The Lazarus Drug
The macro-economic impact of the expansion of anti-retroviral therapy for HIV/AIDS

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Abstract

Does improving health lead to macro-scale economic growth? This paper evaluates the initial economic impacts of the rapid expansion in access to antiretroviral therapy for HIV/AIDS in low and middle-income countries that began in 2001. Access to antiretroviral therapy increased from fewer than 200,000 people in 2002 to 9.7 million in 2012. The expansion was precipitated by a rapid tenfold reduction in the price of antiretroviral drugs faced by developing countries, driven by competition from generic alternatives. Since the scale of a country's antiretroviral therapy program may be correlated with other factors that influence economic growth, I use predicted antiretroviral coverage as an instrument for observed coverage. I find that increasing coverage of antiretroviral drugs to an additional 1% of a country's population is associated with a 5.7% increase in life expectancy and a corresponding 1.6 percentage point increase in growth in GDP per capita. The results suggest that the economic benefits of antiretroviral therapy outweigh the costs by a factor of 3.3 to 1, and explain 44% of observed growth in per-capita GDP in sub-Saharan Africa between 2004 and 2012.

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1 Introduction

Does improving health lead to macro-scale economic growth? Improvements in health have an intrinsic value in improving the quality of life for individuals. Previous studies also confirm that relative improvements in health lead to relative increases in income; healthy individuals are more productive, and individual and family health increases human capital formation. However, a literature dating back to Thomas Malthus raises the concern that changes in health that increase the size of the workforce or population may not lead to growth in per capita wealth because of diminishing marginal returns to labour in the context of fixed factors of production: land, physical capital or other natural resources such as forests or fisheries[1]. In particular, Acemoglu and Johnson's influential study of the international epidemiological transition[2] found that increases in life expectancy led to lower per capita GDP; growth in population outweighed growth in total GDP, resulting in lower per capita levels.

The principal empirical challenge is measuring the causal effect of health improvement on economic growth, given that other, probably unobservable factors may influence both health and income, and given the possibility of reverse causality, as increased incomes increase demand for goods that improve health, including better diets and access to clean water and sanitation facilities. In this paper, I address this empirical challenge by exploiting the dramatic expansion of antiretroviral (ARV) therapy to treat HIV/AIDs, which saw a 30-fold increase in the number of people receiving ARV therapy in low and middle income countries over a 10 year period. I thereby exploit only the variation in ARV therapy coverage that is driven by *global* changes in drug price and availability. I find that increasing coverage of ARV therapy to an additional 1% of a country's population is associated with a 5.7% increase in life expectancy, and a corresponding 1.6 percentage point increase in GDP per capita. In contrast to Acemoglu and Johnson (2007), I find that the corresponding increase in population growth is modest — 0.23 percentage points — and is less robust to the exclusion of outlier countries.

My approach is motivated by the observation that observed levels of ARV therapy coverage in a given country are partly determined by the extent and success of the country's ARV treatment

[1] Young (2005) formalized these trade-offs in a model and simulation of the effect of the AIDS epidemic on economic growth, and concluded that the effect on population growth would lead to higher per-capita incomes in the long run.

[2] Acemoglu and Johnson (2007).

program. Countries with extensive ARV therapy programs may differ from countries with less extensive programs in other respects, and as a result, naïve estimates of the effect of antiretroviral therapy on economic growth are likely to be biased, although the sign of this bias is not *ex ante* obvious. I address this empirical problem by instrumenting for observed ARV coverage with predicted coverage, based on HIV prevalence in 2001 and global coverage of ARV therapy in low and middle-income countries.[3] Predicted coverage reconstructs what ARV therapy coverage would look like if global changes in access to ARV were uniformly distributed across all HIV positive individuals in low and middle-income countries. This strategy yields estimates that are larger than those estimated by a naïve approach which assumes that actual ARV coverage is not endogenous to growth. The results imply that the naïve estimates are biased downwards. A plausible explanation is that the size of a country's ARV treatment program is correlated with lagged economic growth, biasing downwards estimates of changes in growth rates resulting from the ARV treatment program.

The approach of using predicted gains from a global improvement in healthcare was pioneered by Acemoglu and Johnson (2007) in the context of the international epidemiological transition, and later replicated in a number of other contexts with reference to specific diseases including hookworm (Bleakley, 2007) and malaria (Bleakley, 2010; Cutler et al., 2010). Rather than study actual, observed changes in health, these studies exploit predicted changes in health that result from global technological or policy changes, leveraging cross-sectional variation in the extent to which countries should have benefited from these changes, given pre-intervention disease prevalence. The identifying assumption is that pre-intervention disease prevalences do not themselves influence later economic growth, an assumption that some have criticized (e.g. Bloom, Canning, and Fink, 2009, in response to Acemoglu and Johnson, 2007). Most papers that adopt this strategy bolster their claim by showing that trends in income or growth prior to the intervention are similar in high and low prevalence areas. In contrast, I find significant negative trends in outcome variables prior to the onset of ARV expansion in countries with high HIV prevalence, consistent with the hypothesis that HIV/AIDS itself has a negative effect on both life expectancy and economic growth. These trends reverse at the onset of ARV expansion, as shown in Figure 4, and the reversal in trends

[3]Following Acemoglu and Johnson (2007), and others including Bleakley (2007, 2010), Cutler, Fung, Kremer, Singhal, and Vogl (2010).

is contemporaneous with the onset of ARV expansion. However, as a result, I include controls in all specifications for pre-intervention trends, and my estimates reflect deviations from these pre-existing trends.

The expansion in ARV therapy was driven by a number of factors. Effective combinations of ARV drugs were developed in the late 1990s, but the drugs were initially prohibitively expensive with respect to widespread provision in low and middle-income countries. Around the turn of the millennium, countries including India and Brazil began production of generic copies of brand-name drugs. Pharmaceutical companies initially resisted this competition quite aggressively. However, international pressure to make the drugs available on a wider scale increased, and in 2001, facing little or no international support, pharmaceutical companies relaxed their opposition to generic drug manufacturers, and the price of ARV drugs faced by low-income countries fell ten-fold in under a year. Since this time, the price of ARV therapy has fallen still further. International organizations, particularly the Global Fund for AIDS, Tuberculosis and Malaria, have also invested heavily in the scale-up of ARV therapy. Coverage of ARV therapy in low and middle income countries rose as a result from 200,000 people in 2001, to 9.7 million people at the end of 2012. Accurately measuring the change in trends in countries with high HIV-prevalence depends on the assumption that the timing of the scale-up in ARV therapy was otherwise unrelated to the differences in changes in trends between countries with high and low HIV prevalence. However, the drive towards expanding ARV coverage was if anything driven by falling life expectancy and stagnant economic growth in countries with high HIV prevalence. As a result, it is highly implausible that the timing of the ARV scale-up was itself caused by a reversal in relative trends life expectancy and growth in high HIV prevalence countries.

The study exploits cross-sectional variation in the severity of the HIV epidemic, and what is essentially a single, global experiment in time: the scaling-up of ARV therapy across low- and middle-income countries. An inherent limitation of the study is the relatively small number of countries affected by the HIV epidemic. While 40 countries (of a main sample of 86 low and middle-income countries who report HIV prevalence in 2001) have HIV prevalence greater than 1% in 2001, only 15 countries have HIV prevalence greater than 5%. These countries are the object of interest of the study, but the small number of these countries nonetheless raises the concern that the results could be driven by a single outlier country (or several outlier countries). Using a series

of 'leave-one-out' estimates, I show that for life expectancy and growth in GDP per capita and total GDP, the estimated coefficients remains consistent in sign and statistically significant when any one country is dropped from the sample, or when the three largest outliers in HIV prevalence — which have the greatest leverage on the estimates — are together dropped from the sample. However, the estimated effect on population growth is more sensitive to the exclusion of outlier countries, and in particular is not statistically significant when either Zimbabwe or Swaziland is excluded, suggesting the need for some caution in interpreting these results. All countries with HIV prevalence greater than 15% of the population are in sub-Saharan Africa. However, I show that the results remain consistent in sign and statistically significant when I either allow regions to experience different, flexible time trends, or when I limit the analysis to sub-Saharan Africa alone.

The results could be biased by other unobservable factors that influence health and growth, if these are correlated across space with the HIV epidemic, and in time with the global scale-up of ARV therapy. I examine three potential alternative explanations and reject in each case the possibility that these alternative explanations account for the main results. First, I note that the scale-up of ARV therapy is correlated in time with an expansion of Chinese influence in sub-Saharan Africa, whether measured in terms of aid, trade or FDI. Strategic Chinese investment in countries with high levels of mineral resources might explain the results if mines — with high levels of transient workers — act as focal points for HIV epidemics. I allow countries with high levels of mineral resources — measured by the fraction of GDP from mineral rents — to have different, flexible time trends, and find no evidence that these additional controls change the results. Second, I similarly rule out a relationship with dependence on petroleum rents, which also might be associated with strategic Chinese investment in countries with high levels of petroleum resources, and associated with HIV prevalence if lower pump prices lead to greater population mobility and thereby transmission of HIV. Finally, noting that HIV prevalence might also be correlated in space with malaria prevalence and that the Global Fund has also scaled up its activities in malaria control over the same time period, I similarly rule out that the results are driven by different time trends in countries where the climate and ecology is highly suitable for malaria transmission.

My results contribute to the literature on the impact of health on economic growth. Many micro-economic studies show that health has a direct effect on individual or household scale eco-

nomic outcomes[4], but these studies measure the relative impacts of relative improvements in health, and are therefore unable to address the impact of aggregate improvements in health. An extensive macro-economic literature exists which includes health as a variable in cross-country growth comparisons, with or without instruments for the health variables of interest.[5] However, the results of these studies are contentious, because exploiting only cross-sectional variation renders the estimates more sensitive to violations of the identifying assumptions. Empirically, the closest country-scale study is Acemoglu and Johnson (2007), who also exploit a global change in health technology to identify the impacts of improvements in health.

In contrast to Acemoglu and Johnson (2007), I find a robust positive impact on GDP per capita, more consistent with the evidence from the microeconomic literature. There are several potential explanations for these differences. Perhaps most importantly, my results may differ because of the nature of the disease I examine. While Acemoglu and Johnson focused on diseases that largely influence infant mortality — including malaria, measles, diptheria, scarlet fever and whooping cough — HIV/AIDS affects primarily adults of working age who may already be parents, and has significant morbidity impacts as well as mortality impacts. As a result, we would *ex ante* expect the productivity and human capital channels to be important. My results also focus on the short-term impacts, while Acemoglu and Johnson focus on long-term impacts; it is possible that the positive impact on population growth that I observe might lead to a reversal of the effect on per-capita GDP in the long run. Finally, it is worth noting that I control for pre-trends in outcome variables associated with HIV prevalence, and show these to be important and significant, while the identifying assumption in Acemoglu and Johnson (2007) is that pre-trends are equivalent in countries with high and low pre-intervention mortality. If this identifying assumption were not valid, this might also explain the difference in the results.

The results also contribute to explaining the 'growth miracle' in sub-Saharan Africa in the first decade of the new millennium, documented in Young (2012) and Pinkovskiy and Sala-i-Martin (2014), which prompted the *Economist* to lead with the cover story *Africa Rising* in late 2011[6]. Observers have previously attributed this growth to Chinese trade and FDI, foreign aid more

[4]Examples include Bleakley (2007, 2010), Cutler et al. (2010).

[5]Examples include Bhargava, Jamison, Lau, and Murray (2001), Gallup and Sachs (2001), Bloom, Canning, and Sevilla (2004).

[6]Economist, December 3rd 2011

broadly, a boom in commodity prices, a recovery in rainfall, or changes in the quality of institutions. However, the scale-up of antiretroviral therapy, and its apparent reversal of the negative impacts of the HIV/AIDS epidemic has been largely neglected as an explanation. My results suggest that the scale-up of antiretroviral therapy was responsible for 41% of observed growth in per-capita GDP in Sub-Saharan Africa, between 2002 and 2012, suggesting that the scale-up of antiretroviral therapy is an important explanatory factor behind the increase in growth rates in sub-Saharan Africa over this time period.

Overall, my results suggest that ARV coverage in low and middle income countries was responsible for an additional $US 63 billion (in current US$) in GDP growth in 2012. In comparison, a reasonably conservative estimate of the cost of providing antiretroviral drugs to the 9.6 million people in low and middle income countries who received antiretroviral drugs in 2012 is $US 19.2 billion. This suggests that the monetized benefits of funding ARV coverage outweigh the costs by a factor of approximately 3.3 to 1, even without taking into consideration the additional value of directly increased welfare through improved health.

In summary, I find that the expansion in antiretroviral therapy has yielded substantial benefits in terms of economic growth, supporting further expansion and continued support of the program; and provide the first causal evidence that aggregate improvements in health have a positive effect on short-run macro-scale economic growth.

The paper proceeds as follows. Section 2 discusses the HIV/AIDS epidemic and the scale-up of antiretroviral therapy; section 3 describes the data; section 4, the empirical strategy, and section 5, the main results. Section 6 summarizes and concludes.

2 HIV/AIDS and antiretroviral therapy

2.1 The HIV/AIDS epidemic

The Human Immunodeficiency Virus (HIV) is a disease that attacks and weakens the immune system, eventually rendering it susceptible to opportunistic diseases or infections that healthy individuals are able to fight off. The disease has a relatively long latent period — two to fifteen years, depending on the individual, after which the full blown form, Acquired Immunodeficiency Disease (AIDS), develops. AIDS is characterized by a number of particular opportunistic diseases,

including pneumonia, wasting disease and various viral-induced cancers, including the otherwise rare cancer Kaposi's sarcoma.[7]

HIV is a retrovirus, a type of virus characterized by the procedure with which it replicates inside the cells of its host. HIV is transmitted by the exchange of bodily fluids: blood, breast milk, semen and vaginal secretions. As a result, the primary transmission channels are unprotected sex, blood transmissions, and sharing of contaminated needles or other medical equipment. HIV is also transmitted from mothers to their children during pregnancy, labour or breastfeeding.

The first recognised cases of HIV/AIDS were in homosexual men in the United States, among whom an unusually large number of cases of both Kaposi's sarcoma and pneumonia were diagnosed. The name AIDS was coined in 1982 (Kher, 2003) and the virus itself was identified in 1983 (Barré-Sinoussi et al., 1983; Popovic, Sarngadharan, Read, & Gallo, 1984). Medics in Uganda in turn identified a disease causing similar symptoms, locally known as the 'slim disease' because of its wasting effect. There was initial skepticism as to whether the two epidemics were related, given that the affected populations differed so widely in terms of demographic characteristics, until tests showed that the virus was the same. It was later established that HIV as a disease originates in Africa, in a family of viruses that is endemic to primate populations in West and Central Africa, particularly chimpanzees, gorillas and sooty mangabeys (Keele et al., 2006). The disease was passed to humans via cross-species transmission on several separate occasions, although exactly how this happened is not known; the most likely explanation is transmission of bodily fluids during bushmeat hunting.

Most estimates date these events to the first half of the 20th Century, implying that the HIV pandemic had already been established for several decades before testing began (Korber et al., 2000). Multiple hypotheses have been offered to explain how these localized cases of animal-human transmission developed into a full-blown pandemic, including social and medical changes that took place in the 20th Century. Although HIV has been detected in stored blood samples from as early as 1959, it was clearly rare at the time (Nahmias et al., 1986)[8]. By the mid-1990s, the disease had spread into East, Southern and across Western Africa, and overseas, with an estimated 12.9 million people infected in sub-Saharan Africa out of a total of 20.1 million worldwide (Mertens &

[7] A useful and well-referenced source of information on the HIV/AIDS epidemic and antiretroviral therapy is www.avert.org, which provided the background information for much of the following account.

[8] One sample out of 818 collected in 1959 in Leopoldville (now Kinshasha) tested positive for the virus in 1986.

Low-Beer, 1996). Figure 1 shows the distribution of HIV prevalence in 2001.

Although there is a broad consensus among policy-makers that the HIV/AIDS epidemic has had a negative impact on economic growth in sub-Saharan Africa, obtaining unbiased estimates of the impact is difficult. Studies that compare HIV positive individuals to people who are HIV negative may be biased because different demographic groups have different infection rates. In turn, studies that compare countries with high HIV prevalence to those with low or no prevalence may also be biased because the factors that cause HIV to spread and develop, or that determine the extent and success of efforts to control or halt the spread of the disease, may also be correlated with economic growth. Early estimates of the impact of HIV/AIDS on annual growth of GDP per capita ranged from an increase of 0.2% to a decrease of 1.2% (United Nations Department of Economic and Social Affairs, 2004). Estimated effects on total GDP were largely more negative (United Nations Department of Economic and Social Affairs, 2004). More recent, unpublished studies take seriously the endogeneity problem but also vary widely in their estimates, from no impact[9] to substantially negative[10]

There are multiple channels via which HIV/AIDS might influence economic growth, from direct effects on adult productivity, to secondary effects on productivity as a result of carers being forced to leave the workforce, to the consequences for children of being orphaned as a result of both parents succumbing to AIDS. The risk of HIV/AIDS infection alone may also influence investment decisions, effectively leading to a higher discount rate. For example, Forson (2011) finds evidence that HIV/AIDS prevalence has a negative impact on investments in human capital.

2.2 Antiretroviral therapy (ARVs)

Antiretroviral (ARV) therapy describes a class of drugs that interrupt various stages of the retrovirus' life cycle. ARV therapy typically reduces, but does not eliminate viral load; it does not cure patients, but in developed countries at least, it effectively renders HIV a chronic, latent condition, rather than an imminent death sentence. HIV mutates very rapidly, which enables it to adapt quickly and development resistance to ARV therapy.

[9] Ahuja, Wendell, and Werker (2009) use male circumcision rates as an instrument for HIV prevalence and find no measurable impact on economic growth.

[10] Cahu and Fall (2011) use instrumental variables to isolate the independent propagation dynamic of the epidemic and find substantial effects, amounting to a long-run reduction of 12$ in GDP per working age population in Sub-Saharan Africa.

The first antiretroviral drug was developed in 1987, but viral resistance developed very quickly, limiting the drug's effectiveness. In 1996, studies (Hammer et al., 1997; Gulick et al., 1997) established that prescribing a combination of antiretroviral drugs together is substantially more effective, primarily because this reduces the likelihood that the virus can develop resistance. The cocktail of three drugs that became standard reduced viral loads, incidence of opportunistic diseases and mortality by as much as 60-80% (e.g. Moore and Chaisson, 1999), leading to the coining of the nickname *the Lazarus drug*, because of the apparent way in which ARV therapy could bring patients back form the brink of death. Presently, WHO policy is to prescribe ARV therapy to patients above a threshold viral load in several 'lines'; first-line therapy tries the cheapest, most readily available drugs, but second- and even third-line therapy is available should the first-line drugs become ineffective in controlling a patient's viral load. Because ARV therapy reduces the viral load, it also reduces transmission of the virus, particularly from mothers to children.

However, the price of antiretroviral drugs was initially prohibitively high — on the order of $10,000 to $15,000 per patient per year — severely limiting expansion of coverage to the developing world. Between 2000 and 2001 a series of events took place which together combined to reduce the price of the drugs faced by low and middle-income countries by an order of magnitude. India began production of generic versions of the antiretroviral drugs at substantially lower prices. Big pharmaceutical companies initially resisted this violation of intellectual property laws, but this resistance fell away in the face of overwhelming international opprobrium. Two significant events which signalled prevailing opinion were the Clinton administration's decision to ignore violations of American patent law in the case of Sub-Saharan African countries providing antiretroviral drugs to their citizens; and pharmaceutical companies' withdrawal of an attempt to prosecute the South African government for allowing production and importation of generic copies of antiretroviral drugs. By the end of 2001, both brand and generic versions of the three-drug cocktail were available in low and middle-income countries for less than US$1000 per patient per year (Medecins Sans Frontieres, 2001). Figure 2 illustrates this sharp fall in prices, which have since fallen further still; the price of first-line antiretroviral drugs was US$115 per patient per year in 2013 (WHO, 2014).

This fall in prices precipitated a concerted global effort to increase access to antiretroviral drugs in low and middle-income countries. The price of ARV therapy represented one key barrier to expansion of treatment, but effective scaling-up of treatment faced other important barriers, such

as the absence of trained staff and the need to establish HIV testing programs and reliable supply chains for antiretroviral drugs. The WHO have repeatedly issued targets for scaling up access to ARV therapy. The Global Fund for AIDS, TB and Malaria, founded in 2002, estimates that programs sponsored by the fund were responsible for bringing access to ARV therapy to 6.6 million people (by the middle of 2014), approximately two thirds of those with access to ARV therapy in low and middle-income countries. Figure 3 shows ARV therapy coverage as a percentage of people with advanced HIV infection in 2012.

Clinical studies show that combination ARV therapy dramatically reduces both morbidity and mortality (Moore & Chaisson, 1999). Studies in a contemporary developing country setting indicate that ARVs have corresponding impacts in the field. For example, Bor, Herbst, Newell, and Bärnighausen (2013) showed that scale-up of antiretroviral therapy in a population with high HIV prevalence led to large increases in life expectancy; increasing coverage to 7% of the population raised life expectancy from 49.2 years to 60.5 years.

A number of studies provide estimates of the impact of antiretroviral therapy on individual productivity. For example, Thirumurthy, Zivin, and Goldstein (2008) find a 20% increase in the likelihood of labour force participation and a 35% increase in hours worked, while Bor, Tanser, Newell, and Bärnighausen (2012) found a nearly full recovery of employment following antiretroviral therapy. Studies that focus on the individual may underestimate the aggregate impact of antiretroviral therapy on labour market participation, since the impact of HIV/AIDS on employment may also affect carers. Further, the scale-up of ARV therapy may have a direct impact on local economies as a direct result of local employment and procurement associated with the provision of ARV therapy. However, this paper provides what is to my knowledge the first robust evidence as to the macroeconomic impacts of antiretroviral therapy programs on national economies.

3 Data

I use data from the World Bank and UNAIDS. From the World Bank databank, I use data on GDP per capita and GDP in constant 2005 US$; population data; and HIV prevalence data for the population of people aged 15-49, itself drawn from UNAIDS estimates, and available from 1990 onwards. Data on GDP, GDP per capita and population is available for 168 countries including 52

high income countries, 45 upper middle income countries, 44 lower middle income countries and 27 low income countries. HIV prevalence data is only reported in 2001 for 91 countries, of which 5 are high income countries, 23 are upper middle income countries, 38 are lower middle income countries and 25 are low income countries. The sample of 86 low and middle income countries for which HIV prevalence is reported in 2001 constitutes the main sample for the analysis[11].

I also use data on life expectancy, downloaded from the World Bank databank where the data is compiled from other sources[12]. Life expectancy from birth is calculated as the expected lifetime of a hypothetical newborn who experiences prevailing age-specific mortality rates throughout their life time. Calculating life expectancy requires age specific mortality rates. Data on adult mortality are not available for all countries, and coverage is particularly low in Sub-Saharan Africa. In the absence of full data on mortality, life expectancy is calculated using data on infant mortality and appropriate model life tables. For countries with HIV prevalence higher than 2% of the population, the estimates are adjusted to explicitly model the effect of HIV/AIDS, drawing on data collected from UNAIDS including treatment data (UNDESA, 2014). Thus although I present results on life expectancy to demonstrate in a pseudo-'first stage' that scaling up antiretroviral therapy impacts health, the results should be interpreted with caution given that I may be partially recovering a modelled impact.

I also use data from the UNAIDS Global AIDS Response Progress Reporting on the number of people taking antiretroviral drugs in a given country. This is reported on an annual basis since 2004 for between 94 and 111 countries. For the largest set of countries reporting, 9 are high income countries, 36 are upper middle income countries, 40 are lower middle income countries and 26 are low income countries.

I calculate overall proportions of HIV positive patients on antiretroviral therapy using data from reports by UNAIDS and the WHO(WHO, 2011, 2013). These estimates of global coverage suggest that prior to 2004, less than 1% of HIV positive patients in low and middle-income countries received antiretroviral therapy. Lacking better information, I therefore treat antiretroviral therapy coverage as zero in low and middle-income countries before 2004.

[11] In robustness checks, I also test whether the results change when I include other low and middle income countries for which HIV prevalence is not reported, assuming that HIV prevalence is zero in these countries.

[12] Including the United Nations Population Division World Population Prospects; United Nations Statistical Division Population and Vital Statistics Report; and Census reports and other statistical publications from national statistical offices.

4 Empirical Strategy

The reduced form relationship of interest is the following. For country i at time t, what is the impact of increasing coverage of antiretroviral drugs on the outcome variables? Hence I would like to estimate the following equation:

$$y_{i,t} = \pi ARV_{i,t} + \zeta_i + \mu_t + \epsilon_{i,t} \tag{1}$$

where y_{it} is an outcome variable in country i at time t, ζ_i is a country fixed effect capturing the average value of the outcome variable in that country over time, μ_t is a year fixed effect capturing overall time trends and ARV_{it} is the proportion of the population in country i that receives antiretroviral therapy at a time t. I construct the variable ARV_{it} in this way (rather than regarding the variable of interest as the proportion of HIV positive patients receiving antiretroviral therapy) because antiretroviral therapy is likely to influence country-level outcomes to a greater extent when the proportion of HIV-positive patients receiving ARVs is higher, but also when the proportion of the population or workforce who are HIV positive is higher. The principal outcome variables are life expectancy (in logs); and log differences in GDP per capita, total GDP and population, which closely approximate growth rates.

An analysis of the long-run impacts of increasing access to ARV therapy might focus on changes in ARV therapy coverage instead of levels, as do Acemoglu and Johnson in their study of the long-run effects of the international epidemiological transition. In this analysis, I focus on the reduced form relationship between the outcome variables and the level of ARV therapy coverage, because this appears to better match the observed pattern in the data.[13]

π is the variable of interest; the impact of extending ARV therapy to an additional 1% of the population on the outcome variable. Our fundamental concern with this equation is that even conditional on year and country fixed effects, ARV_{it} still may be correlated with other, possibly unobservable factors that influence the outcome variables through other channels. In formal terms, that $\text{cov}\left(ARV_{it}, \epsilon_{i,t}\right) \neq 0$. This would result in biased estimates of θ. *Ex ante*, the sign of this

[13] In future work, I will compare these results to results obtained from considering the variable of interest to be changes in levels of ARV therapy.

bias is not clear: the presence of HIV is a necessary condition for the presence of an ARV therapy programs, and HIV prevalence might influence the estimates of π even after including the set of fixed effects. However, external support for ARV therapy programs might be concentrated in countries with low expectations of economic growth, which *ceterus paribus* would tend to bias the estimates downwards. In contrast, countries that are successful in providing ARV therapy to their citizens might also be successful on other metrics — for example, they may have improving institutions in general. This would tend to bias the estimates upwards.

To isolate variation in ARV_{it} that is otherwise uncorrelated with factors influencing the outcome variables of interest, I exploit a strategy first implemented in Acemoglu and Johnson (2007) with respect to the international epidemiological transition and later replicated in other contexts for specific diseases (e.g. Bleakley, 2007; Bleakley,2010; Cutler et al., 2010). This strategy uses *predicted* coverage of a health intervention as an instrument for *observed* coverage of the health intervention. In this case, I predict observed ARV therapy coverage using the interaction between HIV prevalence in 2001 (at the time when prices fell precipitously) and global coverage of ARV therapy in low and middle income countries in the following first stage equation.

$$ARV_{i,t} = \beta \left(HIV_{i,2001} \times \overline{ARV}_t \right) + \tilde{\zeta}_i + \tilde{\mu}_t + \tilde{\theta} \left(HIV_{i,2001} \times t \right) + \nu_{i,t} \tag{2}$$

where $\bar{ARV}_t$ is the proportion of HIV positive individuals receiving ARV therapy across all low and middle-income countries at time t. I include the term $\tilde{\theta} \left(HIV_{i,2001} \times t \right)$ because countries with high HIV-prevalence experienced different time trends in outcome variables prior to the onset of ARV therapy scale-up, as clearly shown in Figure 4.[14] While the inclusion of this control matters little for the first stage estimates, this will be essential for the validity of the exclusion restriction.

For predicted ARV coverage to be a valid instrument for observed ARV coverage, it must first predict observed ARV coverage in a sufficiently strong 'first stage'. Table 2, Panel A, Column 3, shows the results from this first stage. The F-statistic associated with the coefficient on the instrument is 86.7, indicating that the instrument (predicted ARV coverage) is a strong predictor

[14] In preliminary analysis, I confirm that these differences in trends are statistically significant (Table 1). A more general, but less parsimonious approach, would be to include country-specific linear trends in the regressions; I also implement this strategy and show that the results change very little.

of the endogenous variable (actual ARV coverage). The instrument must also satisfy monotonicity: predicted ARV coverage should always have a positive impact on true ARV coverage. It is difficult to construct a case where countries with high HIV prevalence should have lower total coverage of antiretroviral drugs, since HIV prevalence is a prerequisite for prescribing antiretroviral drugs.

Finally, the instrument must satisfy the exclusion restriction: essentially, that changes in trends in outcome variables following the scale-up of ARV therapies must be uncorrelated with HIV prevalence in 2001 through any other channel. Modifying equation to include the differential time trend term in HIV prevalence gives the following estimating equation:

$$y_{i,t} = \pi ARV_{i,t} + \zeta_i + \mu_t + \theta \left(HIV_{i,2001} \times t \right) + \epsilon_{i,t} \tag{3}$$

in which I instrument for observed ARV coverage, $ARV_{i,t}$, with predicted ARV coverage, given by $HIV_{i,2001} \times \overline{ARV}_t$. Including the differential time trend term means that what I measure is variation in the effect on the change in trends after scale-up of ARV therapy. In more formal terms, the exclusion restriction is that:

$$\text{cov}\left(HIV_{i,2001} \times \overline{ARV}_t, \epsilon_{i,t} \right) = 0 \tag{4}$$

This assumption seems plausible, but could be violated if there are unobservable factors that are correlated across space with the HIV epidemic and across time with the scaling-up of antiretroviral therapies. I test for three plausible alternative explanations. Noting that Chinese influence — whether measured by aid, trade or FDI — follows a similar pattern in time to the scale-up of ARV therapy, I allow countries with high relative levels of mineral and oil resources to have different, flexible time trends. Given that spending on malaria control via the Global Fund for Aids, Tuberculosis and Malaria has also increased over a similar time friend, I also allow countries with different malaria ecologies to have different, flexible time trends. None of these additional controls substantially alters the main results, ruling out these alternative explanations for the main results.

I also obtain very similar results by including country-specific linear trends, a more flexible but

less parsimonious approach to allowing countries to have different pre-intervention trends. In this respect, my approach differs from prior applications (Acemoglu & Johnson, 2007; Bleakley, 2007, 2010) where the identifying assumption — tested to the extent possible — is the equivalence of pre-trends in countries with high and low disease prevalence prior to the intervention. In this case, I clearly reject the possibility that pre-trends are equivalent, and adjust the regression specification accordingly. By construction, the variable does not predict any variation in the outcome variable prior to 2001, because in the absence of data, ARV coverage in low and middle income countries is assumed to be zero before 2004[15].

The outcome variables I study are life expectancy, and growth (log changes) in GDP per capita, total GDP and population. I present the results on life expectancy to illustrate that the expansion of ARV therapies had an impact on health, a necessary pre-condition to measuring how improvements in health affect aggregate economic growth. However, the results on life expectancy may be affected by the way in which life expectancy is calculated in countries with limited data on adult mortality, and in particular, may be partially recovering a modelled effect of the HIV/AIDS epidemic, rather than a measured observation.

Since we expect strong serial correlation in outcome variables over time, I cluster standard errors at the country level. This helps make the correct inference about whether patterns seen across countries represent statistically significant relationships (Bertrand, Duflo, & Mullainathan, 2004). There may also be spatial correlation among observations from a particular year, although this concern is probably less salient with country-level data than with sub-national data. In future versions of this paper, I will report standard errors that also account for possible spatial correlation.[16]

5 Results

In this section, I first present parametric and non-parametric evidence to illustrate the trend break that takes place at the same time as the beginning of ARV scale-up. I then present the main results, showing that covering an additional 1% of the population with antiretroviral therapy leads to a 5.7% increase in life expectancy and a 1.6 percentage point increase in the growth rate of GDP

[15] Global ARV coverage at this time is below 1% of HIV positive patients.

[16] *Ex ante*, these may be smaller or larger than the standard errors reported in this version, depending on whether spatial correlation is negative or positive.

per capita. This last result corresponds to a 1.8 percentage point increase in the growth rate of total GDP, and a 0.2 percentage point increase in the population growth rate.

I then show that these results are largely robust to variations in the specification or sample. The exception is the result for population growth, which no longer significant if I drop either Zimbabwe or Swaziland from the dataset, or when I drop the three highest HIV-prevalence countries collectively. In Zimbabwe at least, the reversal in population growth rates appears real and is coincident with the onset of antiretroviral therapy, but the change in the results when single countries are excluded suggests that the results on population growth may not be robust or generalizable.

I then examine in detail three alternative plausible mechanisms which might explain the results, rejecting in each case the possibility that the results are driven by these alternative mechanisms. Finally, I use the main estimates to value the scale-up of antiretroviral drugs in terms of its contribution to overall economic growth.

Throughout, I present results on life expectancy to demonstrate that scaling up ARVs has a first order effect on health. However, the results on life expectancy should be interpreted with caution, given that life expectancy is calculated using modelled data where statistical data is missing or unreliable, and in particular, incorporates explicit modelling of the HIV/AIDs epidemic in countries with significant HIV prevalence. As a result, the analysis may partially recover modelled effects.

5.1 Preliminary analysis

As a preliminary exercise, I show that countries with high HIV prevalence experience different trends — relative to countries with low HIV prevalence — before and after the precipitous fall in ARV prices in 2001. Figure 4 illustrates these trend breaks: countries with high levels of HIV prevalence have lower life expectancies than other low- and middle-income countries in 1990, and these differences widen until just after 2001. The trend then reverses and the gap in life expectancies begins to close. Countries with high HIV prevalence have similar annual growth rates in GDP per capita in 1990, with growth rates actually slightly higher in high HIV prevalence countries than in other low- and middle-income countries. Growth rates decline relative to other low and middle income countries over the following decade but this trend then reverses after 2001. Note that the take-off of antiretroviral therapies is slow in the first years after 2001, but I focus on 2001 as the

discontinuity as this is when the large drop in prices took place.[17] A visual comparison suggests that the shape of the response after 2001 is consistent with the shape of the ARV scale-up curve. Figure 5 shows similar patterns for growth in total GDP and population growth.

The results shown in Table 1 confirm that changes in trends after 2001 are associated with HIV prevalence in 2001, and that these relationships are statistically significant. To be specific, I estimate the following equation:

$$y_{i,t} = \theta_1 \left(HIV_{i,2001} \times t\right) + \theta_2 \left(HIV_{i,2001} \times POST_{2001}\right) + \theta_3 \left(HIV_{i,2001} \times POST_{2001} \times t\right) + \zeta_i + \mu_t + \epsilon_{i,t} \quad (5)$$

where $HIV_{i,2001}$ is HIV prevalence in 2001; t is event time (time relative to 2001) and $POST_{2001}$ is an indicator which takes the value one after 2001. The coefficient θ_1 captures pre-ARV trends associated with high HIV prevalence; the coefficient θ_3 captures the change in these trends after ARV scale-up begins. Rejecting the null hypothesis that $\theta_3 = 0$ implies that there are statistically different time trends in countries with high HIV prevalence before and after 2001. I include the interaction term associated with the coefficient θ_2 for completeness. As in all specifications, I cluster standard errors at the country level.

HIV prevalence is associated with significant negative downward trends in life expectancy, growth in per-capita GDP and growth in total GDP prior to 2001, and significantly positive changes in trends in these variables after 2001. The coefficients on the changes in trend are larger than the initial negative downwards trends, indicating that the negative trend more than reverses, consistent with Figures 4 and 5. The only variable for which the downward trend is not significant is population growth, but comparison with Figure 5 illustrates that population growth follows the same overall pattern, and the non-significant trend coefficient is a product of selecting 2001 as the year for the trend break rather than 2003 or 2004, where the visual kink in the ARV curve is located.

The interaction between the post-2001 dummy variable and HIV prevalence in 2001, included for completeness, is smaller than the trend variable and not significant across all regressions, consistent with a trend break — rather than a change in levels — and consistent with the timing of the observed 'kink' in the antiretroviral therapy scale-up curve.[18]

[17] The results are somewhat strengthened by using HIV prevalence in 2004 instead of 2001.

[18] The magnitude and significance of the coefficient on the interaction term both typically reduce if I instead

This preliminary analysis illustrates the need to measure impacts relative to pre-existing trends. In the remaining specifications I achieve this in one of two ways: either by including the interaction term between HIV prevalence in 2001 and a linear time trend, or by including country specific linear time trends. Either of these two approaches yields very similar results.

5.2 Main results

Table 2 shows the main results. I find that increasing coverage of ARV therapy leads to substantial increases in life expectancy and growth in GDP in both total and per-capita terms; and increases in population growth which are statistically significant, but an order of magnitude smaller and less robust to specification changes.

Panel A shows the first stage regression, which demonstrates that the instrument (predicted ARV coverage) is a strong predictor of true ARV coverage. Panels B, C, D and E show the results from a series of specifications for the outcome variables: life expectancy, growth in per capita GDP, growth in total GDP and population growth, respectively.

In column 1), I show the raw correlations between the outcome variables and observed ARV coverage in the country. Countries with higher observed ARV coverage have much lower life expectancies, precisely because these countries have high HIV prevalence. They have slightly higher growth rates over time in per capita GDP and total GDP. These correlations could be biased upwards if countries with higher growth rates more successfully implement ARV scale-up programs. Population growth is weakly lower in countries with higher levels of ARV rollout.

In column 2), I show how these correlations alter when I include controls to remove overall global time trends, differences between countries reflecting time-invariant country characteristics, and trends in the outcome variable associated with HIV prevalence. These regressions correspond to estimating Equation 3 without instrumenting for observed ARV coverage. After including these controls, the sign on life expectancy reverses: life expectancy increases after countries scale up antiretroviral therapy programmes relative to previous trends associated with HIV prevalence. However, the coefficient is not statistically significant. The coefficients in panels c) and d) increase slightly in magnitude, but are not statistically significant. The coefficient on population growth also changes sign, but remains small and imprecisely measured.

consider a trend break in 2004, more consistent with the observed 'kink' in the ARV scale-up pattern.

Column 3) shows the reduced form results, in which I regress the outcome variable directly on the instrument and controls from Equation 3. Column 4) shows the results from implementing the instrumental variables strategy, in which I use predicted ARV coverage as an instrument for observed ARV coverage. The coefficients resulting from the reduced form and IV estimates are consistent in sign with the OLS regressions that include controls, but are substantially larger than the OLS relationships, and are statistically significant. This pattern of results suggests that observed ARV coverage is correlated with other factors that are negatively associated with changes in trends in life expectancy, economic growth and population growth. At this time, the most plausible explanation seems to be that the scale of a country's ARV therapy program, conditional on HIV prevalence, is correlated with higher than average growth in the years preceding widespread availability of antiretroviral drugs. As a result, the OLS estimates of the change in growth trends after ARV scale-up are biased downwards.

Column 5) shows results obtained using a similar approach to that of column 4), including country-specific linear trends instead of including the term which captures differential pre-intervention time trends associated with HIV-prevalence. Since the instrument is only correlated with country-specific linear trends via the linear relationship with HIV prevalence in 2001, including country-specific linear trends makes very little change to either the coefficient or standard errors. As a result, I proceed with the specification that controls for differential trends as a function of HIV prevalence, as the more parsimonious specification.

5.3 Robustness checks

Table 3 shows that the main results are largely robust to changes in the specification or sample. The exception is the results on population, which are discussed further in detail below. Column 1) replicates the main results from Table 2, column 4) for comparison. Panels A to D show the results for the outcome variables: life expectancy, growth in per capita GDP, growth in total GDP and population growth, respectively.

Since all of the countries with high HIV prevalence[19] are in Sub Saharan Africa, a primary concern regarding the results is that they might conflate general differences in trends between Sub Saharan Africa and other low and middle income countries with the causal impact of providing

[19] e.g. HIV prevalence above 5% of the population

antiretroviral therapy. In column 2), I include region-year fixed effects in the main specification[20] These region-year fixed effects capture different, flexible time trends across regions, narrowing the comparison to countries in the same region at the same time. The results are largely consistent in terms of magnitude and statistical significance, although the coefficient on growth in per-capita GDP falls from 1.57 to 1.36.

The main sample consists of countries which report HIV prevalence in 2001. In column 3), I extend the analysis to all low and middle-income countries[21], assuming that where HIV prevalence is not reported it is zero, and therefore ARV coverage is also zero. This also results in largely similar results, which are generally slightly larger and more precisely estimated (with the exception of population growth); I exclude these countries from the main analysis as the more conservative sample choice. In column 4), I focus only on sub-Saharan Africa. This considerably reduces the sample size but yields largely consistent results, with coefficients approximately similar to the results shown in column 2), estimated using a specification in which I control for region-year fixed effects. This confirms that the results are primarily driven by within-region variation in Sub-Saharan Africa.

In columns 5), 6) and 7), I test whether the estimates are sensitive to dropping countries or observations with extreme values of either right hand side or left hand side variables. A particular concern is there are a relatively small number of countries with high levels of HIV prevalence, and the distribution of HIV prevalence is highly skewed.[22] To examine the influence of individual countries on the results, I run a series of leave-one-out regressions, identical to the main specification but in each case dropping one country. The resulting estimates of the effect of antiretroviral therapy on the outcome variable (coefficients and p-values) are illustrated in Appendix Tables A1, A2, A3 and A4. Broadly, these figures show that as expected the countries with the highest HIV prevalence — Botswana, Swaziland and Zimbabwe — have a large influence on the results. Excluding Zimbabwe tends to decrease the magnitude of the estimated impacts; excluding Botswana or Swaziland tends to increase the magnitude of the estimated impacts. For life expectancy and growth in per capita GDP and total GDP, the estimated impact nonetheless remains statistically significant when any individual country is dropped from the regression. For population growth, the coefficient is no

[20]The regions included in the main sample are East Asia and Pacific (6 countries); Europe and Central Asia (9 countries); Latin American and the Caribbean (17 countries); Middle East and North Africa (6 countries); South Asia (6 countries); Sub Saharan Africa (39 countries).

[21]To be more specific, all low and middle-income countries that report the outcome variables.

[22]Appendix Table A2 lists all countries with HIV prevalence above 1% in 2001, in rank order.

longer statistically significant when I drop either Swaziland or Zimbabwe, and only marginally so when I drop Lesotho.

Given the influential nature of the observations from Botswana, Swaziland and Zimbabwe — the countries with highest HIV prevalence — I also test whether the results are robust to the exclusion of all three of these countries. I show these results in column 5). Dropping these three countries does not generally alter the results, with the exception of the result for population growth, which is reduced in magnitude by more than two thirds and is no longer statistically significant. Further examination of the case of Zimbabwe shows that it experienced a remarkable turnaround in its population growth rate over the time period, falling from approximately 2.5% a year in 1990 to less than 0.5% in the early 2000s, before recovering following the rollout of antiretroviral drugs to almost 3% in 2012. However, the influence of individuals countries on the estimate suggests the need for caution in interpreting the results on population growth.

In columns 6 and 7), I test whether observations with extreme values of the dependent variable are influencing the results. In column 6, I exclude the three countries associated with the largest absolute values of the dependent variable in each regression[23] In column 7), I winsorize the top and bottom 1.5% of observations. The results in column 6) and 7) are again largely consistent with the other results, and all estimates remain statistically significant throughout.

5.4 Alternative explanations

The results presented in Table 2 could be biased by unobserved factors that influence the outcome variables if these unobserved factors are correlated in space with HIV prevalence, and in time with the global scale-up of antiretroviral drug coverage. In this section, I discuss three plausible alternative explanations, but show that none of them can explain the main results. I present the results for log life expectancy and growth in GDP per capita in Tables 4 and 5 respectively[24]

First, I observe that Chinese overseas influence experiences similar patterns in time to the scale-up of antiretroviral therapy. The stock of Chinese FDI investments in Sub Saharan Africa increased by an order of magnitude between 2005 and 2012, and official records show similar patterns in both

[23]These are: Rwanda, Sierra Leone and Zambia, for life expectancy; Georgia, Liberia and Rwanda, for changes in log GDP per capita and log GDP; and Guinea, Liberia and Rwanda, for changes in log population.

[24]Noting that the results on population growth are less robust to the exclusion of individual countries, I include similar tables for growth in total GDP and population growth in the appendix, but do not focus on them in the main text.

exports and imports between China and Africa (Information Office of the State Council, 2013; Chinese Ministry of Commerce, 2009; Heritage Foundation, 2004). Chinese aid flows are also likely to be highly correlated in time and space with other measures of Chinese influence. If factors correlated with HIV prevalence were also correlated with factors that predict Chinese investment, trade or aid; and changes in Chinese investment, trade or aid also influence the outcome variables, then the main results would be biased.

One plausible channel is via the presence of mineral resources. Chinese overseas investment is widely believed to be correlated with the local availability of commodities such as minerals, and mines attract large populations of transient workers who have historically been associated with high rates of HIV prevalence (e.g. Corno and de Walque, 2012). In columns 1) to 3), of Tables 4 and 5, I show how the main results change when I alter the specification to allow countries with high dependence on mineral rents — measured by the fraction of GDP coming from mineral rents — to have different time trends before and after 2001. For this and the following analyses, I model both differential linear time trends, and flexible time trends (fraction of GDP from mineral rents interacted with year dummies), and report results both for the main sample and for Sub-Saharan Africa only.

Countries with high mineral dependency do not appear to have any systematically different trends in log life expectancy, and the coefficient measuring the impact of antiretroviral therapy on log life expectancy accordingly changes very little (columns 1 to 3, Table 4). Countries with high mineral dependency do have systematically different trends in growth in GDP per capita — falling, relative to other low and middle income countries before 2001, and rising afterwards (column 1, Table 5).[25] However, the coefficients on antiretroviral therapy increase when I include these controls, suggesting that this cannot explain the results on antiretroviral therapy (columns 1 to 3, Table 5).

Second, Chinese investment may also be correlated with the location of oil. If there is any correlation between oil extraction and HIV prevalence — perhaps through lower local pump prices, increased mobility and hence increased transmission of HIV — this could also bias the results. In columns 4) to 6) of Tables 4 and 5, I show how the main results change when I alter the specification

[25]This distinctive pattern is largely driven by countries outside of Sub-Saharan Africa: within Sub-Saharan Africa, dependency on mineral rents is only significantly correlated with a negative overall time trend.

to allow countries with high dependence on petroleum rents, measured by the fraction of their GDP coming from this source, to have different time trends before and after 2001. Countries with high petroleum dependence do not demonstrate any systematic differences in trends in life expectancy (column 4, Table 4). Accordingly, the estimates of the impact of antiretroviral therapy on log life expectancy change very little.

However, they do experience relatively higher growth in GDP per capita after 2001 (column 4, Table 5) although this is a level change, rather than the trend break observed in Figure 4 and measured in Table 1. Including linear or flexible controls for petroleum dependence results in a slightly reduced coefficient on ARV therapy, reducing from 1.57 to 1.49 for the main sample and 1.34 to 1.26 for Sub Saharan Africa. The coefficient on ARV therapy becomes marginally insignificant for Sub Saharan Africa alone (p-value 0.112). However, the small change in the point estimate, the relative lack of explanatory power and the inconsistency with the observed trend break suggest that this mechanism is unlikely to explain the main results.

Finally, global investment in fighting malaria also likely increased over a relatively similar time period, after the founding of the Global Fund for Aids, Tuberculosis and Malaria. Malaria prevalence may be correlated with HIV prevalence, perhaps through climatic or ecological variables, given that malaria thrives in warm, wet climates, and HIV originates in primate populations with forest habitats. If this is the case, this might lead me to overestimate the impact of ARV therapy alone, confounding it with other interventions in malaria control which took place at the same time. Malaria control programs are highly endogenous to other health and economic factors, so I focus instead on geographical variation in climate and ecology that influences malaria transmission.

I use the malaria ecology index developed in Kiszewski et al. (2004), using the population-weighted country dataset developed by McCord (n.d.). The malaria ecology index is highly skewed and has many zeros. To reduce skewness, I transform the variable by taking the arcsinh[26]. To facilitate interpretation of the coefficient, I then normalize the variable by its maximum across the main sample. The raw coefficient on malaria ecology can then be interpreted as the change in the outcome variable resulting from going from zero malaria ecology to its highest value in the sample.

Table 4, column 7 shows that countries with relatively high malaria ecology do experience

[26]This transformation increases the explanatory power of the malaria ecology variable as a control; without this transformation, the malaria ecology index has little predictive power and less influence on the coefficients of interest.

different trends in life expectancy after 2001, with relatively higher life expectancy in levels, and a relative increasing trend in life expectancy. The coefficient on antiretroviral therapy falls slightly in the main sample, but rises for Sub-Saharan Africa.

Malaria ecology also has some predictive power for growth in per-capita GDP. Table 5, column 7 shows that countries with high malaria ecology are experiencing relatively increasing growth in per-capita GDP after 2001. This effect seems to be primarily driven by countries outside of Sub-Saharan Africa; the coefficients on the malaria ecology interaction terms in a regression with the same specification as that in column 7, but limited to Sub-Saharan Africa, are not significant.

Including the malaria ecology interaction terms slightly decreases the coefficient on antiretroviral therapy in the main sample (1.57 falls to 1.22 or 1.20) and the coefficient becomes marginally statistically insignificant (p-values 0.105 and 0.109). However, including the malaria ecology interaction terms increases the coefficient on antiretroviral therapy in the sample including only Sub-Saharan Africa (1.34 rises to 1.52), although the coefficient also becomes marginally statistically insignificant (p-value 0.102), as the standard errors also increase. Taken together, these results suggest that confounding investment in fighting malaria is unlikely to explain the main results.

One important caveat is that I am unable to replicate this analysis for tuberculosis (TB) infection rates, as the TB epidemic is closely connected to the HIV epidemic; the WHO estimates that one third of people living with HIV are also infected with TB. Treatment programs for TB are also delivered alongside ARV treatment programs. Where improvements to treatment for TB are scaled up at the same time as ARV therapy in the same places, my results will therefore capture the effects of the full package of treatment for both HIV and TB.

In conclusion, although there is some evidence that each of these alternative mechanisms has some explanatory power for changes in life expectancy and growth rates in per capita GDP over the time period of the study, there is no compelling evidence to suggest the measured effect of antiretroviral therapy can be attributed to any of these alternative mechanisms.

5.5 Estimates of total value of access to antiretroviral therapy

Using the estimates derived in the previous section, I can provide a first order estimate of the value of scaling-up access to antiretroviral across low and middle-income countries. The main estimates (presented in column 3, panel C of Table 2) suggest that a 1 percentage point increase

in coverage of a country's population with antiretroviral drugs increases the growth rate of per capita GDP by 1.6 percentage points. This compares to a mean growth rate in per-capita GDP in my main sample of 1.7%, rising on average by 0.23 percentage points a year throughout the study period.[27]

To value the total impact of this change, I calculate the additional GDP added to these economies by multiplying the percentage of the population in country i at time t who are covered by ARV therapy by the coefficient on ARV therapy from the regression with changes in log GDP as an outcome variable (column 3, panel D of Table 2). In this way I retrieve the component of the growth rate that I estimate to be caused by the scale-up of antiretroviral therapy. I multiply this growth rate by the contemporaneous GDP to calculate the additional GDP added to a country's economy as a result of ARV scale-up. In 2012, this calculation implies that an average additional $729 million (current US$) was added to low and middle-income countries' GDPs. Across 86 countries, this yields a total of US$63 billion (current US$) in additional GDP.

The observed mean increase in GDP across these countries was $5.4 billion (current US$). Compared to the mean predicted increase in GDP of $729 million calculated from ARV therapy coverage in 2012, these calculations imply that that the scale-up of antiretroviral drugs explains 13% of observed growth in 2012 in the main sample of low and middle-income countries. The results from a similar exercise for Sub-Saharan Africa suggest that the scale-up of antiretroviral drugs explains 80% of observed growth in 2012.[28]

To estimate the extent to which the scale-up of antiretroviral therapy explains the reversal in growth trends in Sub-Saharan Africa observed in the first decade of the new millennium, I repeat the above exercise for growth in per-capita GDP. I estimate that between 2004 (when ARV coverage is first reported consistently) and 2012, ARV scale-up contributed on average an additional 1.1 percentage points to annual growth in per-capita GDP across Sub-Saharan Africa. Observed mean growth in per-capita GDP was 2.5 percentage points. This suggests that the scale-up of antiretroviral therapy explains around 44% of the observed growth in per-capita GDP between 2002 and 2012.

[27] Note that growth rates in countries with high HIV prevalence appear to be depressed by the presence of HIV/AIDS itself in the first half of the study period

[28] In high HIV prevalence countries, the estimated component of growth due to the expansion of ARV therapy coverage is larger than observed growth, because the counterfactual scenario is one of contracting total GDP as a result of an unchecked HIV/AIDS epidemic.

These valuations come with several important caveats. First, I estimate the average value of covering an additional person with antiretroviral drugs over time. If the people receiving antiretroviral therapy are less sick as time goes on — for example, because the threshold for treatment with antiretroviral therapy is decreasing — then my estimates will tend to overstate the benefits in 2012. Similarly, if there are diminishing marginal returns to covering larger numbers of people with antiretroviral therapy, then my estimates will tend to overstate the benefits in 2012. My instrumental variables estimates also yield a Local Average Treatment Effect that may not be equivalent to the Average Treatment Effect. In particular, if the Local Average Treatment Effect is higher than the true treatment effect for countries with high ARV coverage, my valuation will tend to be biased upwards.

For comparison, UNAIDS (2012) estimated that in 2011 total spending on HIV was US$16.8 billion across all low and middle countries. At this time, ARV coverage in low and middle-income countries was 8.1 million. This implies a conservative total global cost of approximately US$2000 per person per year. The estimate is conservative since this figure represents total spending on HIV, and not just the costs of providing ARV therapy. This estimate also conceals considerable heterogeneity in costs per person; between 75 and 80% of the people covered by antiretroviral therapy in 2011 were from Sub-Saharan Africa, but Sub-Saharan Africa accounted for less than half the spending on HIV in low and middle-income countries. A 2012 study of facility-level treatment costs in five African countries found that ART costs averaged US$200 per patient-year across Ethiopia, Malawi, Rwanda and Zimbabwe; and US$682 in South Africa. Costs of antiretroviral drugs also continue to fall; to US$115 per person per year for first line ARV therapy and US$330 per person per year for second line ARV therapy by 2013 (WHO, 2014). If we take the figure of US$2000 per person per year as a conservative estimate of total costs, and compare this to the estimated value of ARV coverage of US$63 billion, the estimated economic benefits outweigh the costs of ARV provision by 3.3 to 1.

6 Conclusions

In summary, the paper shows that providing antiretroviral (ARV) therapy to HIV-positive patients results in substantial improvements in life expectancy and economic benefits in terms

of increases in GDP per capita. Increasing coverage of ARV therapy to an additional 1% of the population leads to a 5.7% increase in life expectancy. In contrast to Acemoglu and Johnson (2007)'s seminal study of country-scale improvements in health, I find a 1.6 percentage point increase in the growth rate of GDP per capita, and relatively small increases in population growth — 0.2 percentage points — and these results are more sensitive to the exclusion of individual countries from the specification. Taken together, there is a resultant increase in total GDP of 1.8 percentage points. A first order estimate of the benefit/cost ratio of providing antiretroviral therapy in low and middle income countries suggests that ARV therapy added US$63 billion to the world economy in 2012, in comparison to a conservative cost estimate of US$19 billion.

While the estimated effects are substantial, mean per-capita GDP in the low and middle-income countries between 2002 and 2012 was on average only $1,823 (constant 2005 US$) in the main sample, and $1,283 (constant 2005 US$) in sub-Saharan Africa. These figures imply that additional growth of per-capita GDP of 1.6 percentage points translates into an additional US$29 in annual per-capita income in the main sample, or US$21 in sub-Saharan Africa (both in constant 2005 US$). Given mean life expectancy of 65 years in the main sample, and 57 years in sub-Saharan Africa, the increases in life expectancy translate to increases of 3.7 and 3.2 years respectively. While these are meaningful increases, the magnitudes of the effects are nonetheless plausible. However, the size of the impacts suggests multiple channels through which the scale-up of antiretroviral therapy influences short-run economic growth. For example: the direct impacts of local employment and procurement associated with the scale-up; increases in labour market participation for both HIV patients and their carers; and possibly, changes in investment decisions resulting from changes in beliefs about the risk and consequences of infection with HIV/AIDS.

It is important to note a key caveat in that I am unable to separate out the effect of ARV therapy alone on the overall effect of the full package of interventions delivered alongside ARV therapy. For example, testing for HIV is a necessary prerequisite for ARV therapy provision, and TB treatment is delivered alongside ARV therapy, given the prevalence of TB-HIV coinfection. However, the variation in time that I exploit stems directly from the fall in prices and resultant expansion of ARV therapy in the years following 2001, suggesting that the results would not have been produced without the component of ARV therapy. The cost of TB treatment is probably substantially less than the cost of ARV therapy, so interpreting the results as the combined impact

of TB treatment and ARV therapy do not substantially alter the main conclusions regarding the benefit to cost ratio, especially since my cost estimates are derived from total spending on HIV rather than spending on ARV therapy alone.

My results on life expectancy come with the important caveat that life expectancy estimates rely on modelled data as well as statistical evidence. As a result, it is possible that the results are at least partially recovering a *modelled* impact of the HIV/AIDS epidemic. However, the findings on life expectancy are supported by additional evidence. In particular, the results are similar in magnitude to those of Bor, Herbst, et al. (2013), who studied the impact of antiretroviral therapy on life expectancy in a high HIV prevalence region of South Africa. Their findings correspond to a 3.0% increase in life expectancy associated with an additional 1% of the population being treated with ARV therapies.[29] This estimate is within the confidence interval of my estimate on life expectancy. The authors note, however, that their estimate is biased downwards by not considering the reversal of the clear prior downward trend in life expectancy, whereas my results take this into consideration; an approximate adjustment to their results to reflect this would imply a figure of 4.2%, closer to my estimated treatment effect.

The measured effect of treating an additional percent of the population with antiretroviral therapy can be interpreted as a lower-bound estimate of the impact of an additional percent of the population suffering from the negative impact of AIDS. It is an estimate of the impact of AIDS rather than HIV because current policy is to treat HIV patients only after functioning of their immune system falls below a specified threshold, or if they fall within other distinct groups[30]. My results are therefore inconsistent with those of Ahuja et al. (2009), who found no impact of HIV/AIDS on economic growth, using male circumcision rates as an instrument for HIV infection rates. Their results may differ from mine if the exclusion restriction in their study is not valid i.e. if male circumcision rates are correlated with economic growth through alternative channels such as institutions. My results are consistent in sign with Cahu and Fall (2011) and similar in magnitude; their results suggest that a 1 percentage point increase in HIV prevalence induces a 2.75 percentage point long-run decrease in GDP per working age adult.

[29] The authors find a 21% increase in life expectancy associated with coverage of 7% of the population by antiretroviral therapy

[30] As of 2013: children below 5 years, pregnant women, people coinfected with TB and HIV, people with chronic severe liver disease, serodiscordant couples.

My results are also comparable to a projection of the benefit/cost ratio of scaling up ARV therapy carried out in 2011, which estimated a benefit/cost ratio of approximately 2.4:1 (Resch et al., 2011), or slightly less than my estimated benefit/cost ratio. They generated their estimates by explicitly modelling three particular channels: labour force participation, avoided costs of orphan care, and avoided end of life health expenses. My results suggest that the projected benefits were if anything too conservative, perhaps because they were not able to model secondary effects such as labour force participation of carers.

I estimate the contemporaneous effect of ARV therapy coverage on outcomes the same year (recalling that life expectancy is calculated as the expected value of life length, if a person were to experience current age-specific mortality rates over their entire lifetime). This relationship may well be the salient one given that ARV therapy leads to very rapid improvements in health, but that removal of ARV therapy likely leads to the equally rapid reversal of these improvements. However, I am unable to measure the lagged effects in this context[31]. My estimates will therefore understate the impact if there are significant lagged effects of the same sign as the contemporaneous effects; for example, if there are important effects on growth that operate through human capital accumulation. In particular, this might be important if children who would otherwise be orphaned or required to care for their parents are more like to attend school as a result of their parents gaining access to ARV therapy.

My results provide the first robust empirical evidence that health improvements lead to growth in per-capita income at a country scale in the short term, and the first robust empirical estimates of the global benefits of scaling up antiretroviral therapy in low and middle-income countries. My results also highlight a previously neglected factor in Sub-Saharan Africa's 'growth miracle' in the first decade of the new millennium: the reversal of the negative effects of the HIV/AIDS epidemic. My results also confirm that over and above the direct benefits of improving health and avoiding orphaning children, antiretroviral therapy has substantial and important effects on economic growth, that outweigh the costs by a factor of approximately 3.3 to 1. I conclude that overall the results provide compelling evidence for the continued and extended support of ARV therapy programs in low and middle-income countries.

[31]The instrument that I construct only exploits one dimension of cross sectional variation and one dimension of temporal variation. As a result, the instrument and its lags are colinear.

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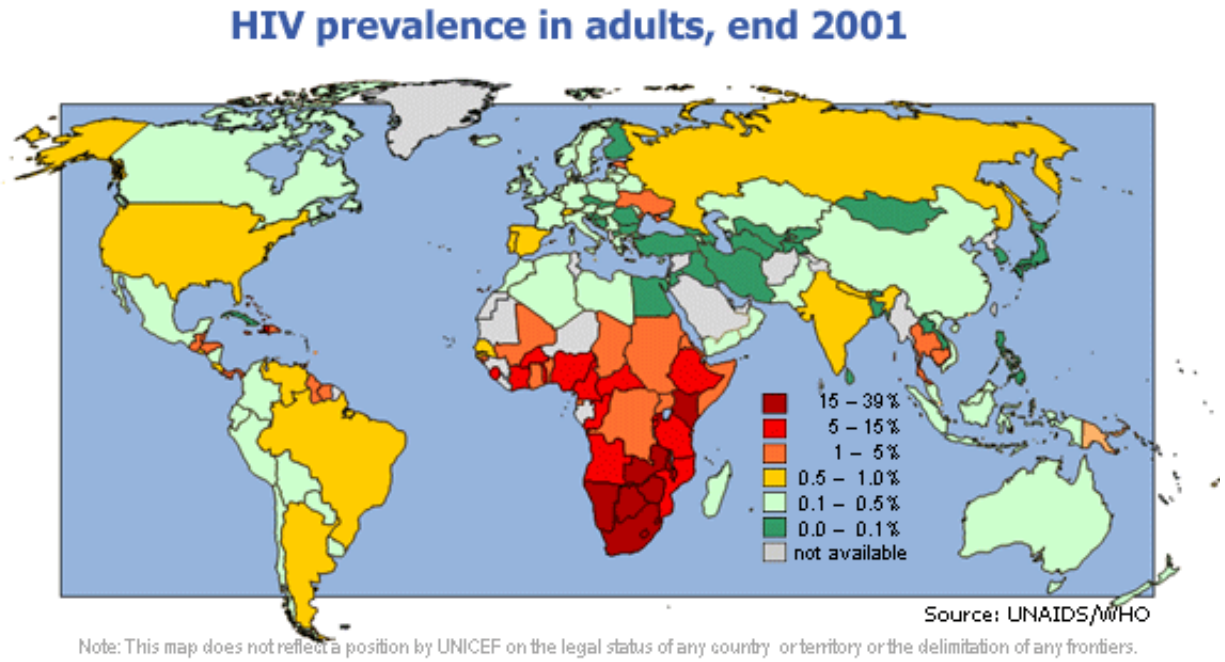
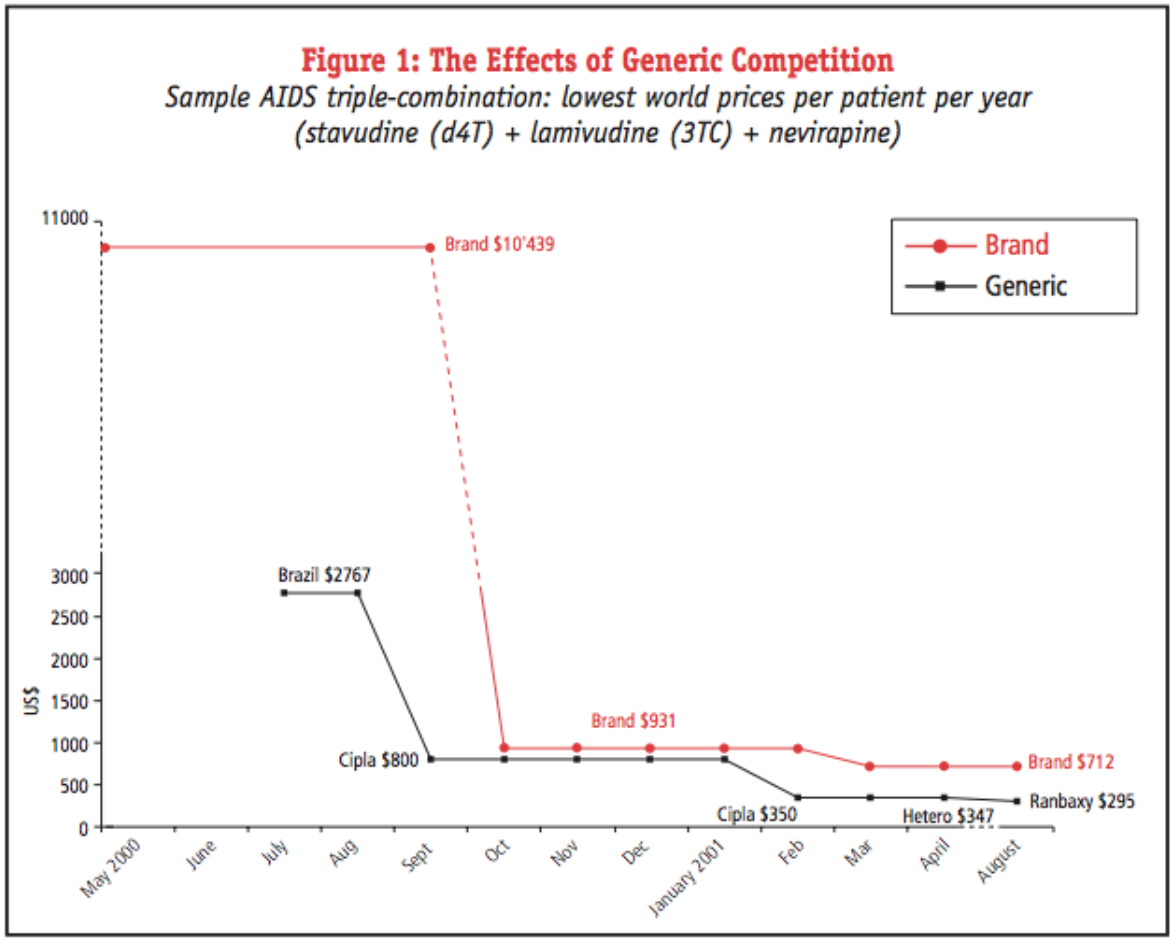
Figures and Tables

Figure 1: HIV Prevalence in 2001



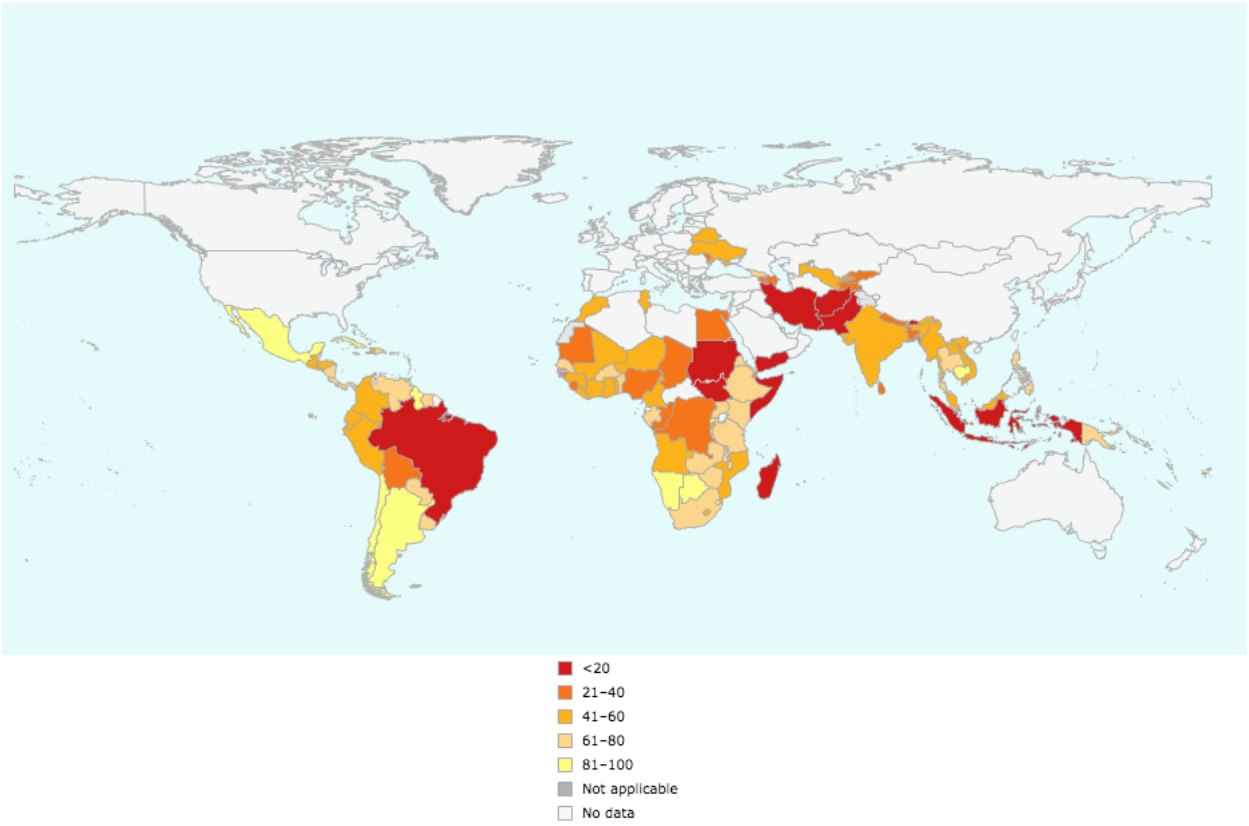
Notes Placeholder map to be replaced with one drawn with my own data.

Figure 2: Fall in ARV prices in 2001



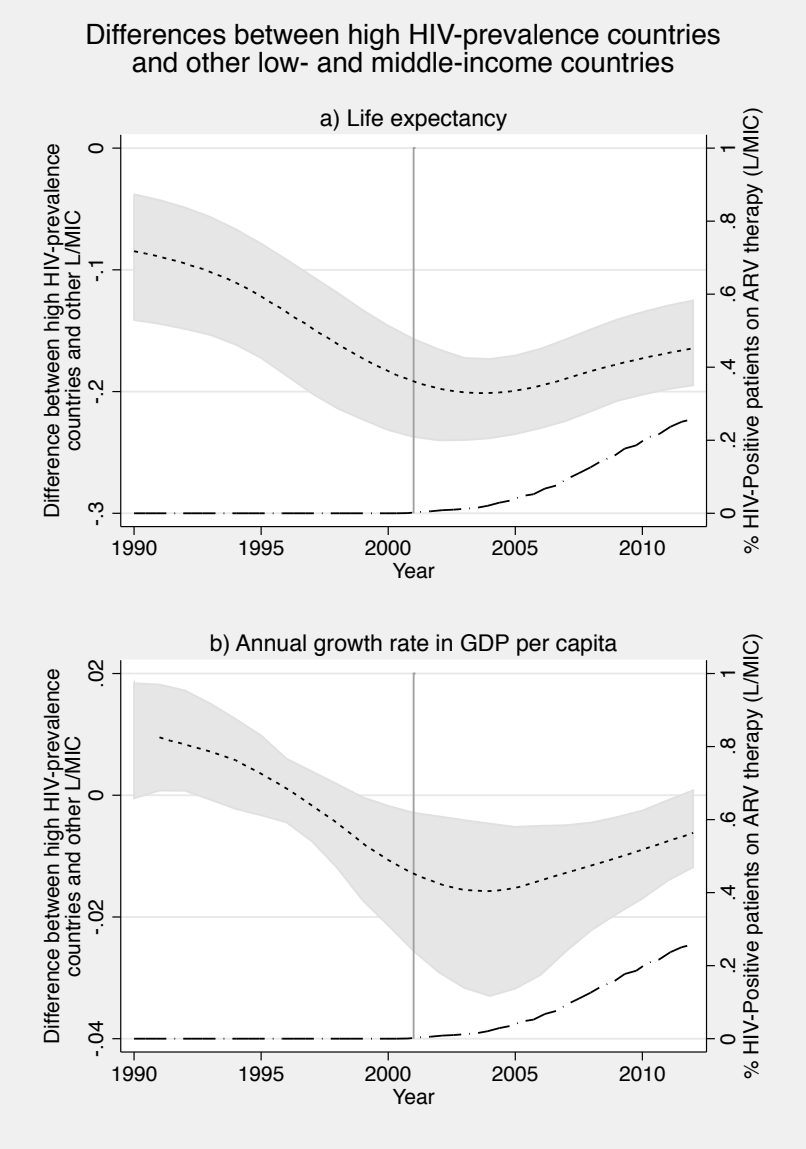
Notes Figure reproduced from Medecins Sans Frontieres (2001).

Figure 3: Antiretroviral coverage among people with advanced HIV infection in low and middle-income countries (%), 2012



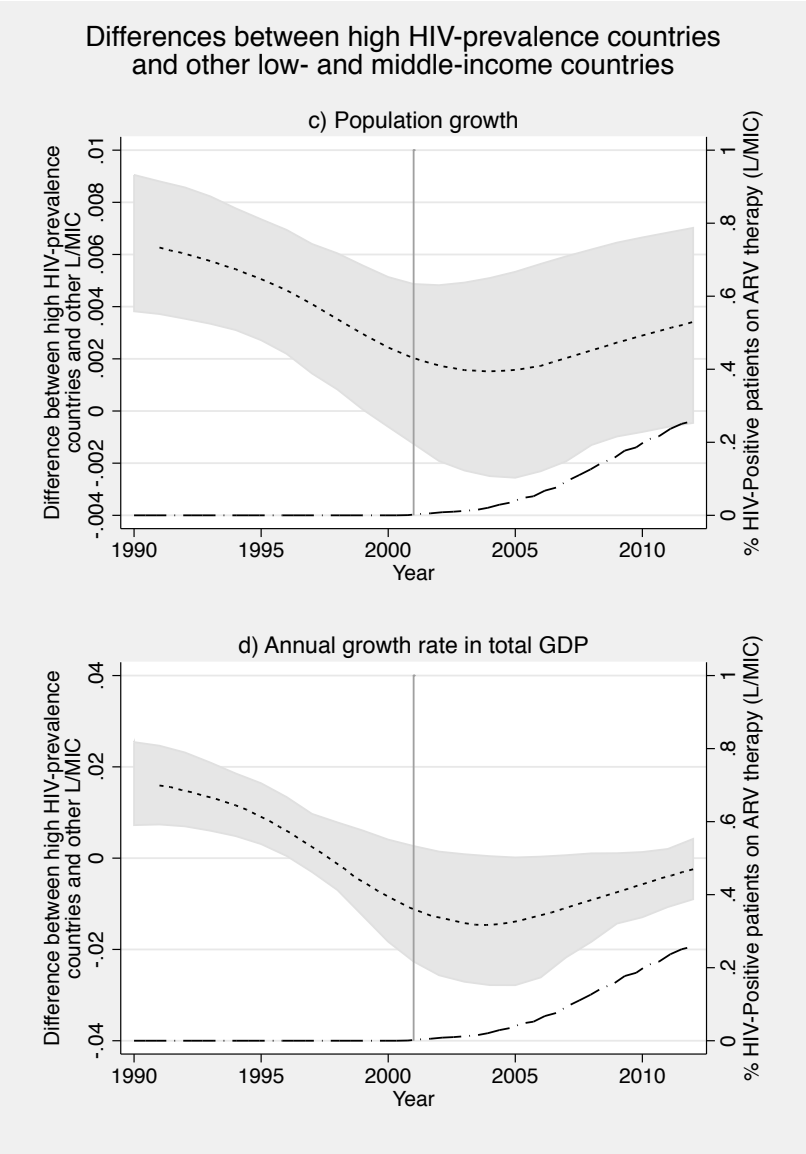
Notes From WHO interactive chart. Placeholder map to be replaced with one drawn with my own data.

Figure 4: Differences between high and low HIV-prevalence countries before and after ARV scale-up



Graphs show results from a local linear regression of the difference in the outcome variable between 15 high HIV prevalence countries (HIV prevalence $> 5\%$ in 2001) and 71 other low and middle income countries (HIV prevalence $< 5\%$ in 2001). The vertical grey line indicates the year in which the price of antiretroviral therapy fell; the dashed line shows the proportion of HIV positive individuals receiving antiretroviral therapy in all low and middle income countries. Country-clustered bootstrapped 90% confidence intervals are shown in grey.

Figure 5: Differences between high and low HIV-prevalence countries before and after ARV scale-up



Graphs show results from a local linear regression of the difference in the outcome variable between 15 high HIV prevalence countries (HIV prevalence $> 5\%$ in 2001) and 71 other low and middle income countries (HIV prevalence $< 5\%$ in 2001). The vertical grey line indicates the year in which the price of antiretroviral therapy fell; the dashed line shows the proportion of HIV positive individuals receiving antiretroviral therapy across all low and middle income countries. Country-clustered bootstrapped 90% confidence intervals are shown in grey.

Table 1: HIV Prevalence in 2001 and post-2001 trends in growth rates

		Log life expectancy	Growth in per-capita GDP	Growth in total GDP	Growth in population
		(1)	(2)	(3)	(4)
$HIV\ Prevalence_{2001}$ x $Post_{2001}$ x t	Coefficient	0.155***	0.042**	0.047**	0.005*
	s.e.	0.028	0.018	0.019	0.003
$HIV\ Prevalence_{2001}$ x $Post_{2001}$	Coefficient	-0.260***	-0.079	-0.112	-0.033***
	s.e.	0.056	0.121	0.127	0.010
$HIV\ Prevalence_{2001}$ x t	Coefficient	-0.108***	-0.025**	-0.027**	-0.002
	s.e.	0.011	0.010	0.010	0.002
	N	1978	1892	1892	1892

Note: Coefficients from regressions of outcome variable on listed variables, year and country fixed effects, and other time controls where indicated. Main sample consists of a balanced panel of 86 countries for which HIV prevalence data is available, for 1990 to 2012. Standard errors clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Impact of increasing ARV Coverage on health, economic and population growth

		OLS (1)	OLS (2)	OLS (3)	IV (4)	IV (5)
Panel A: % of country population treated with ARVs						
HIV Prevalence$_{2001}$ x global treatment coverage$_t$	Coefficient			0.95***		
	s.e.			0.10		
	N			1966		
Panel B: Log life expectancy						
% of population treated with ARVs	Coefficient	-4.04***	2.09		5.72***	5.72***
	s.e.	0.70	1.32		1.53	1.53
HIV Prevalence$_{2001}$ x global treatment coverage$_t$	Coefficient			5.43***		
	s.e.			0.97		
HIV Prevalence$_{2001}$ x t	Coefficient		-0.068***	-0.103***	-0.104***	
	s.e.		0.016	0.012	0.011	
	N	1966	1966	1978	1966	1966
Panel C: Change in log GDP per capita						
% of population treated with ARVs	Coefficient	0.24*	0.77		1.57*	1.57*
	s.e.	0.13	0.47		0.81	0.81
HIV Prevalence$_{2001}$ x global treatment coverage$_t$	Coefficient			1.48**		
	s.e.			0.69		
HIV Prevalence$_{2001}$ x t	Coefficient		-0.016**	-0.024**	-0.025***	
	s.e.		0.007	0.010	0.009	
	N	1880	1880	1892	1880	1880
Panel D: Change in log GDP						
% of population treated with ARVs	Coefficient	0.18	0.79		1.79**	1.80**
	s.e.	0.15	0.52		0.88	0.88
HIV Prevalence$_{2001}$ x global treatment coverage$_t$	Coefficient			1.70**		
	s.e.			0.74		
HIV Prevalence$_{2001}$ x t	Coefficient		-0.018**	-0.028***	-0.028***	
	s.e.		0.007	0.010	0.010	
	N	1880	1880	1892	1880	1880
Panel E: Change in log population						
% of population treated with ARVs	Coefficient	-0.05	0.03		0.23**	0.23**
	s.e.	0.05	0.10		0.11	0.11
HIV Prevalence$_{2001}$ x global treatment coverage$_t$	Coefficient			0.21**		
	s.e.			0.10		
HIV Prevalence$_{2001}$ x t	Coefficient		-0.002	-0.004**	-0.004**	
	s.e.		0.002	0.002	0.002	
	N	1880	1880	1892	1880	1880
	Controls	No	Yes	Yes	Yes	Yes
	Country linear trends	No	No	No	No	Yes

Note: Coefficients from regressions of outcome variable on listed variables and controls where indicated. Controls include year and country fixed effects. Main sample consists of a balanced panel of 86 low and middle-income countries for which HIV prevalence data is available, for 1990 to 2012. 10 countries are missing ARV coverage data for 1 year and 1 country is missing ARV coverage for 2 years. In columns 3) and 5), % of population treated by ARVs is instrumented with global coverage of ARVs interacted with HIV prevalence in 2001. Standard errors clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Robustness of main results to changes in the sample and specification

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Log life expectancy								
% of population treated with ARVs	Coefficient	5.72***	5.26***	5.70***	5.22***	7.08***	5.70***	5.72***
	s.e.	1.53	1.60	1.50	1.60	0.68	1.61	1.51
HIV Prevalence$_{2001}$ x t	Coefficient	-0.10***	-0.12***	-0.10***	-0.12***	-0.08***	-0.11***	-0.10***
	s.e.	0.01	0.01	0.01	0.01	0.02	0.01	0.01
	N	1966	1966	2349	891	1897	1897	1966
Panel B: Change in log GDP per capita								
% of population treated with ARVs	Coefficient	1.57*	1.36*	1.66**	1.34*	1.51**	1.37*	1.22*
	s.e.	0.81	0.81	0.79	0.81	0.74	0.78	0.71
HIV Prevalence$_{2001}$ x t	Coefficient	-0.02***	-0.02**	-0.03***	-0.02**	-0.02*	-0.02**	-0.02**
	s.e.	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	N	1880	1880	2254	852	1814	1815	1880
Panel C: Change in log GDP								
% of population treated with ARVs	Coefficient	1.79**	1.74*	1.91**	1.73*	1.58**	1.61*	1.43*
	s.e.	0.88	0.93	0.87	0.93	0.74	0.86	0.78
HIV Prevalence$_{2001}$ x t	Coefficient	-0.03***	-0.03***	-0.03***	-0.03***	-0.02*	-0.02***	-0.02***
	s.e.	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	N	1880	1880	2254	852	1814	1815	1880
Panel D: Change in log population								
% of population treated with ARVs	Coefficient	0.23**	0.39**	0.20*	0.39**	0.07	0.25**	0.23**
	s.e.	0.11	0.16	0.11	0.16	0.15	0.11	0.11
HIV Prevalence$_{2001}$ x t	Coefficient	-0.004**	-0.007***	-0.003*	-0.007***	0.000	-0.004***	-0.004**
	s.e.	0.002	0.002	0.002	0.002	0.003	0.002	0.002
	N	1880	1880	2254	852	1814	1815	1880
	Region year F.E.	No	Yes	No	No	No	No	No
	Sample	Main	Main	Extended	SSA	Trim 1	Trim 2	Winsor

Note: Coefficients from IV regressions of outcome variable on listed variables, year and country fixed effects. % of population treated with ARVs is instrumented with the interaction between global ARV coverage and HIV prevalence in 2001. Main sample consists of a balanced panel of 86 low and middle-income countries for which HIV prevalence data is available, for 1990 to 2012. 10 countries are missing ARV coverage data for 1 year and 1 country is missing ARV coverage for 2 years. Extended sample consists of all low- and middle-income countries, assuming that HIV prevalence and hence ARV coverage is zero where HIV prevalence data is missing. Trimmed samples are constructed as follows: 1) drop three highest HIV prevalence countries 2) drop three countries with most extreme values for the outcome variable. In column 7, the top and bottom 1.5% of values for the outcome variable are winsorized. Standard errors clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Impact of ARVs on log life expectancy: Alternative explanations

		Log life expectancy								
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% of population treated with ARVs	Coefficient	5.73***	5.72***	5.22***	5.75***	5.75***	5.29***	5.50***	5.49***	5.93***
	s.e.	1.53	1.53	1.61	1.53	1.53	1.61	1.51	1.51	2.12
Fraction GDP mineral $rents_{2001}$ x t	Coefficient	-0.022								
	s.e.	0.016								
Fraction GDP mineral $rents_{2001}$ x Post 2001	Coefficient	-0.033								
	s.e.	0.030								
Fraction GDP mineral $rents_{2001}$ x Post 2001 x t	Coefficient	0.000								
	s.e.	0.001								
Fraction GDP petroleum $rents_{2001}$ x t	Coefficient				-0.003					
	s.e.				0.004					
Fraction GDP petroleum $rents_{2001}$ x Post 2001	Coefficient				0.016					
	s.e.				0.015					
Fraction GDP petroleum $rents_{2001}$ x Post 2001 x t	Coefficient				0.001					
	s.e.				0.000					
Malaria ecology x t	Coefficient							0.000		
	s.e.							0.002		
Malaria ecology x Post 2001	Coefficient							0.020***		
	s.e.							0.006		
Malaria ecology x Post 2001 x t	Coefficient							0.0005***		
	s.e.							0.0002		
	N	1966	1966	891	1966	1966	891	1966	1966	891
Heterogeneous trends		Linear	Flexible	Flexible	Linear	Flexible	Flexible	Linear	Flexible	Flexible
Sample		Main	Main	SSA	Main	Main	SSA	Main	Main	SSA

Note: Coefficients from IV regressions of outcome variable on listed variables, year and country fixed effects, and HIV prevalence in 2001 interacted with a linear time trend. % of population treated with ARVs is instrumented with the interaction between global ARV coverage and HIV prevalence in 2001. Main sample consists of a balanced panel of 86 low and middle-income countries for which HIV prevalence data is available, for 1990 to 2012. 10 countries are missing ARV coverage data for 1 year and 1 country is missing ARV coverage for 2 years. Where flexible trends are included, these comprise interactions between the relevant cross-sectional variable and year dummies. *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.

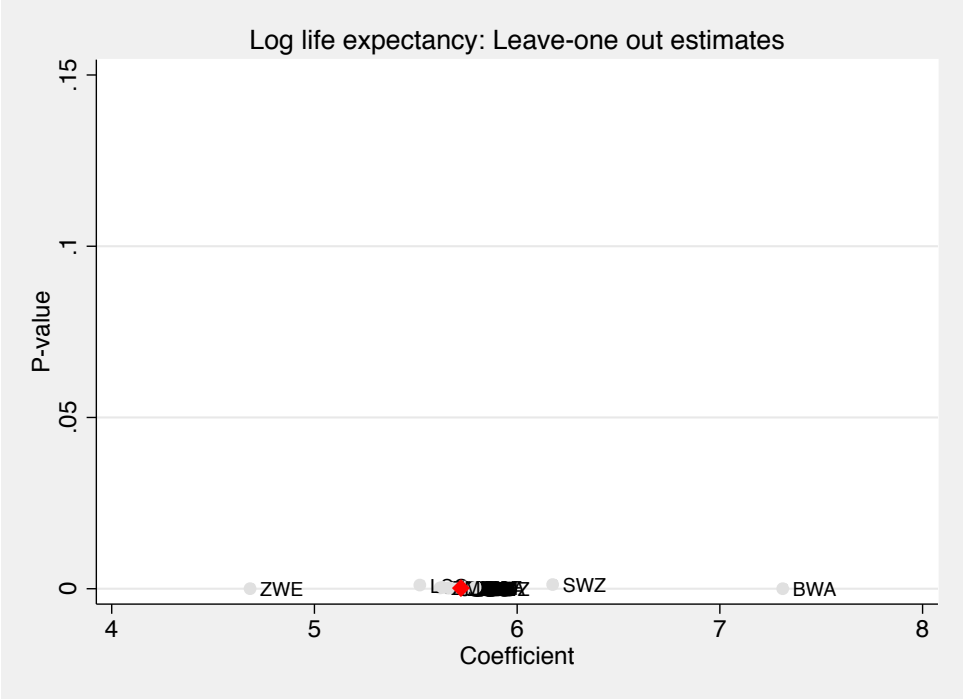
Table 5: Impact of ARVs on growth in per-capita GDP: Alternative explanations

		Growth in per-capita GDP								
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% of population treated	Coefficient	1.73**	1.73**	1.38*	1.49*	1.49*	1.26	1.22	1.20	1.52
with ARVs	s.e.	0.82	0.82	0.83	0.80	0.80	0.79	0.75	0.75	0.93
Fraction GDP mineral	Coefficient	-0.086***								
$rents_{2001}$ x t	s.e.	0.031								
Fraction GDP mineral	Coefficient	0.385**								
$rents_{2001}$ x Post 2001	s.e.	0.165								
Fraction GDP mineral	Coefficient	0.010***								
$rents_{2001}$ x Post 2001 x t	s.e.	0.003								
Fraction GDP petroleum	Coefficient				0.003					
$rents_{2001}$ x t	s.e.				0.010					
Fraction GDP petroleum	Coefficient				0.067*					
$rents_{2001}$ x Post 2001	s.e.				0.036					
Fraction GDP petroleum	Coefficient				-0.001					
$rents_{2001}$ x Post 2001 x t	s.e.				0.001					
Malaria ecology x t	Coefficient							-0.005		
	s.e.							0.004		
Malaria ecology x Post	Coefficient							0.000		
2001	s.e.							0.027		
Malaria ecology x Post	Coefficient							0.001*		
2001 x t	s.e.							0.000		
	N	1880	1880	852	1880	1880	852	1880	1880	852
	Heterogeneous trends	Linear	Flexible	Flexible	Linear	Flexible	Flexible	Linear	Flexible	Flexible
	Sample	Main	Main	SSA	Main	Main	SSA	Main	Main	SSA

Note: Coefficients from IV regressions of outcome variable on listed variables, year and country fixed effects, and HIV prevalence in 2001 interacted with a linear time trend. % of population treated with ARVs is instrumented with the interaction between global ARV coverage and HIV prevalence in 2001. Main sample consists of a balanced panel of 86 low and middle-income countries for which HIV prevalence data is available, for 1990 to 2012. 10 countries are missing ARV coverage data for 1 year and 1 country is missing ARV coverage for 2 years. Where flexible trends are included, these comprise interactions between the relevant cross-sectional variable and year dummies. Standard errors clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.

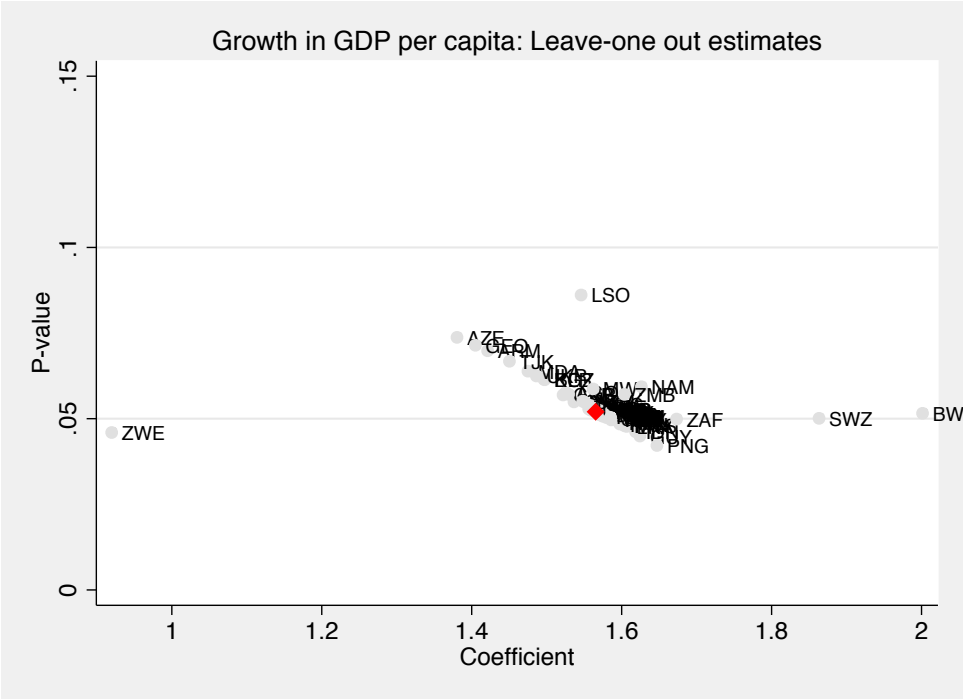
Appendices

Figure A1: Leave-one-out estimates: Life expectancy



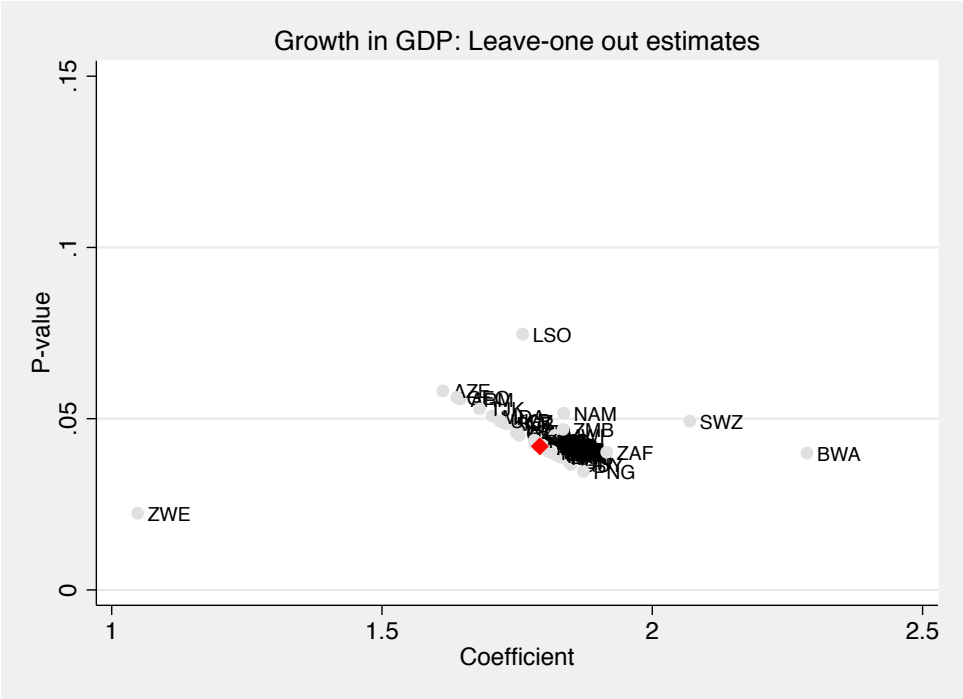
Notes Graph shows coefficients on antiretroviral therapy coverage and associated p-values from repeated estimates, in each case excluding the labelled country. Estimates are from a 2SLS regression where antiretroviral therapy coverage is instrumented with the interaction between HIV prevalence in 2001 and global ARV coverage. Regressions include year and country fixed effects, and HIV-prevalence-specific linear time trends. Standard errors clustered at the country level. The main estimate is shown in red.

Figure A2: Leave-one-out estimates: Growth in per-capita GDP



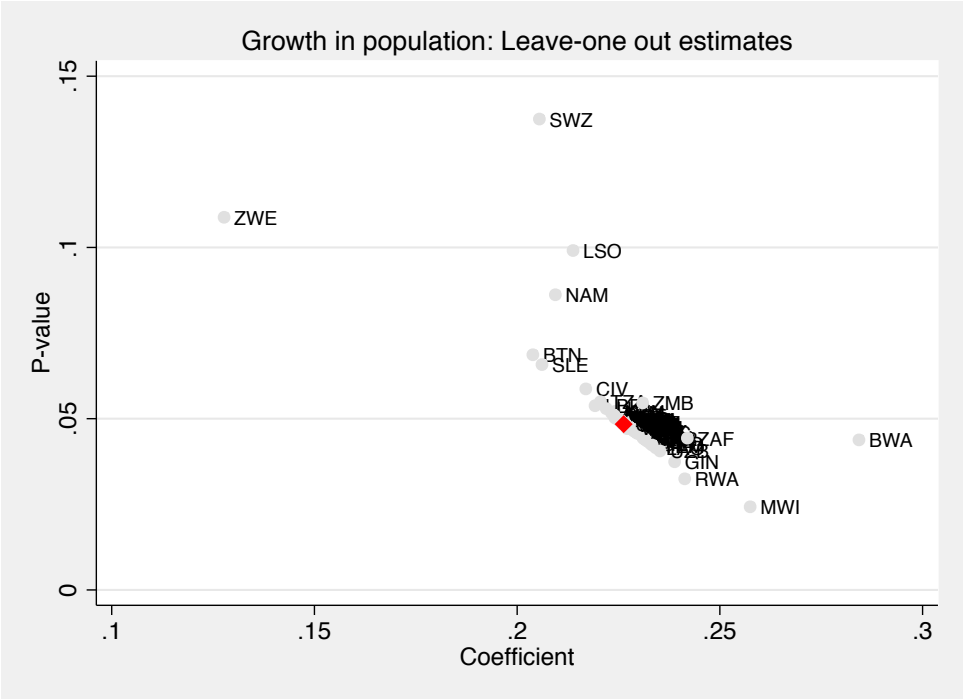
Notes Graph shows coefficients on antiretroviral therapy coverage and associated p-values from repeated estimates, in each case excluding the labelled country. Estimates are from a 2SLS regression where antiretroviral therapy coverage is instrumented with the interaction between HIV prevalence in 2001 and global ARV coverage. Regressions include year and country fixed effects, and HIV-prevalence-specific linear time trends. Standard errors clustered at the country level. The main estimate is shown in red.

Figure A3: Leave-one-out estimates: Growth in GDP



Notes Graph shows coefficients on antiretroviral therapy coverage and associated p-values from repeated estimates, in each case excluding the labelled country. Estimates are from a 2SLS regression where antiretroviral therapy coverage is instrumented with the interaction between HIV prevalence in 2001 and global ARV coverage. Regressions include year and country fixed effects, and HIV-prevalence-specific linear time trends. Standard errors clustered at the country level. The main estimate is shown in red.

Figure A4: Leave-one-out estimates: Population growth



Notes Graph shows coefficients on antiretroviral therapy coverage and associated p-values from repeated estimates, in each case excluding the labelled country. Estimates are from a 2SLS regression where antiretroviral therapy coverage is instrumented with the interaction between HIV prevalence in 2001 and global ARV coverage. Regressions include year and country fixed effects, and HIV-prevalence-specific linear time trends. Standard errors clustered at the country level. The main estimate is shown in red.

Table A1: List of countries with HIV Prevalence > 1% in 2001

	Country	HIV Prevalence (2001)
1	Botswana	.281
2	Swaziland	.248
3	Zimbabwe	.243
4	Lesotho	.234
5	Malawi	.155
6	South Africa	.153
7	Zambia	.151
8	Namibia	.15
9	Mozambique	.09
10	Kenya	.085
11	Tanzania	.075
12	Uganda	.068
13	Cote d'Ivoire	.064
14	Gabon	.061
15	Cameroon	.052
16	Congo, Rep.	.047
17	Togo	.045
18	Rwanda	.044
19	Chad	.038
20	Ethiopia	.036
20	Equatorial Guinea	.036
22	Bahamas, The	.035
22	Nigeria	.035
24	Burundi	.029
25	Guinea-Bissau	.028
26	Djibouti	.023
26	Ghana	.023
26	Liberia	.023
29	Burkina Faso	.022
30	Angola	.018
30	Belize	.018
30	Thailand	.018
33	Benin	.016
33	Mali	.016
35	Dominican Republic	.013
35	Guinea	.013
35	Trinidad and Tobago	.013
38	Honduras	.012
38	Panama	.012
38	Suriname	.012

Table A2: List of countries with highest coverage of ARV therapy (by total population) in 2012

	Country	ARV Coverage as % of population (2012)
1	Botswana	.1058346
2	Swaziland	.0711089
3	Namibia	.0516453
4	Lesotho	.0452084
5	Zimbabwe	.041217
6	South Africa	.0411455
7	Zambia	.0341685
8	Malawi	.0254696
9	Kenya	.0139892
10	Mozambique	.012294
11	Uganda	.0120658
12	Rwanda	.0100035
13	Gabon	.0091916
14	Tanzania	.009047
15	Cameroon	.0056583
16	Cote d'Ivoire	.0055631
17	Guyana	.0046733
18	Togo	.0045629
19	Congo, Rep.	.0039737
20	Belize	.0038913
21	Guinea-Bissau	.0036674
22	Thailand	.00358
23	Chad	.0032797
24	Ethiopia	.0031412
25	Burundi	.0029566
26	Nigeria	.0029083
27	Burkina Faso	.0027892
28	Ghana	.0027544
29	Benin	.0025904
30	Suriname	.0025667
31	Guinea	.0023286
32	Dominican Republic	.0021623
33	Angola	.0020464
34	Gambia, The	.0019936
35	Mali	.0019356
36	Cabo Verde	.0017476
37	Djibouti	.001724
38	Papua New Guinea	.0016414
39	Brazil	.0015765
40	Panama	.001558
41	Venezuela, RB	.0014366

Table A3: Impact of ARVs on growth in GDP: Alternative explanations

		Change in log GDP								
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% of population treated with ARVs	Coefficient	1.97**	1.97**	1.81*	1.73**	1.73**	1.67*	1.46*	1.45*	2.08*
	s.e.	0.90	0.90	0.95	0.88	0.88	0.92	0.84	0.84	1.11
Fraction GDP mineral $rents_{2001}$ x t	Coefficient	-0.092***								
	s.e.	0.029								
Fraction GDP mineral $rents_{2001}$ x Post 2001	Coefficient	0.419***								
	s.e.	0.153								
Fraction GDP mineral $rents_{2001}$ x Post 2001 x t	Coefficient	0.010***								
	s.e.	0.003								
Fraction GDP petroleum $rents_{2001}$ x t	Coefficient				0.002					
	s.e.				0.010					
Fraction GDP petroleum $rents_{2001}$ x Post 2001	Coefficient				0.076**					
	s.e.				0.038					
Fraction GDP petroleum $rents_{2001}$ x Post 2001 x t	Coefficient				-0.001					
	s.e.				0.001					
Malaria ecology x t	Coefficient							-0.005		
	s.e.							0.005		
Malaria ecology x Post 2001	Coefficient							0.001		
	s.e.							0.030		
Malaria ecology x Post 2001 x t	Coefficient							0.001		
	s.e.							0.000		
	N	1880	1880	852	1880	1880	852	1880	1880	852
	Heterogeneous trends	Linear	Flexible	Flexible	Linear	Flexible	Flexible	Linear	Flexible	Flexible
	Sample	Main	Main	SSA	Main	Main	SSA	Main	Main	SSA

Note: Coefficients from IV regressions of outcome variable on listed variables, year and country fixed effects, and HIV prevalence in 2001 interacted with a linear time trend. % of population treated with ARVs is instrumented with the interaction between global ARV coverage and HIV prevalence in 2001. Main sample consists of a balanced panel of 86 low and middle-income countries for which HIV prevalence data is available, for 1990 to 2012. 10 countries are missing ARV coverage data for 1 year and 1 country is missing ARV coverage for 2 years. Where flexible trends are included, these comprise interactions between the relevant cross-sectional variable and year dummies. Standard errors clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Impact of ARVs on population growth: Alternative explanations

		Change in log population								
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
% of population treated with ARVs	Coefficient	0.23**	0.23**	0.43***	0.23**	0.23**	0.41**	0.24**	0.25**	0.56**
	s.e.	0.11	0.11	0.16	0.12	0.12	0.16	0.12	0.12	0.26
Fraction GDP mineral $rents_{2001}$ x t	Coefficient	-0.006								
	s.e.	0.007								
Fraction GDP mineral $rents_{2001}$ x Post 2001	Coefficient	0.034								
	s.e.	0.035								
Fraction GDP mineral $rents_{2001}$ x Post 2001 x t	Coefficient	0.000								
	s.e.	0.001								
Fraction GDP petroleum $rents_{2001}$ x t	Coefficient				-0.001					
	s.e.				0.001					
Fraction GDP petroleum $rents_{2001}$ x Post 2001	Coefficient				0.009					
	s.e.				0.007					
Fraction GDP petroleum $rents_{2001}$ x Post 2001 x t	Coefficient				0.000					
	s.e.				0.000					
Malaria ecology x t	Coefficient							0.000		
	s.e.							0.001		
Malaria ecology x Post 2001	Coefficient							0.001		
	s.e.							0.005		
Malaria ecology x Post 2001 x t	Coefficient							0.000		
	s.e.							0.000		
	N	1880	1880	852	1880	1880	852	1880	1880	852
	Heterogeneous trends	Linear	Flexible	Flexible	Linear	Flexible	Flexible	Linear	Flexible	Flexible
	Sample	Main	Main	SSA	Main	Main	SSA	Main	Main	SSA

Note: Coefficients from IV regressions of outcome variable on listed variables, year and country fixed effects, and HIV prevalence in 2001 interacted with a linear time trend. % of population treated with ARVs is instrumented with the interaction between global ARV coverage and HIV prevalence in 2001. Main sample consists of a balanced panel of 86 low and middle-income countries for which HIV prevalence data is available, for 1990 to 2012. 10 countries are missing ARV coverage data for 1 year and 1 country is missing ARV coverage for 2 years. Where flexible trends are included, these comprise interactions between the relevant cross-sectional variable and year dummies. Standard errors clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.