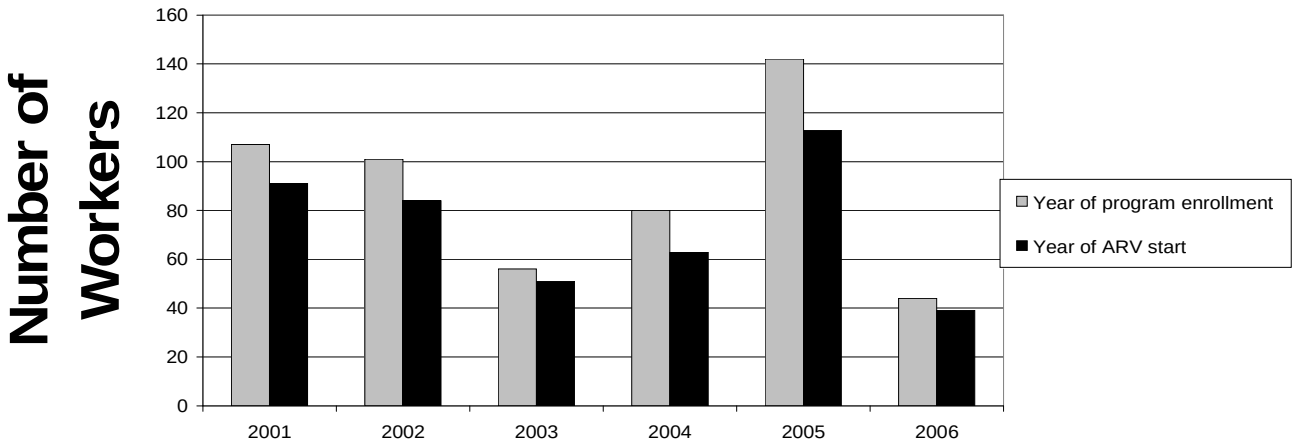
We show the results for two levels θ_h $[0.45w, 0.33w]$ and two assumptions about the efficacy of treatment on presenteeism β $[0.9, 0.6]$. Assuming that $\theta_h \approx 0.45w$ and that $\beta = 0.9$, willingness to pay as a fraction of total annual treatment costs ranges from 13% in Botswana to just under 50% in South Africa. Assuming that treatment is not as efficacious, $\beta = 0.6$, reduces this range to 10-40%. Furthermore assuming a shallower productivity-wage-tenure relationship ($\theta_h = 0.33w, \beta = 0.6$), reduces this range even further to 7-21%.

[47] These numbers come from Figure 1 in Postel-Vinay and Robin(2002).

[48] It is difficult to derive reliable estimates of β from Larson et. al. (2008), since workers choose when to undertake the piece-rate task. In their results, conditional on choosing the piece-rate task, there is no difference in productivity for treated males, but a 10-15% negative gap for treated female workers. We use the lower bound estimate for women as our estimate of β.

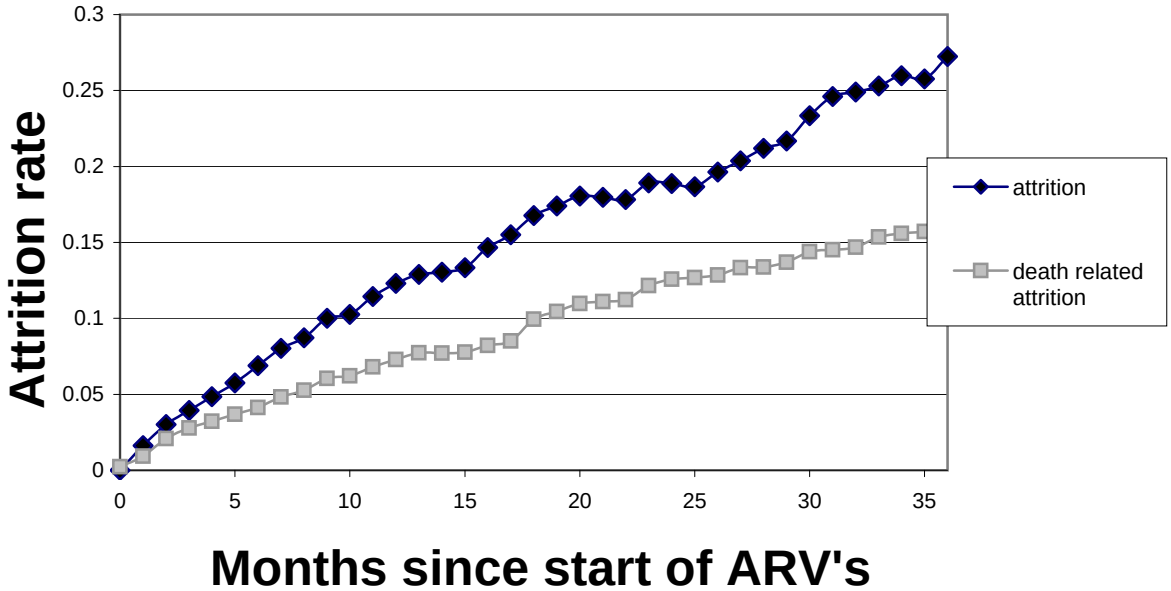
[49] These numbers are based on costs of the AMPATH treatment program in Kenya. The breakdown is about \$150 for first line ARV drugs and \$200 are the remaining treatment related costs (such clinic, medical and lab expenditures). The Botswana estimate is derived from Debswana's per patient costs. The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

Figure 1A: Timing of program enrollment and ARV treatment start



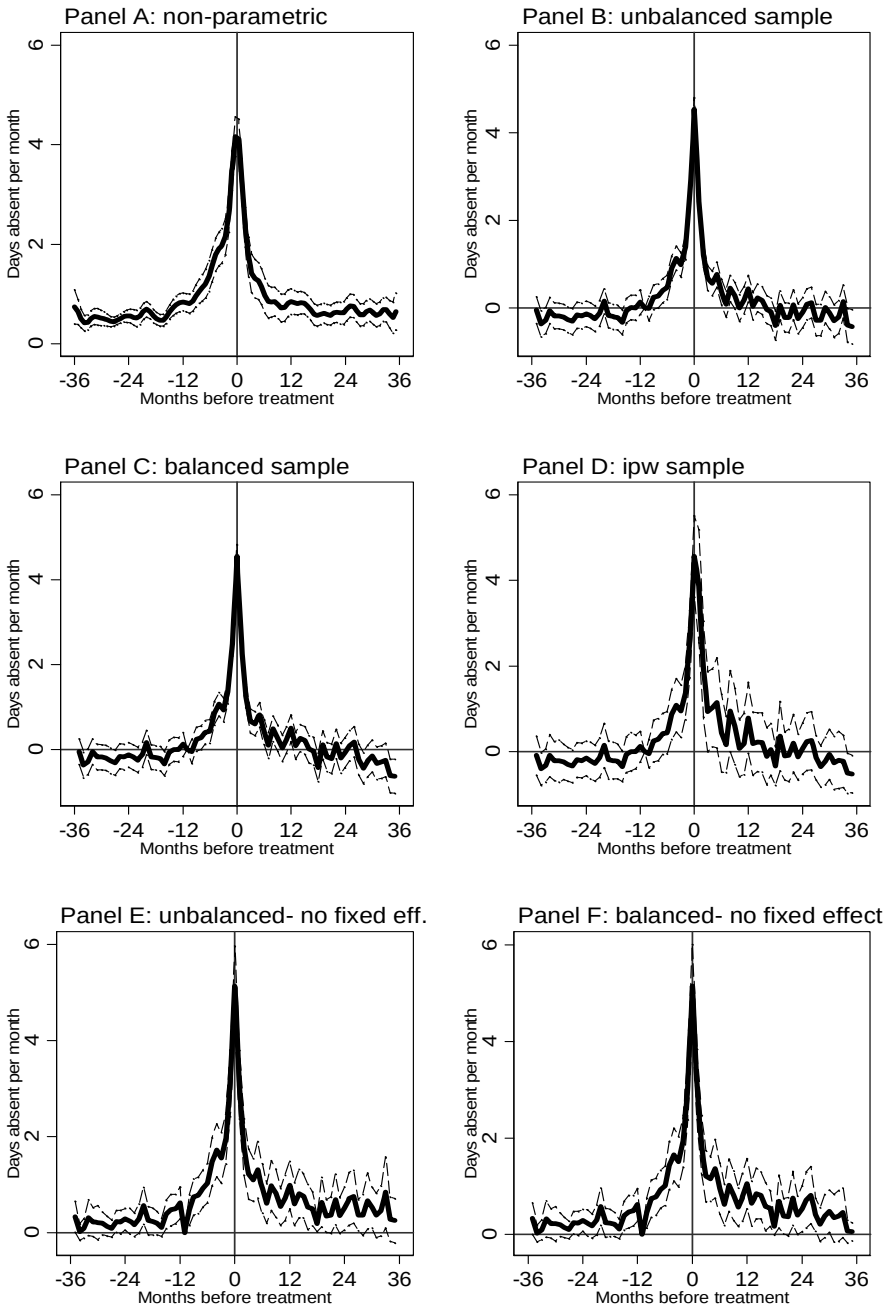
Source: Authors' calculations based on HR and ART program data.

Figure 1B: Attrition since start of ARV's



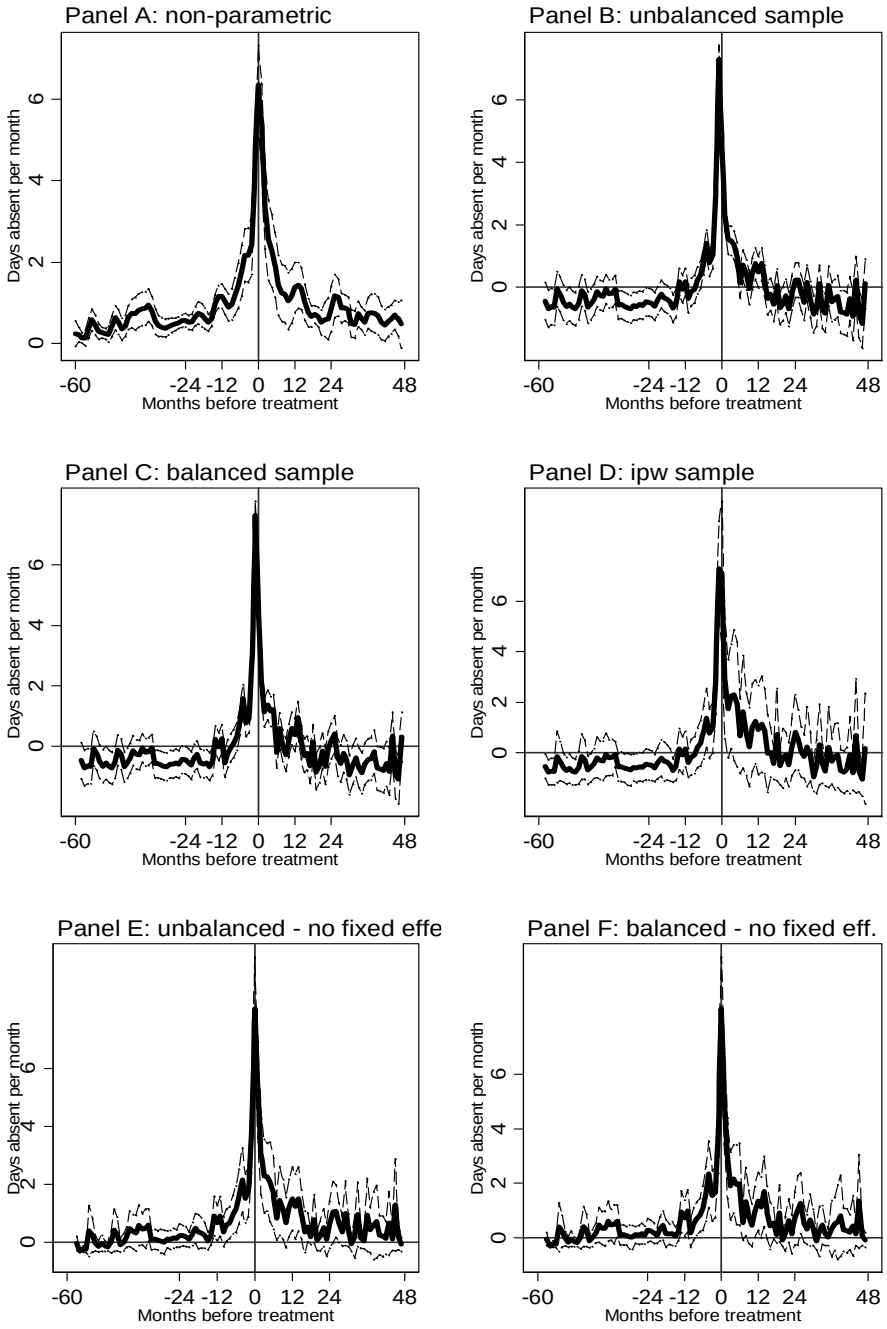
Source: Authors' calculations based on HR and ART program data.

Figure 2 : Effect of ARV treatment - Three year window



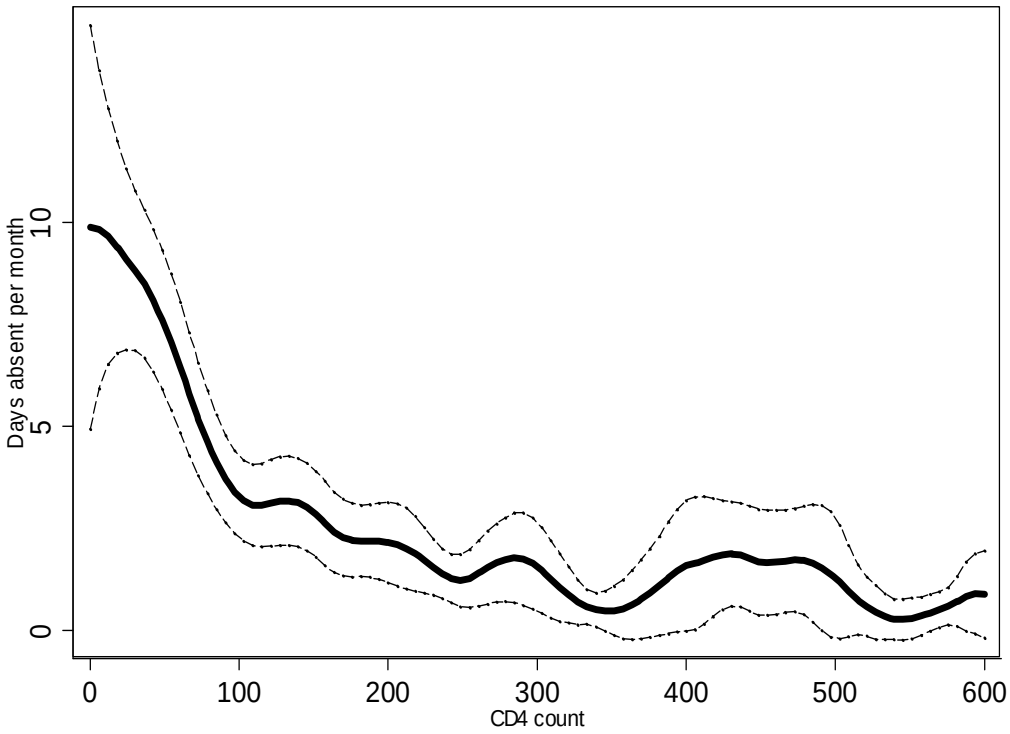
Note: Panels A is from a Non-parametric Fan locally weighted regression with bootstrapped standard errors clustered by worker. Panels B, C and D are from a fixed effect regression that includes worker and month fixed effects. Panels E and F are based on OLS regressions that include month fixed effects. Sickness-related absence duration data comes from the company's HR database. The interval used is three years before and after the onset of ARV treatment. Panels A, B and E use an unbalanced sample, panels C and F a balanced sample and panel D a sample with weights based on inverse probability weights (IPW).

Figure 3 : Effect of ARV treatment - Jwaneng mine



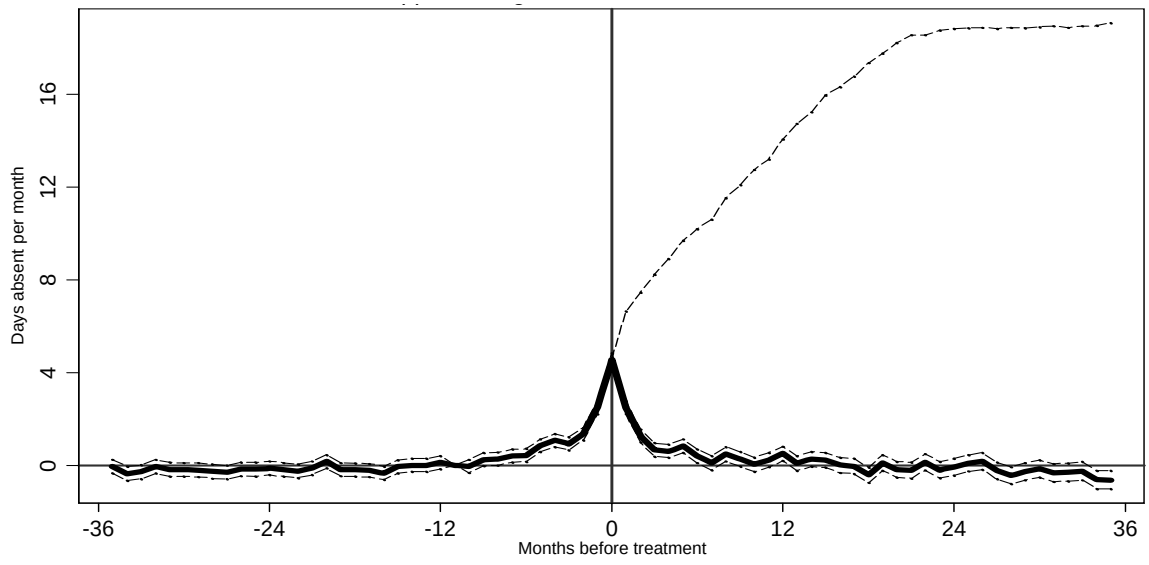
Note: Panels A is from a Non-parametric Fan locally weighted regression with bootstrapped standard errors clustered by worker. Panels B, C and D are from a fixed effect regression that includes worker and month fixed effects. Panels E and F are based on OLS regressions that include month fixed effects. 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, B and E use an unbalanced sample, panels C and F a balanced sample and panel D a sample with weights based on inverse probability weights (IPW).

Figure 4: 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. The sample is unbalanced.

Figure 5: Counterfactual Results



Note: The thick line represents actual absences for workers on treatment based on a balanced sample and on a fixed effect regression that includes worker and month fixed effects. The dotted line represents the counterfactual absenteeism rate in the absence of treatment discussed in section 5 of the paper.

Table 1: 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 2: CD4 Counts and Absenteeism from Work

	Number of Sick Days per Month					
	OLS unbalanced	*OLS balanced*	*OLS ip-weights*	*Fixed Effects unbalanced*	*Fixed Effects balanced*	*Fixed Effects ip-weights*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
CD4 count	**-0.0109*** **	**-0.0071*** **	**-0.0103*** **	**-0.0111*** **	**-0.0098*** **	**-0.0103*** **
	[0.0015]	[0.0015]	[0.0023]	[0.0021]	[0.0027]	[0.0031]
Mean of dep. variable	**3.22**	**2.16**	**2.39**	**3.22**	**2.16**	**2.39**
Observations	845	414	844	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 in columns (1)-(3) 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 (4)-(6) are based person fixed effects regressions. The regressions in columns (1) and (4) use an unbalanced sample, the regressions in columns (2) and (5) use a balanced sample that includes only patients with three CD4 mesures and the regressions in columns (3) and (6) use inverse probability weights (IPW).*** significant at 1% level. ** significant at 5% level. * significant at 10% level.

Appendix Table 1

Panel A: Summary 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

Panel B: Treatment program statistics (May 2001 - April	Number
Enrollment in Treatment Program	
- Total	721
- Spouses	183
- Workers	538
- Workers (with matched HR data)	530
Patients ever on ARVs among those enrolled in program	
- Total	606
- Spouses	157
- Workers	449
- Workers (with matched HR data)	441

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.

Appendix Table 2: Share of Annual Treatment Costs Firms Willing to Pay

Country		**θ_h=0.45w, θ_n =0.13w**		**θ_h=0.33w, θ_n =0.13w**	
	Monthly Wage in 2005$	Treatment Efficacy: β=0.9	Treatment Efficacy: β=0.6	Treatment Efficacy: β=0.9	Treatment Efficacy: β=0.6
Tanzania	53	14.8	11.7	8.5	8.2
Eritrea	62	17.2	13.6	9.9	9.6
Uganda	73	20.3	16.1	11.7	11.3
Zambia	79	22.0	17.4	12.7	12.3
Kenya	110	30.7	24.3	17.7	17.1
Nigeria	136	37.9	30.0	21.8	21.1
Botswana	157	13.0	10.3	7.5	7.3
Swaziland	189	15.7	12.4	9.1	8.7
Namibia	299	24.9	19.7	14.3	13.9
South Africa	412	49.4	39.1	19.8	19.1

Notes: Column (1) shows median monthly wages for production workers using manufacturing firm surveys conducted between 2002 and 2005. Column (2) provides estimates of the percentage of treatment costs a firm would be willing to pay under the baseline scenario. Column (3) shows how changing beta affects willingness to pay. In Columns (4) and (5) present corresponding estimates when productivity-tenure profile is not as steep θh=0.33w).