AIDS, Human Capital and Development

Online Appendix

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This appendix provides further clarification and illustration to supplement the main body of the paper. Section A gives the supporting analytical results in solving individuals' problem in our model. Section B includes the derivations on the demographic distribution. Section C describes on the data sources and variable definitions. Section D provides details on the benchmark model calibration and presents the country-period specific parameters, as well as the model-data comparison of the calibration targets. Section E provides supporting evidence on the model fit to various moments of human capital in our cross-country sample. Section F gives the robustness checks for our calibration strategy. Section G goes over the literature relevant for our calibration of morbidity and treatment features.

A Analytical results on the individuals' problem

Proposition 1. *$m(a;\lambda) = \frac{1-e^{-\lambda(R-a)}}{\lambda}$ is a strictly decreasing and convex in λ for any $a < R$.*

Proof. The derivative of m with respect to λ is:

$$\frac{\partial m}{\partial \lambda} = (R-a)\frac{e^{-\lambda(R-a)}}{\lambda} - \frac{1-e^{-\lambda(R-a)}}{\lambda^2} = \frac{1}{\lambda}\left[(R-a)(e^{-\lambda(R-a)}) - \frac{1-e^{-\lambda(R-a)}}{\lambda}\right]$$

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The value of the derivative at retirement is $\frac{\partial m(a;\lambda)}{\partial \lambda}|_{a=R} = 0$. Moreover, for any $a < R$, the cross derivative is:

$$\frac{\partial^2 m(a;\lambda)}{\partial \lambda \partial a}|_{a=R} = \frac{1}{\lambda}\left[-e^{-\lambda(R-a)} + (R-a)\lambda e^{-\lambda(R-a)} + e^{-C(R-a)}\right] = (R-a)e^{-\lambda(R-a)} > 0$$

Hence the derivative of m with respect to λ is strictly increasing in a, and it reaches to 0 at $a = R$. This gives that m is strictly decreasing in λ.

Next, we turn to the convexity with respect to λ. Denote $\tilde{a} \equiv R - a$. We need to show that:

$$\frac{\partial^2 m}{\partial \lambda^2} = -2\frac{e^{-\lambda\tilde{a}}[1+\lambda\tilde{a}] - 1}{\lambda^3} + \frac{-\tilde{a}e^{-\lambda\tilde{a}}[1+\lambda\tilde{a}] + \tilde{a}e^{-\lambda\tilde{a}}}{\lambda^2} \geq 0$$

$$\iff -e^{-\lambda\tilde{a}}(1+\lambda\tilde{a})\tilde{a}\lambda + e^{-\lambda\tilde{a}}\tilde{a}\lambda - 2\left[e^{-\lambda\tilde{a}}(1+\lambda\tilde{a}) - 1\right] \geq 0$$

$$\iff 2 + e^{-\lambda\tilde{a}}\lambda\tilde{a} - e^{-\lambda\tilde{a}}(1+\tilde{a}\lambda)(2+\tilde{a}\lambda) \geq 0$$

$$\iff -\tilde{a}\lambda e^{-\lambda\tilde{a}} - (\lambda\tilde{a})^2 e^{-\lambda\tilde{a}} + \tilde{a}\lambda e^{-\lambda\tilde{a}} \geq 2\left[e^{-\lambda\tilde{a}}(1+\lambda\tilde{a}) - 1\right]$$

$$\iff 2e^b \geq 1 + b + b^2, \text{where } b \equiv \lambda\tilde{a}$$

This condition is satisfied at $b = 0$. The slope of the lhs is higher than the slope of the rhs for any $b > 0$, which shows that last condition is satisfied. This in turn, shows that m is convex in λ.

□

Proposition 2. *The marginal value term $V_1^H(a;\theta)$ in equation (3) of the paper is increasing in θ if $\lambda_B < \lambda_H + \eta$.*

Proof. Rearranging the equation (3) of the paper, we get $V_1^H(a) =$

$$m(a;\lambda_H+\eta) + \frac{\eta\theta\nu_B}{\lambda_H+\eta-\lambda_B}\left[m(a;\lambda_B) - m(a;\lambda_H+\eta)\right] + \frac{\eta(1-\theta)\nu_A}{\lambda_A-\lambda_H-\eta}\left[m(a;\lambda_H+\eta) - m(a;\lambda_A)\right]$$

Taking the derivative with respect to θ:

$$\frac{\partial V_1^H(a)}{\partial \theta} = \frac{\eta\nu_B}{\lambda_H+\eta-\lambda_B}\left[m(a;\lambda_B) - m(a;\lambda_H+\eta)\right] - \frac{\eta\nu_A}{\lambda_A-\lambda_H-\eta}\left[m(a;\lambda_H+\eta) - m(a;\lambda_A)\right]$$

$$> \eta\nu_B\left[\frac{m(a;\lambda_B) - m(a;\lambda_H+\eta)}{\lambda_H+\eta-\lambda_B} - \frac{m(a;\lambda_H+\eta) - m(a;\lambda_A)}{\lambda_A-\lambda_H-\eta}\right] \equiv X$$

where the last inequality follows from our assumption that $\nu_B > \nu_A$. By defining $\Delta_1 \equiv \lambda_H+\eta-\lambda_B$ and $\Delta_2 \equiv \lambda_A - \lambda_B$ we have:

$$X = \eta\nu_B\left[\frac{m(a;\lambda_B) - m(a;\lambda_B+\Delta_1)}{\Delta_1} - \frac{m(a;\lambda_B+\Delta_1) - m(a;\lambda_B+\Delta_2)}{\Delta_2-\Delta_1}\right]$$

The first ratio in brackets is the rate of increase in $m(a)$ from $\lambda_B+\Delta_1$ to λ_B, and the second term is that from $\lambda_B+\Delta_2$ to $\lambda_B+\Delta_1$. Since $\Delta_1 > 0$, and $m(a;\lambda)$ is convex and decreasing in λ, we have $X > 0$. This shows that $V_1^H(a;\theta)$ is increasing in θ.

□

Proposition 3. *The marginal value term for a healthy adult that ignores treatment probability, $\hat{V}_1^H$, given in Equation (4) of the paper is decreasing in η.*

Proof. The slope of the $\hat{V}_1^H$ with respect to η is:

$$\frac{\partial \hat{V}_1^H}{\partial \eta} = \left(1 - \frac{\eta\nu_A}{\lambda_H+\eta-\lambda_A}\right)\frac{\partial m}{\partial \eta}(a;\lambda_H+\eta) + \frac{\nu_A(\lambda_H-\lambda_A)}{(\lambda_H+\eta-\lambda_A)^2}\left[m(a;\lambda_A) - m(a;\lambda_H+\eta)\right] \quad (1)$$

If $\lambda_H+\eta \geq \lambda_A$ then both terms on the rhs of (1) are negative (given that $m(a;x)$ is decreasing in x) which implies $\frac{\partial \hat{V}_1^H}{\partial \eta} < 0$. Hence, we study below the case with $\lambda_H+\eta < \lambda_A$. The convexity of $m(a;x)$ with respect to x implies:

$$m(a;\lambda_A) > m(a;\lambda_H+\eta) + \frac{\partial m}{\partial \eta}(a;\lambda_H+\eta)(\lambda_A-\lambda_H-\eta)$$

Since $\lambda_A \geq \lambda_H$:

$$\frac{\nu_A(\lambda_H-\lambda_A)}{(\lambda_H+\eta-\lambda_A)^2}\left[m(a;\lambda_A) - m(a;\lambda_H+\eta)\right] \leq -\frac{\partial m}{\partial \eta}(a;\lambda_H+\eta)\frac{(\lambda_H-\lambda_A)\nu_A}{\lambda_H+\eta-\lambda_A}$$

which shows that $\frac{\partial \hat{V}_1^H}{\partial \eta}$ given in (1) is negative.

□

B The Distribution of the Population

In this Appendix we show how to compute the Kolmogorov Forward Equation that yields the aggregate joint distribution of age, health status and time of infection.

To see the factors that affect the distribution of the population consider the healthy population. Let $N^H(a, p^*; t)$ be the number of healthy individuals of age less than a (for $a \geq p^*$) at time time t. This population changes because some people age (and are no longer in the age category), individuals who reach age p^* now belong to this population, and some people die or become infected. Let the mass of people in between ages p^* and a be denoted by $M^H(a, p^*; t)$. Formally, $M^H(a, p^*; t) = N^H(a, p^*; t) - N^H(p^*, p^*; t)$. It follows that the evolution of the population in this group satisfies

$$\frac{\partial M^H}{\partial a}(a, p^*; t) + \frac{\partial M^H}{\partial t}(a, p^*; t) = -(\lambda_H + \eta) M^H(a, p^*; t) + \frac{\partial N^H}{\partial a}(p^*, 0; t).$$

For healthy individuals younger than p^* –and hence free from infection risk– the relevant equations is

$$\frac{\partial N^H}{\partial a}(a, 0; t) + \frac{\partial N^H}{\partial t}(a, 0; t) = -\lambda_H N^H(a, 0; t) + B^H(t)$$

where $B^H(t)$ is the number of people born at time t. Similar equations describe the evolution of the population of individuals infected as a function of the date of infection.

We concentrate on the balanced growth stationary distribution and assume that population is growing at a constant rate. This implies that $N^H(a, 0; t) = \Phi^H(a, 0) G(t)$, with $\dot{G}(t) = gG(t)$ for some g that depends on fertility and mortality parameters.

As mentioned in Section 2 of the paper, we assume common birth rate β for all groups. All the births from healthy parents start in health category H. All the births from infected and treated parents also start healthy. Finally, from the births of infected and non-treated parents, fraction

$(1-m)$ start healthy, $(1-\theta)m$ start (and remain) infected and non-treated, and θm start (and remain) infected and treated. Denote by β_K^J the number of births per population in an infected category J (treated (B) or non-treated (A)) that are born in health status $K \in \{H, B, A\}$.[1].

Then, the mass of children starting their life healthy is:

$$B^H(t) = \beta \bar{N}^H(t) + \beta_H^A \bar{N}^A(t) + \beta_H^B \bar{N}^B(t)$$

where $\bar{N}^J(t)$ is the total population with health status J at time t, for $J, K \in \{H, A, B\}$. Imposing the balanced growth condition –and hence that $\bar{N}^J(t) = \bar{N}^J e^{gt}$, for $J \in \{H, A, B\}$– we can characterize the cross sectional distribution of the populations.

Proposition 4. *The distribution of the population is characterized by*

$$\Phi^H(a) = \begin{cases} \frac{\bar{B}^H}{\lambda_H+g}\left[1 - e^{-(\lambda_H+g)a}\right] & \text{for } a \leq p^* \\ \frac{\bar{B}^H e^{-(\lambda_H+g)p^*}}{\lambda_H+\eta+g}[1 - e^{-(\lambda_H+\eta+g)(a-p^*)}] + \frac{\bar{B}^H}{\lambda_H+g}\left[1 - e^{-(\lambda_H+g)p^*}\right] & \text{for } a > p^* \end{cases}$$

$$\Phi^j(a,p) = \frac{\eta\tilde{\theta}_j \bar{B}^H e^{-(\lambda_H+g)p^*} e^{-(\lambda_H+\eta+g)(p-p^*)}}{\lambda_j+g}\left[1 - e^{-(\lambda_j+g)(a-p)}\right], \text{ for } a \geq p \geq p^*$$

$$\Phi^j(a,0) = \frac{\beta_A^j \bar{N}^A}{\lambda_j+g}\left[1 - e^{-(\lambda_j+g)a}\right], \text{ for } a \leq p^*$$

for $j \in \{A, B\}$ *with* $\tilde{\theta}_j = \theta$ *for* $j = B$ *and* $\tilde{\theta}_j = 1-\theta$ *for* $j = A$

$$\bar{B}^H = \beta \bar{N}^H + \beta_H^A \bar{N}^A + \beta_H^B \bar{N}^B.$$

and

$$\max\left[0, \int_{p^*}^{\bar{T}} \Phi^j(\bar{T}, p)dp\right] + \Phi^j(\bar{T}, 0) = \bar{N}^j, \quad j \in \{A, B\}$$

$$\Phi^H(\bar{T}) = 1 - \bar{N}^A - \bar{N}^B = \bar{N}^H$$

[1]Accordingly, we have $\beta_H^B = \beta$, $\beta_A^B = \beta_B^B = 0$ for the births from treated infected; and we have $\beta_H^A = (1-m)\beta$, $\beta_B^A = m\theta\beta$ and $\beta_A^A = m(1-\theta)\beta$ for the births from non-treated infected.

Proof. Consider the evolution of the healthy population depending on whether they are susceptible (i.e. $a \geq p^*$) or non-susceptible. Let $N^H(a, p^*; t)$ be the number of healthy individuals of age less than a (for $a \geq p^*$) at time time t, and $N^H(a, 0; t)$ be the corresponding mass of young individuals (i.e. $a \geq p^*$). Let the mass of people in between ages p^* and a be denoted by $M^H(a, p^*; t)$. Formally, $M^H(a, p^*; t) = N^H(a, p^*; t) - N^H(p^*, p^*; t)$.

For healthy individuals younger than p^* –and hence free from infection risk– the relevant equations is

$$\frac{\partial N^H}{\partial a}(a, 0; t) + \frac{\partial N^H}{\partial t}(a, 0; t) = -\lambda_H N^H(a, 0; t) + B^H(t)$$

where $B^H(t)$ is the number of people born at time t.

Given the balanced growth assumption, we have $N^H(a; t) = \Phi^H(a)e^{gt}$, $M^H(a, p^*; t) = C(a)e^{gt}$, $B^J(t) = \bar{B}^J e^{gt}$, and $\bar{N}^J(t) = \bar{N}^J e^{gt}$, $J \in \{H, A, B\}$. Finding the solution to the partial differential equations that describe the evolution of the population is equivalent –given the balanced growth assumption– to finding the solution of the following two differential equations

$$\dot{\Phi}^H(a) = -(\lambda_H + g)\Phi^H(a, 0) + \bar{B}^H,$$

$$\dot{C}(a) = -(\lambda_H + \eta + g)C(a) + \bar{B}^H e^{-(\lambda_H + g)p^*}$$

The solution to the differential equations is

$$\Phi^H(a) = \frac{\bar{B}^H}{\lambda_H + g}\left[1 - e^{-(\lambda_H + g)a}\right] \text{ for } a \leq p^*$$

and

$$C(a) = \frac{\bar{B}^H e^{-(\lambda_H + g)p^*}}{\lambda_H + \eta + g}[1 - e^{-(\lambda_H + \eta + g)(a - p^*)}]$$

which is the unique solution that satisfies $C(p^*) = 0$. Since $C(a) = \Phi^H(a) - \Phi^H(p^*)$, it follows that $\Phi^H(a) = C(a) + \Phi^H(p^*)$ for $a \geq p^*$. This proves the result for $\Phi^H(a)$. Note that the total fraction of healthy individuals is:

$$\bar{N}^H = \Phi^H(\bar{T}) = \frac{\bar{B}^H e^{-(\lambda_H + g)p^*}}{\lambda_H + \eta + g}[1 - e^{-(\lambda_H + \eta + g)(\bar{T} - p^*)}] + \frac{\bar{B}^H}{\lambda_H + g}\left[1 - e^{-(\lambda_H + g)p^*}\right].$$

Let $N^j(a,p;t)$ be the number of people of age less than a who were infected at age p, with $p \in \{0\} \cup [p^*, \bar{T}]$, that are treated if $j = B$ and non-treated if $j = A$. Then, the evolution of this population for $p \neq 0$ satisfies

$$\frac{\partial N^j}{\partial a}(a,p;t) + \frac{\partial N^j}{\partial t}(a,p;t) = \eta\tilde{\theta}_j \frac{\partial N^H}{\partial a}(p;t) - \lambda_j N^j(a,p;t), \text{ for } a \geq p$$

with boundary condition $N^j(p,p;t) = 0$. If $p = 0$ (this corresponds to individuals born with HIV/AIDS) the appropriate expression is

$$\frac{\partial N^j}{\partial a}(a,0;t) + \frac{\partial N^j}{\partial t}(a,0;t) = -\lambda_j N^j(a,0;t) + B^j(t),$$

where, paralleling the previous formulation we have $B^j(t) = \beta_j^A \bar{N}^A(t)$, since we assume that only HIV/AIDS infected non-treated individuals can give birth to HIV/AIDS newborns. The relevant boundary condition is $N^j(0,0;t) = 0$, and the stationary distributions are

$$\Phi^j(a,p) = \frac{\eta\tilde{\theta}_j \bar{B}^H e^{-(\lambda_H+g)p^*} e^{-(\lambda_H+\eta+g)(p-p^*)}}{\lambda_j + g} \left[1 - e^{-(\lambda_j+g)(a-p)}\right]$$

$$\Phi^j(a,0) = \frac{\beta_A^j \bar{N}^A}{\lambda_j + g} \left[1 - e^{-(\lambda_j+g)a}\right].$$

The infected population (as a share of the total) between ages 0 and a is:

$$\int_{p^*}^{a} \Phi^j(a,p)dp + \Phi^j(a,0) = \bar{N}^j(a).$$

The healthy population (again as share of the total) is: $\Phi^H(a) = \bar{N}^H(a)$. Consistency requires:

$$\max\left[0, \int_{p^*}^{\bar{T}} \Phi^j(\bar{T},p)dp\right] + \Phi^j(\bar{T},0) \;\; = \;\; \bar{N}^j, \;\; j \in \{A,B\}$$

and that $\bar{N}^A + \bar{N}^B + \bar{N}^H = 1$. □

The solution for the life expectancy. As mentioned in the Section 3 of our paper, we calibrate the country- and period-specific mortality rates due to non-HIV reasons, λ_H, targeting the life-expectancy at age 5. Using our solution for the distributions, we can write the life expectancy analytically. In our model this unconditional life expectancy is given by:

$$L(5) = L^H(5)\frac{\partial \Phi^H(5)}{\partial a} + L^A(5)\frac{\partial \Phi^A(5,0)}{\partial a} + L^B(5)\frac{\partial \Phi^B(5,0)}{\partial a}$$

where life expectancy of healthy and infected individuals is:

$$\begin{aligned} L^H(5) &= \frac{1-e^{-\lambda_H(p^*-5)}}{\lambda_H} + \left\{ \left(1 - \frac{\eta\theta}{\lambda_H+\eta-\lambda_B} - \frac{\eta(1-\theta)}{\lambda_H+\eta-\lambda_A}\right)\frac{1-e^{-(\lambda_H+\eta)(T-p^*)}}{\lambda_H+\eta} \right. \\ &\quad \left. + \frac{\eta\theta}{\lambda_H+\eta-\lambda_B}\frac{1-e^{-\lambda_B(T-p^*)}}{\lambda_B} + \frac{\eta(1-\theta)}{\lambda_H+\eta-\lambda_A}\frac{1-e^{-\lambda_A(T-p^*)}}{\lambda_A} \right\} e^{-\lambda_H(p^*-5)} \end{aligned}$$

and the life expectancy of an infected child, treated ($j = B$) or not treated ($j = A$) is given by:

$$L^j(5) = \frac{1}{\lambda_j}\left[1 - e^{-\lambda_j(\bar{T}-5)}\right]. \tag{2}$$

C Data

Basics. We use the Penn World Tables (PWT) 9.1 to get the output (GDP) per worker (rgdpe/emp), population (pop). We take the US price level (pl_con) for each year also from the PWT, which we only need to use to convert the intervention costs in the literature into 2011 US dollars.

The interest rates we refer to in the calibration are from the World Development Indicators provided by the World Bank, with variable name (FR.INR.RINR) and the variable definition in the data is "Real interest rate (%)".

Overall demographics. We get the crude birth rate (SP.DYN.CBRT.IN), life expectancy at birth (SP.DYN.LE00.IN) from the WDI. Since our model does capture the additional reasons infant mortality, we focus on rates from the perspective of age 5 instead of age 0. Accordingly,

we transform the crude birth rate to the rate of infants beginning age 5 using the mortality rate under age 5 (SH.DYN.MORT) as:[2]

$$\text{Rate of starting age } 5 = \text{Crude birth rate} \times (1 - \text{Mortality under } 5).$$

Similarly, we convert the life expectancy at birth to life expectancy at age 5 assuming the life expectancy of a new-born conditional on not surviving to age 5 is equal to 1:

$$L(5) = \frac{L(0) - \text{Mortality under } 5 \times 1}{1 - \text{Mortality under } 5} - 5.$$

HIV-related demographic data. To the extent possible, we use the WDI to get the HIV-related moments. These include the prevalence (SH.DYN.AIDS.ZS) and the incidence rate among adults (SH.HIV.INCD.ZS) between ages 15-49, and the number of children (0-14) living with HIV (SH.HIV.0014). We convert the latter statistic to a prevalence rate among children using the fraction of the corresponding ages within the entire population (SP.POP.0014.TO.ZS) also from the WDI together with the level of the population.

We use the data on the number of HIV-related deaths from the UNAIDS data set (*Number of AIDS-related deaths Population All ages*) to get the HIV-related mortality rates of the infected non-treated as:

$$\text{HIV-reld mortality} = \frac{\text{No. HIV-reld deaths}}{\text{Overall prevalence} \times (1 - \text{Treatment rate}) \times \text{Population}}$$

where we use the aforementioned prevalence statistics for adults and children, and the fraction of children in the population to obtain the overall prevalence rate. For the treatment rates, we use the variable *People living with HIV receiving ART (%) Population All ages* from the same data. For the rates of suppressed viral loads, we use *People living with HIV who have suppressed viral loads (%) Population All ages* also from UNAIDS.

[2]Some of the rates in the data set are per 1000 people, some are percentages. We convert them as appropriate before applying these formulations.

Human capital. The years of schooling is from the Barro-Lee data set ("yr_sch"). (See Barro and Lee (2013).)

The data on education expenditure is provided by the World Bank Education Statistics. For education expenditure, we use total government expenditure on education (% of GDP) (SE.XPD.TOTL.GD.ZS). For pre-primary expenditure, we use government expenditure on pre-primary education as (% of GDP) (UIS.XGDP.0.FSGOV).

We also use the WDI to get three of the additional measures of human capital given in Figure 1. For secondary and tertiary enrollment, the variables are *School enrollment, secondary (% gross)* (SE.SEC.ENRR) and *School enrollment, tertiary (% gross)* (SE.TER.ENRR). For the adult literacy, the variable is *Literacy rate, adult total (% of people ages 15 and above)* (SE.ADT.LITR.ZS). The fourth variable we use in Figure 1 is an alternative measure of *Mean years of schooling*. This is provided by the Human Development Data of the UN.[3]

We use the earnings ratio of ages 64 to 55 and 55 to 35 for South Africa in 2000 in our calibration. For this we use Income and Expenditure Survey (2000) provided by Statistics South Africa. We compute labor income by adding *"Salaries and wages for normal hours"* (P2401Q0101), *"Bonuses and income from overtime"* (P2401Q0102), *"Commission and director's fees"* (P2401Q0103), *"Part-time work and cash allowances"* (P2401Q0104), *"Net profit from business/professional practice/farming"* (P2401Q02). We run an OLS regression of this income on age, age-squared and gender indicator for ages between 18 and 64 among people who worked in the past week. We compute the ratios using the predicted income for ages 64, 55 and 35.[4]

Treatment costs. Dutta et al. (2015) categorizes the countries into income group-region pairs. There are three groups that include countries in our sample. The *low income - Africa* group includes 14 of our countries, *lower-middle - Africa* includes 6, and *upper-middle - Africa* includes 5. See Table 1 in that paper for country groupings. We take the weighted averages across costs reported for year 2015, for the corresponding income groups for Africa. The costs components we add up are the ART costs, tests, laboratory expenditure, personnel & overhead costs. For

[3]This data can be downloaded at http://hdr.undp.org/en/indicators/103006.

[4]Statistics South Africa. Income and Expenditure 2000 [dataset]. Version 2. Pretoria: Statistics South Africa [producer], 2007. Cape Town: DataFirst [distributor], 2011. DOI: https://doi.org/10.25828/wcyp-vf28

ART drugs, we use only the first line costs for adults reported in their Table 3. We omit the distinction between the ART for adults and children since the costs estimated in this paper for these two are very similar. The other three cost components come from their Table 4. In 2014 US dollars, the weighted averages that we compute across the country groups for the ART costs is \$110.52, testing is \$44, laboratory is \$36.9, and overhead and personnel are \$123.2. These add up to \$314.6. In 2011 dollars, this gives \$301.9.

There are a few remarks to be made regarding our imputation. First, we assume away the costs of pre-ARV as in our model infected individuals that will eventually be receiving the ART start the treatment immediately. Stover et al. (2016) assumes this will happen by year 2020 in their projections. We also omit second-line ARV costs. Second, it is recognized that the treatment costs, especially those of purchasing the drugs are bound to decline over time. See for instance Dutta et al. (2015)'s estimates for 2020. Nevertheless, our calibration is for 2010-2017, hence using the 2015 costs is the natural approach. Third, we assume uniform costs across countries mainly because costs for the first three items we capture (drugs, testing, laboratory) are quite stable across groups as listed in Dutta et al. (2015). The only large variation in costs appears in the overhead and personnel costs which is more than four times as large in the richest group of African countries reported than the other groups, and we choose to have uniform to avoid influencing the results due to this single item.

Condom promotion costs. Stover et al. (2017) estimate the infections averted and the implied costs of two scenarios following the UNAIDS targets regarding condom promotion. They study two scenarios (high and medium scale), and two horizons (2015-2020 and 2015-2030). In the paper, they provide estimates at the region level, but in the Supplement File, they give these estimates for each country. We divide the total difference in the costs of high vs. low, and high vs. median scale, with the difference in the number of HIV infections high vs. low, and high vs. median scale. To this end, we use (i) the infections averted in each scenario-horizon (Sheet "*DALYs Averted Summary*", variables "*HIV infections Medium over Low*" and "*HIV infections High over Low*"), (ii) and the costs of each scenario-horizon (Sheets "*Cost calculation high/medium/low*", variable "*Annual Cost of Condom Provision - HIV Total*".)

For our experiments, we use the median of this ratio from the high volume scenario between 2015-2030, which is $1235. In any case, using their estimates for the interval 2015-2020 instead of 2015-2030, or for the medium-scale scenario instead of high-scale, gives similar numbers. In particular, for the interval 2015-2020, the estimate is $1391. The numbers for the medium volume scenario are only available for 12 countries in our sample, and the median cost per infection averted among these is 1096 for the longer horizon, and 888 for the shorter horizon.

D Calibration details.

In Section 3 of the paper, we discussed the calibration strategy deferring the values of calibrated parameters specific to country and period to the current section. In particular, we show here the model match of the targeted moments, and provide the aforementioned parameter values. Tables 1 and 2 provide the parameter values for the first and second period, respectively. Tables 3 and 4 compare the targeted moments in the data and in the model for these periods.

Table 1: Country-period specific parameter values for 1995-2004

Country	μ	λ_A	m_A	θ	λ_H	β	z
Benin	0.021	0.059	0.128	0.000	0.012	0.037	0.621
Burundi	0.023	0.090	0.851	0.000	0.015	0.037	0.537
Cameroon	0.040	0.058	0.135	0.000	0.012	0.036	0.710
C. African Republic	0.042	0.076	0.303	0.000	0.014	0.034	0.604
Congo	0.029	0.080	0.360	0.000	0.013	0.034	0.707
Cote d'Ivoire	0.035	0.085	0.392	0.000	0.013	0.035	0.723
D.R. of the Congo	0.019	0.091	0.676	0.000	0.014	0.039	0.541
Gabon	0.036	0.061	0.140	0.000	0.011	0.031	1.011
Ghana	0.025	0.073	0.307	0.000	0.012	0.032	0.717
Kenya	0.046	0.071	0.393	0.000	0.012	0.036	0.687
Lesotho	0.095	0.047	0.074	0.000	0.005	0.027	0.747
Malawi	0.062	0.067	0.276	0.000	0.010	0.036	0.592
Mali	0.020	0.075	0.416	0.000	0.014	0.040	0.658
Mozambique	0.060	0.051	0.106	0.000	0.009	0.037	0.541
Namibia	0.069	0.052	0.097	0.000	0.008	0.029	0.917
Niger	0.013	0.069	0.192	0.000	0.013	0.041	0.529
Rwanda	0.034	0.082	0.370	0.000	0.015	0.033	0.558
Senegal	0.015	0.059	0.157	0.000	0.012	0.034	0.723
Sierra Leone	0.021	0.071	0.246	0.000	0.018	0.034	0.654
South Africa	0.073	0.033	0.048	0.000	0.008	0.022	1.000
Togo	0.033	0.061	0.209	0.000	0.012	0.035	0.607
Tanzania	0.040	0.073	0.257	0.000	0.012	0.036	0.600
Uganda	0.045	0.084	0.441	0.000	0.013	0.041	0.623
Zambia	0.064	0.070	0.234	0.000	0.011	0.038	0.668
Zimbabwe	0.078	0.070	0.240	0.000	0.009	0.029	0.786

Note: Table gives the values of country-period specific parameters calibrated targeting the data moments in Table 3. The parameters are the infection efficiency (μ), mortality rate of infected non-treated (λ_A), mother-child transmission rate (m_A), treatment probability upon infection (θ, set 0 for this period), mortality rate of healthy (λ_H), birth rate (β) and the TFP (z).

Table 2: Country-period specific parameter values for 2010-2017

Country	μ	λ_A	m_A	θ	λ_H	β	z
Benin	0.015	0.068	0.416	0.240	0.012	0.034	0.653
Burundi	0.010	0.087	1.000	0.217	0.013	0.038	0.531
Cameroon	0.027	0.071	0.494	0.134	0.013	0.034	0.723
C. African Republic	0.028	0.085	0.586	0.073	0.015	0.032	0.575
Congo	0.023	0.071	0.450	0.112	0.012	0.033	0.802
Cote d'Ivoire	0.021	0.085	0.674	0.127	0.014	0.033	0.771
D.R. of the Congo	0.011	0.089	1.000	0.094	0.013	0.039	0.553
Gabon	0.027	0.061	0.457	0.245	0.011	0.031	1.058
Ghana	0.018	0.069	0.501	0.106	0.012	0.029	0.767
Kenya	0.028	0.064	0.796	0.283	0.011	0.030	0.712
Lesotho	0.080	0.049	0.190	0.245	0.013	0.026	0.799
Malawi	0.048	0.051	0.470	0.347	0.011	0.035	0.581
Mali	0.018	0.069	0.481	0.122	0.013	0.039	0.668
Mozambique	0.060	0.056	0.220	0.157	0.010	0.036	0.599
Namibia	0.058	0.060	0.591	0.468	0.012	0.029	0.992
Niger	0.008	0.075	0.517	0.176	0.012	0.043	0.533
Rwanda	0.020	0.066	0.924	0.390	0.011	0.032	0.603
Senegal	0.006	0.067	1.000	0.194	0.011	0.035	0.730
Sierra Leone	0.018	0.063	0.381	0.092	0.014	0.031	0.660
South Africa	0.067	0.031	0.180	0.299	0.011	0.021	1.042
Togo	0.021	0.074	0.701	0.169	0.012	0.032	0.609
Tanzania	0.033	0.054	0.311	0.255	0.011	0.036	0.654
Uganda	0.038	0.062	0.423	0.259	0.012	0.039	0.649
Zambia	0.053	0.053	0.369	0.363	0.011	0.036	0.789
Zimbabwe	0.050	0.068	0.651	0.329	0.012	0.033	0.628

Note: Table gives the values of country-period specific parameters calibrated targeting the data moments in Table 4. The parameters are the infection efficiency (μ), mortality rate of infected non-treated (λ_A), mother-child transmission rate (m_A), treatment probability upon infection (θ), mortality rate of healthy (λ_H), birth rate (β) and the TFP (z).

Table 3: Targeted moments for 1995-2004, data vs. model

	Data						Model			
Country	Inci.	HIV-reld death	Child prev.	L(5)	Birth rate	Y/L	Inci.	Child prev.	L(5)	Y/L
Benin	0.164	0.047	0.109	59.6	0.037	0.121	0.164	0.109	59.5	0.121
Burundi	0.203	0.075	0.761	53.1	0.037	0.050	0.203	0.760	53.1	0.050
Cameroon	0.624	0.046	0.436	55.0	0.036	0.217	0.624	0.436	55.0	0.217
C. African Republic	0.673	0.062	0.903	48.9	0.034	0.079	0.673	0.903	48.9	0.079
Congo	0.337	0.066	0.518	53.9	0.034	0.199	0.337	0.518	53.9	0.200
Cote d'Ivoire	0.475	0.072	0.720	53.5	0.035	0.223	0.475	0.720	53.4	0.223
D.R. of the Congo	0.140	0.077	0.364	54.8	0.039	0.056	0.140	0.364	54.8	0.056
Gabon	0.509	0.050	0.389	59.0	0.031	1.323	0.509	0.389	59.0	1.324
Ghana	0.237	0.061	0.347	58.7	0.032	0.232	0.237	0.347	58.6	0.232
Kenya	0.809	0.059	1.463	53.0	0.036	0.177	0.809	1.463	53.0	0.177
Lesotho	3.581	0.042	1.354	50.1	0.027	0.228	3.581	1.354	50.0	0.228
Malawi	1.498	0.057	1.752	49.8	0.036	0.081	1.498	1.752	49.8	0.081
Mali	0.156	0.061	0.280	54.3	0.040	0.151	0.156	0.280	54.4	0.151
Mozambique	1.418	0.042	0.742	54.0	0.037	0.058	1.418	0.742	54.1	0.058
Namibia	1.891	0.044	1.025	52.8	0.029	0.695	1.891	1.025	52.7	0.696
Niger	0.069	0.056	0.054	59.2	0.041	0.058	0.069	0.054	59.1	0.058
Rwanda	0.448	0.068	0.716	49.8	0.033	0.053	0.448	0.716	49.9	0.053
Senegal	0.083	0.048	0.071	61.5	0.034	0.263	0.083	0.071	61.4	0.263
Sierra Leone	0.172	0.053	0.221	46.4	0.034	0.105	0.172	0.221	46.4	0.105
South Africa	2.120	0.025	0.942	56.3	0.022	1.000	2.120	0.942	56.2	1.000
Togo	0.417	0.048	0.465	56.2	0.035	0.099	0.417	0.465	56.2	0.099
Tanzania	0.628	0.061	0.679	53.4	0.036	0.091	0.628	0.679	53.4	0.090
Uganda	0.771	0.071	1.172	49.2	0.041	0.107	0.771	1.171	49.2	0.107
Zambia	1.616	0.059	1.427	47.8	0.038	0.142	1.616	1.427	47.8	0.142
Zimbabwe	2.352	0.061	2.456	45.9	0.029	0.264	2.352	2.456	45.9	0.264

Note: Table gives the targeted moments in the data, and their model counterparts for the 1995-2004 period. The moments shown are the adult incidence rate, HIV-related death rate, prevalence among children, life expectancy at age 5, birth rate and output per worker relative to South Africa's average output per worker in 1995-2004. For the model, HIV-related death rate and the birth rate are directly determined by assumed parameters (by $\lambda_A - \lambda_H$ and β, respectively), hence their model counterparts are omitted. Treatment rates in the data for this period are assumed zero, which is also the case for our calibration.

Table 4: Targeted moments for 2010-2017, data vs. model

	Data							Model				
Country	Inci.	HIV-reld death	Child prev.	Treatment rate	L(5)	Birth rate	Y/L	Inci.	Child prev.	Treatment rate	L(5)	Y/L
Benin	0.070	0.056	0.124	43.8	62.1	0.034	0.159	0.070	0.124	43.7	62.1	0.159
Burundi	0.032	0.074	0.355	43.5	58.9	0.038	0.056	0.032	0.121	43.6	58.9	0.056
Cameroon	0.239	0.059	0.542	28.4	57.5	0.034	0.243	0.239	0.542	28.3	57.5	0.243
C. African Republic	0.273	0.071	0.686	19.1	52.4	0.032	0.066	0.273	0.686	19.1	52.4	0.066
Congo	0.189	0.059	0.398	24.5	60.9	0.033	0.431	0.189	0.398	24.6	60.9	0.431
Cote d'Ivoire	0.154	0.071	0.431	29.9	55.8	0.033	0.310	0.154	0.431	29.9	55.8	0.310
D.R. of the Congo	0.044	0.077	0.224	22.9	60.1	0.039	0.071	0.044	0.177	22.8	60.1	0.071
Gabon	0.220	0.049	0.505	43.5	62.4	0.031	1.764	0.220	0.505	43.6	62.4	1.765
Ghana	0.119	0.057	0.327	23.9	61.1	0.029	0.327	0.119	0.327	23.8	61.1	0.327
Kenya	0.216	0.053	0.876	49.9	61.9	0.030	0.231	0.216	0.876	50.0	61.9	0.232
Lesotho	1.881	0.036	1.919	42.3	49.1	0.026	0.286	1.881	1.918	42.2	49.1	0.286
Malawi	0.590	0.040	1.259	51.9	59.3	0.035	0.086	0.590	1.259	52.0	59.3	0.086
Mali	0.108	0.056	0.229	24.5	59.1	0.039	0.180	0.108	0.229	24.5	59.1	0.180
Mozambique	1.193	0.046	1.138	29.4	55.9	0.036	0.098	1.193	1.138	29.4	55.9	0.098
Namibia	0.704	0.048	1.529	68.3	58.3	0.029	1.124	0.704	1.529	68.4	58.3	1.122
Niger	0.019	0.063	0.034	33.6	61.3	0.043	0.065	0.019	0.034	33.6	61.3	0.065
Rwanda	0.095	0.055	0.377	61.6	64.5	0.032	0.108	0.095	0.377	61.8	64.5	0.108
Senegal	0.012	0.056	0.086	37.4	64.8	0.035	0.297	0.013	0.069	37.3	64.8	0.296
Sierra Leone	0.112	0.048	0.255	19.1	54.8	0.031	0.136	0.112	0.255	19.2	54.8	0.136
South Africa	1.234	0.020	1.872	42.0	58.7	0.021	1.297	1.234	1.872	42.1	58.7	1.296
Togo	0.148	0.061	0.495	35.3	59.3	0.032	0.103	0.148	0.495	35.3	59.3	0.103
Tanzania	0.324	0.043	0.467	41.4	60.8	0.036	0.162	0.324	0.467	41.5	60.8	0.162
Uganda	0.418	0.050	0.683	43.6	58.9	0.039	0.160	0.417	0.683	43.5	58.9	0.160
Zambia	0.702	0.042	1.002	54.1	59.3	0.036	0.408	0.702	1.002	54.2	59.3	0.408
Zimbabwe	0.665	0.056	1.690	55.9	55.6	0.033	0.112	0.665	1.690	55.8	55.6	0.112

Note: Table gives the targeted moments in the data, and their model counterparts for the 2010-2017 period. The moments shown are the adult incidence rate, HIV-related death rate, overall treatment rate, prevalence among children, life expectancy at age 5, birth rate and output per worker relative to South Africa's average output per worker in 1995-2004. For the model, HIV-related death rate and the birth rate are directly determined by assumed parameters (by $\lambda_A - \lambda_H$ and β, respectively), hence their model counterparts are omitted.

E Additional Results on Non-targeted Moments

In Section 3 of the paper, we show the model's fit to the data in various non-targeted features in terms of demographics and human capital. Within the latter group of features, we showed the model performance in replicating the average years of schooling as provided by the WDI. Nevertheless, the WDI offers alternative measures of education and human capital that we can also compare to the predictions of the model in reduced form. In the first two panels of Figure 1, we compare our predicted schooling levels for each country with the observed enrollment rates, as a percentage of the corresponding age group of children, for secondary and tertiary education. The model's predictions and the enrollment rates shows a positive correlation (0.7) which gives us reassurance that we are capturing an important component of human capital.

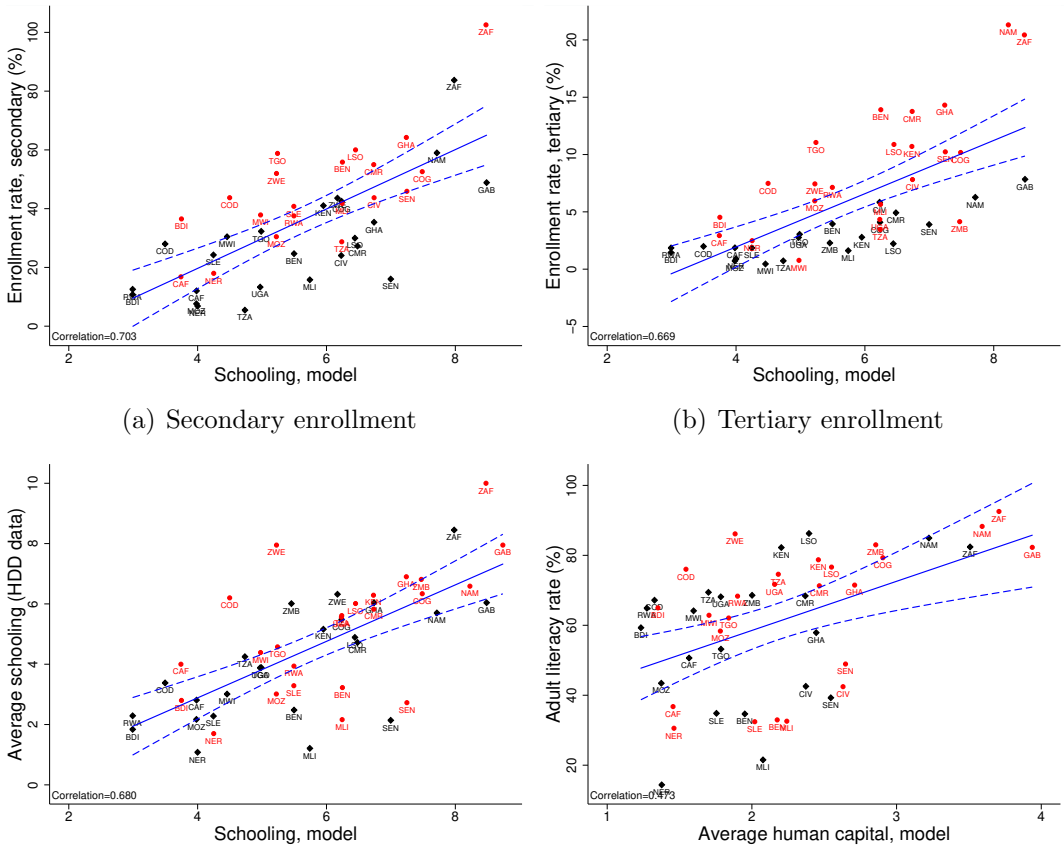
In Panel (c) of Figure 1, we use an alternative measure of schooling provided by the Human Development Data of the United Nations, which gives similar conclusions to our comparison with the Barro-Lee measure of schooling. In particular, the correlation between this measure of schooling and our model-implied levels is at 0.67. In the last panel, we compare the literacy rates among adults, provided by the WDI, with our average human capital. These two correlate positively and significantly, with a correlation of 0.47.

Overall, we think that our calibrated model performs reasonably well and we view it as a useful framework to study the effects of interventions that affect the disease environment.

F Robustness

In this section we discuss the robustness of findings with respect to changes in some of the potentially relevant calibration choices. Our approach to showing the robustness of our model results to alternative calibration choices is to plot the implied schooling levels against those in the benchmark. This is done for brevity. As it will be evident, the similarities in this dimension are rather pronounced, hence these exercises serve to summarize the little quantitative relevance

Figure 1: Enrollment and literacy rates



(a) Secondary enrollment

(b) Tertiary enrollment

(c) Average schooling, alternative data

(d) Adult literacy

Note: Panels (a) and (b) plot the enrollment rates in the secondary and tertiary education by the corresponding age groups (y-axis) against the average schooling in the model (x-axis) for our sample countries. Panel (c) uses in the y-axis an alternative schooling data (Human Development Data by the UN) to the one we use in Figure 2 of the paper. Panel (d) uses the literacy rates in y-axis, and average human capital in the model in the x-axis. Black diamonds correspond to 1995-2004 interval, and red circles correspond to 2010-2017. The second panel shows the changes between the two intervals. The solid blue line gives the linear fit of the x-axis to the y-axis, and the blue dashed lines give 95% confidence intervals. See Appendix C for data details.

of the studied calibration choices.[5,6]

[5]Repeating the same figures for the implied average human capital or the calibrated TFP levels across countries exhibit correlations with similar coefficients as in the case of schooling.

[6]In these robustness checks, we follow the exact same strategy as in our benchmark. Nevertheless, it was not necessary to update all calibrated parameters that are common across countries and time since their targets are still matched with their baseline values. For $r = 7\%$ exercise, we updated γ_1 to 0.29, and z_h to 0.32. For $R = 70$, we updated z_h to 0.279. For the $h(6) = 0.5$ exercise, we have $z_h = 0.246$, and for $p^* = 17$, we have it at 0.283. For $\nu_A = 0.85$ calibration, it was not necessary to recalibrate any common parameter. Among these robustness checks, only $p^* = 17$ exercise is affects the demographics, hence only for this one we had to recalibrate the country- and time-specific demographic parameters. For brevity, we omit the updated values of country- and time-specific parameters.

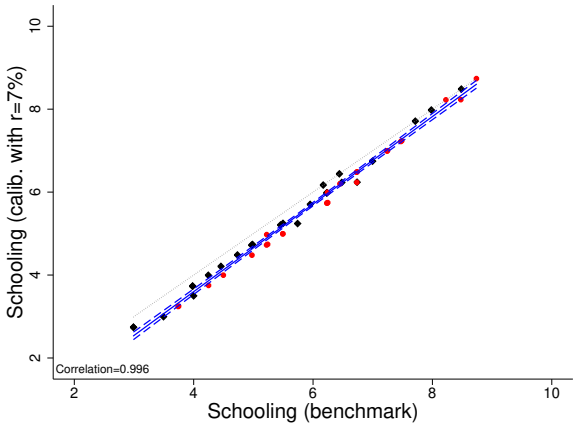
Risk-free interest rate, r. In our calibration we set the interest rate, common across periods and countries, at 5 percent since this is a standard value and we would like to abstract from any variation in the borrowing ability within our sample, or between our sample and more developed countries. As a robustness check, we run our calibration with an interest rate of 7 percent. Figure 2 Panel (a) shows that, once recalibrated to hit the same targets, the implied schooling levels are very well-aligned with the benchmark, with a correlation of 0.996.

Retirement age, R. Our benchmark assumes a time- and country-invariant retirement age of 64 years. While being a standard value for developed countries, this value might be too optimistic for the context of Sub-Saharan Africa, where might keep supplying labor longer. The sensitivity analysis we run here is to recalibrate the model with a retirement age of 70. Panel (b) of Figure 2 shows that the correlation between the average schooling in the benchmark and in this alternative model is also close to 1, and the levels are also very similar to each other.

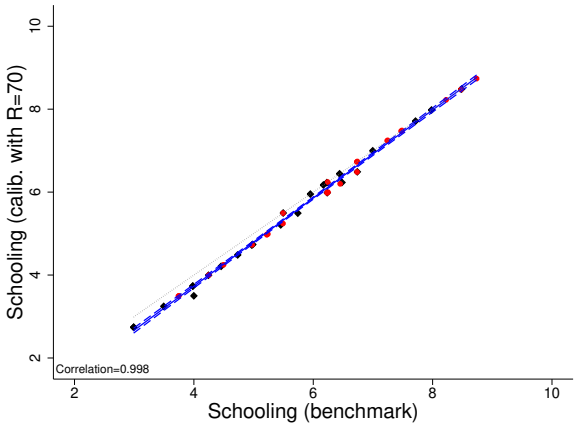
Morbidity for the non-treated infected, ν_A. In the baseline calibration we assumed that $\upsilon_A = 0.926$ following the results of Habyarimana et al. (2010). To evaluate how sensitive the results are to this specification, we recalibrate the model by decreasing this parameter to $\nu_A = 0.85$, implying a morbidity that is about twice as severe. Panel (c) of Figure 2 shows that the assumed value for ν_A does not play a significant role for the results.

Initial human capital, $h(6)$. In our benchmark, we assume that all the children in an economy start their schooling period with a human capital stock of 1 unit. Our quantitative result is that the value assumed for this stock is practically irrelevant for our results to the extent that we recalibrate the efficiency of human capital accumulation function, z_h to match the same average schooling for a given economy (which we do so targeting South Africa 1995-2004 in our calibration). Figure 2 Panel (d) highlights the correspondence between the schooling levels implied in the benchmark, and in this alternative calibration with $h(6) = 0.5$.

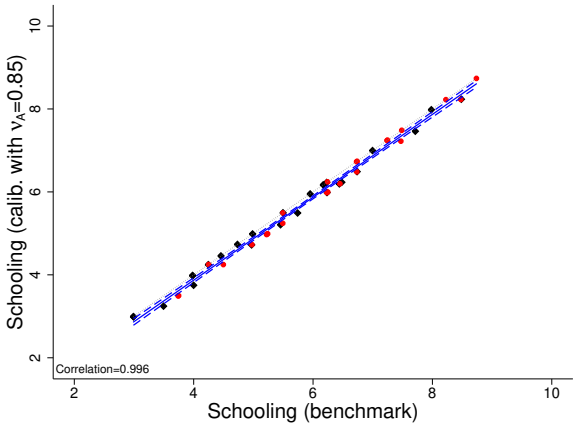
Figure 2: Schooling in alternative calibrations vs. benchmark



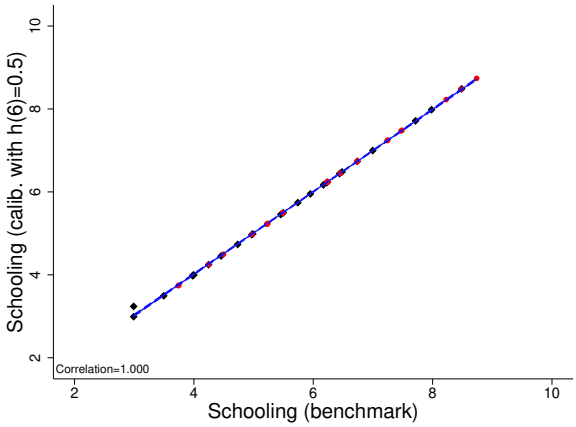
(a) Higher interest rate, $r = 7\%$



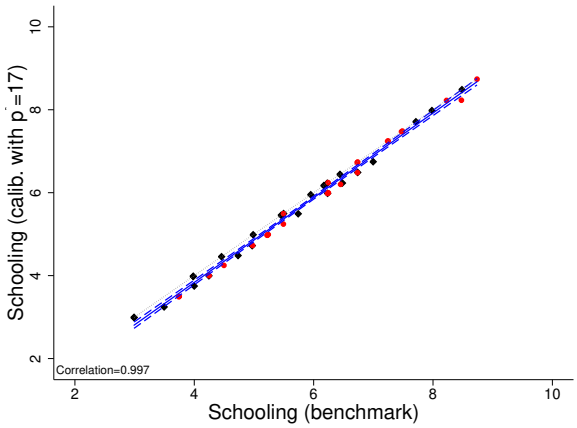
(b) Later retirement, $R = 70$



(c) More severe morbidity, $\nu_A = 0.85$



(d) Lower initial human capital, $h(6) = 0.5$



(e) Longer non-susceptible period, $p^* = 17$

Note: Each figure plots the implied average schooling across country-period pairs in the benchmark against those in an alternative calibration. Black circles (red diamonds) represent a country calibration for 1995-2004 (2010-2017). The solid line gives the linear fit, and the dashed lines give 95% confidence intervals. In the benchmark calibration, interest rate (r) is 5 percent, retirement age (R) is 64, total time of non-treated infected available for work (ν_A) is 0.926, the initial human capital $h(6)$ is 1, and the length of non-susceptible period is $p^* = 16$ years.

Length of the non-susceptible period, p^*. In the model, the period during which healthy children have zero risk of contracting HIV/AIDS is given by the ages between 0 and p^*. In our base calibration, we set $p^* = 16$. To explore the sensitivity of the results to the chosen value of p^* we experimented increasing it to 17. Panel (e) of Figure 2 shows that the model-implied schooling levels in this alternative and in the benchmark are very close to each other, with a correlation of 0.997 in between.

G Calibration: Relevant Literature

AIDS and Morbidity Bignami-Van Assche et al. (2011) use data on households from rural Malawi in 2004 to find that men's labor supply does not respond to the HIV infection, whereas women respond through their allocation of time into different type of activities. Sonnenberg et al. (2011) study patterns of labor supply of gold miners in South Africa from 1992-2002 to show that HIV positive miners work about 95 percent of the HIV negative workers. Levinsohn et al. (2013) use South African data from 2005 to find that HIV-infected adults have 6-8 percent higher probability of not being employed. Larson et al. (2008) use a sample of tea plant workers in Kenya to find that non-treated infected workers worked 22 percent fewer days in the year before starting an ART treatment.

The Effect of ART Treatment In different contexts, other studies also find substantial gains in the labor supply of the infected soon after starting the treatment. Thirumurthy and Graff Zivin (2012) use panel data from a rural Kenya region between 2004 and 2006 to find that labor force participation increases by around 20 percentage points as soon as the third quarter after starting ART treatment, and the total hours worked increases by about 10 hours (more than 50 percent of the month before treatment) within the first 6 months. These gains remain relatively stable thereafter, which suggests that by then the labor supply resembles that of a non-infected individual. They also find that these responses are similar to those of health (measured by the weight of the patient) to the ART treatment. See also Thirumurthy et al. (2008), who find similar results for the same context with a 7.3 hours (37 percent) increase in total hours 3

months after starting an ARV treatment, that remain stable afterwards.Larson et al. (2008) find that within 12 months after starting the treatment, the workers recover almost all of their labor supply.

Thirumurthy et al. (2008) show that the CD4 counts recover to asymptomatic levels as soon as 10 weeks after starting the treatment. Habyarimana et al. (2010) argue that the CD4 counts reach to pre-infection levels within a year. A large randomized trial experiment (HPTN052, 2011) ran by the HIV Prevention Trials Network in nine countries showed that early ART treatment reduces the number of infections by 96 percent. See also Karim and Karim (2011) survey of the medical literature on the effectiveness of ART treatment, and other prevention methods on reducing the infectiousness. Cohen et al. (2011) also report a 89 to 96 percent reduction in the number of infectious cases due with early ART initiation. Mortality effects of ART treatments are also parallel to those of CD4 counts and the infectiousness. For instance, Mermin et al. (2008) use a sample from Uganda to show that antiretroviral treatment reduce the mortality of the infected adults by 95%. Alistar et al. (2014) calibrate a model for the effects of ART in South Africa, in which they use a mortality for the treated at early stage HIV that is one-eighth of that of the non-treated. Their ratio for the late stage HIV is one-fifth.

UNAIDS provides estimates of the fraction of infected people with suppressed viral loads. This dataset coincides with the UNAIDS data on treatment rate for 16 country-year pairs in our sample. Median ratio of the suppression rate over treatment rate among the individuals with infected, in our country-year sample is 0.86, minimum ratio is 0.66 and the maximum is 0.94. The correlation between the treatment rate and the suppression rate is 0.99. Even though this is a small sample, these numbers are reassuring in terms of assuming away the HIV-related mortality, morbidity and infectiousness of the treated infected individuals in our calibration.

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