HIV-related Risk Taking Behavior and Income Uncertainty: Empirical Evidence from Sub-Saharan Africa*

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Abstract

This paper addresses the issue of the positive observed relationship between GDP and HIV prevalence in Sub-Saharan Africa. We examine the role of the volatility of GDP per capita in lowering the incentives to invest in self-protection and, empirically, in the spread of the epidemic. Using a panel dataset of Sub-Saharan African countries over the 1990-2007 time period and a dynamic panel data framework, a more unstable GDP distribution is found to accelerate the spread of AIDS. The positive relationship between HIV prevalence and economic volatility is robust to the inclusion of additional control variables and to the definition of the measure of GDP volatility.

JEL Codes: I12, O1, E32, J11

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1 Introduction

Over the past 25 years, public policies to fight AIDS have been focused on increasing the supply of self-protective measures such as providing condoms either at subsidized price or for free, and providing information about the risk of HIV-transmission. This type of policy is efficient under two implicit assumptions. The first assumption is that the risk of being HIV-infected is driven by ignorance and misfortune, meaning that people get infected by HIV only if they are ignorant about the risk they take during an unprotected sexual intercourse. Secondly this type of policy assumes that as soon as self-protective devices become available, people will start to use them. Looking backwards, the evidence suggests that the epidemic of HIV/AIDS is still spreading among African countries despite the improved level of knowledge and the increased access to condoms, implying that HIV-infection is not only due to ignorance but might also be driven by low incentives to invest in self-protection and to change one's sexual behavior towards safer practices. The same pattern is found in the literature on road safety devices showing that as the risk of accidents decreases with the introduction of airbag and seat belts, people start driving faster, counteracting the effect on risk and leading to no radical fall in the number of road accidents nor in road mortality (Peltzman, 1975; Evans and Graham, 1991; Peterson *et al*, 1994; Sen and Mizzen, 2007).

The HIV/AIDS epidemic in Africa exhibits complex patterns that contradict standard microeconomic theory that would argue that educated and wealthy people should be less likely to be HIV-infected. Its relation to income is puzzling because worldwide the epidemic affects poorer countries while amongst Sub-Saharan Africa the richer ones experience the greater prevalence. UNAIDS (2008; 2009) estimates of HIV prevalence provide some insights about these two assertions. In 2008, 0.8% of the population around the world was living with HIV (UNAIDS, 2009). While only 0.3% and 0.6% of the adult population were HIV-infected in Western and Central Europe and North America respectively, the prevalence rate reached 5.2% in Sub-Saharan Africa in 2008. By contrast, from UNAIDS (2008), the HIV prevalence rates within Sub-Saharan Africa reveal that the richest regions are the most affected by the epidemic. In 2007 the HIV prevalence rate among the adult population was 16.36% in Southern Africa (GDP per capita[1]: 4,584.6), 4.06% in Central Africa (5,694.3), 2.51% in East Africa (1,215.9) and 1.79% in West Africa (1,110.8). A

[1]Data source: World Development Indicators (2008)

series of studies documents the sensitivity of the HIV/AIDS epidemic to income at both macroeconomic and microeconomic levels and confirms the positive relation within Africa. At the same time, developing countries and particularly countries in Sub-Saharan Africa have vulnerable economies and experience frequent fluctuations in income.

This paper addresses the issue of the positive relationship between income and the spread of the epidemic by taking into account income uncertainty, a variable omitted from the current literature that is found to play a significant role in the epidemic in Sub-Saharan Africa. The bottom line is that in Africa, the widespread instability and the lack of protection against the occurrence of exogenous risks and against their negative consequences might influence the individual choice and attitudes towards the risk of infection, and namely, might reduce the value people grant to the risk of infection. Individuals face so many risks in their everyday life that actually they might not be concerned in taking one additional and deliberated risk, even though the cost of protection is low and self-protective devices are available.

Only a few papers consider HIV-related risky behaviors as a deliberated choice made by the individual (e.g. Geoffard and Philipson (1996), Kremer (1996), Clark and Vencatachellum (2003), Oster (2009)). From this respect, this paper is very close to Oster (2009) that investigates how individual response to HIV risk varies according to non HIV mortality risk and income. Here we are interested in the effect of income risk in reducing the incentives to self-protect against the risk of HIV-infection and to a macroeconomic test of this relationship.

Firstly, this paper presents a model of rational choice between self-protection and exposure to the risk of HIV-infection and highlights how income uncertainty alters the incentive to invest in self-protection. We find that for a given average income, the presence of income uncertainty induces the agent to be more likely to engage in HIV-related risky behavior, and even more so when income risk increases. Secondly, using a panel dataset of Sub-Saharan African countries over the period 1990-2007, we investigate the empirical relationship between GDP per capita instability and HIV prevalence in a dynamic panel model, and show that a one-standard deviation increase in the GDP volatility leads to a rise in HIV prevalence by between 0.32 and 0.43 percentage point.

Traditionally, the empirical analysis between income and prevalence is based on individual or country cross-sections. Microeconometric evidence suggests for a couple of African countries that rich individuals are more likely to be HIV-infected than their counterparts. Lachaud (2007) provides a detailed study of the determinants of HIV-infection in Burkina Faso. Using the Demographic and Health Survey collected in 2003, he shows that the probability of being HIV-infected increases with non monetary welfare, proxied by an index of physical assets. Distinguishing men and women, de Walque (2006) does not confirm the positive relation found in the case of Burkina Faso but he validates this pattern in Cameroon for both males and females and in Ghana, Kenya and Tanzania where rich women are found more likely to be infected than the poor. Kazianga (2004) and Luke (2006) give some insights into two channels through which wealth might be related to a higher risk of HIV-infection. It is documented that in Sub-Saharan Africa, beyond transactions with commercial sex workers, money and gifts are driving most extramarital or casual sex. A rich man seems more vulnerable due to his potentially extended sexual network. The role of transfers is all the more crucial considering that Luke (2006) points out a negative relationship between transfers and condom use in informal relationships in urban Kenya. On the other hand, Kazianga (2004) demonstrates that the demand for casual sex increases with wealth for urban men in Burkina Faso and rural men in Guinea and Mali.

Cross-country empirical works have documented the positive relationship between income and the state of the HIV/AIDS epidemic in developing countries, and with a special focus on Sub-Saharan Africa. Bonnel (2000) tests for the role of growth in GDP per capita on HIV prevalence for 60 developing countries and finds that its effect is positive but not statistically significant. Zanakis *et al* (2007) test for the same hypothesis using cross sections of 151 countries and show that the number of adults aged 15-49 living with HIV/AIDS and the number of AIDS-related deaths among adults and children are both positively related to the gross national product. In the special case of Sub-Saharan Africa, macroeconomic evidence claims that HIV prevalence level increases with wealth (Bloom *et al* 2001; Clark and Vencatachellum, 2003; Lachaud, 2007). At the regional level, Lachaud (2007) finds that the regional disparities in terms of prevalence in a country like Burkina Faso are linked to the variations in living standards and demonstrates that the level of regional prevalence increases with wealth and that the result is robust to the choice of proxy used. Clark and Vencatachellum (2003) explain the positive observed relationship in Africa by the fact that in industrialized countries, the wage of one agent depends not only on his own productivity but also on the productivity of his colleagues, reduced by HIV-infection. Hence if one agent anticipates that most of his colleagues will engage in risky behavior and get HIV-infected with a given likelihood, this reduces one's incentives to self-protect individually. Clark and Vencatachellum (2003) explain the puzzling relation between GDP and HIV prevalence by what they call the "human-capital externalities", while in this paper, we propose to explain it by taking into account another omitted variable, namely GDP volatility.

This paper departs from the previous empirical literature in two ways. Firstly, from a methodological point of view, we use a dynamic panel data model instead of country cross-sections to capture country-specific unobserved heterogeneities and to consider the state-dependent nature of the prevalence rate. Secondly, the cross-country empirical papers have focused on the first moment of GDP distribution while this paper studies the complementary role played by the second moment of the distribution.

Our work relates to the literature on economic shocks and health outcomes that has been investigated in the context of the developed countries. Ruhm examines the role of short-run recessions on health outcomes and documents that economic downturns improve health in two related papers. In Ruhm (2000), using a panel dataset of US states over the period 1972-1991, the total mortality rate is found to decrease with the unemployment rate. In a companion paper, Ruhm (2005) provides microeconomic evidence that the employment rate increases the prevalence of risky behaviors such as smoking, obesity and physical inactivity. Using the British Household Panel Survey over 1997-2005, Apouey and Clark (2009) study a sub-sample of lottery winners and shows that mental health increases with the prize money won, while this has no statistically significant effect on general health nor on physical health outcomes (e.g. diabetes, allergies). Additional results suggest that individuals are more likely to adopt risky behaviors, such as smoking and social drinking, when they have won a lottery. Adda et al (2008) provide mitigating microeconometric evidence about the effect of income innovations on health outcomes. Very recent papers have documented the observed macroeconomic relationship between mortality and business cycles (see Chen *et al*, 2010; Gonzalez and Quast, 2010; Svensson and Kruger, 2010).

The role of shocks on HIV-related behaviors is not yet established. Using panel data for the youth in Cape Town, Dinkelman *et al* (2008) investigates how the age of sexual debut, the recourse of multiple sexual partners and the use of condoms are sensitive to the shocks experienced by households using an aggregated measurement of shocks that encompasses job loss, illness and death. The relation is marginally significant suggesting that shocks are not a good predictor of HIV-related behaviors. However the lack of significance might be linked to the fact that household shocks are taken into account instead of personal shocks. One might guess that the relation would have been statistically significant when predicting the behaviors of the adults living in the household instead of the teenagers. The pattern is probably different for adults since they are precisely those who have to face the negative shocks.

The paper is organized as follows. Section 2 develops a simple model of individual choice between safe and unsafe sex to highlight how income instability alters the incentives to invest in self-protection. This theoretical framework aims to shed some light on the microeconomic foundations that are behind our empirical investigations. Section 3 presents the econometric model, the panel data and comments on the primary results. In section 4, some robustness checks are performed to rule out the possibility that other mechanisms drive the significant and positive relation between income risk and the spread of the epidemic. The framework is applied to other indicators of economic instability that confirm the findings that instability enhances HIV prevalence in Sub-Saharan Africa. Section 5 concludes.

2 Economic Intuitions

The Setting

The crucial link in this line of analysis is the concept of interacting risks. A very simple model brings out the logics of this problem. Assume that an individual has to choose between indulging in unprotected sex or not, with the probability of getting infected from such an intercourse without protection $\rho\beta$, denoting by ρ the HIV prevalence rate among the sexually active population and by β, the transmission rate. This formulation makes the following three implicit assumptions. Firstly, all infected agents are assumed to engage in exposure[2]. Secondly, the agent is assumed to choose one's sexual partner randomly such that the probability of having an infected partner is equal to the proportion of people living with HIV[3]. Thirdly,

[2] This assumption simplifies our calculations and does not diminish the insights to be drawn from the results. Relaxing this assumption leads to more risk taking because with a fraction of infected agents engaging in safe sex, the probability of encountering an infected partner through exposure and hence the probability of contracting AIDS falls. A negative feedback of altruism among infected agents would emerge.

[3] Formally, the probability of encountering an infected partner is equal to the share of HIV-infected agents among the people engaged in unsafe sex. The latter encompasses the infected agents and the proportion of susceptible agents who are risk takers. Likewise this probability is

perfect matching is assumed, meaning that people opting for unsafe sex match all together.

To take into account the cost of getting protected, consider that unprotected sex brings an extra-utility equal to an exogenous Δ. This instantaneous benefit from unsafe sex is a standard assumption in the literature on individual choice in the presence of HIV/AIDS (Geoffard and Philipson 1996; Clark and Vencatachellum 2003). Then, assume that the agent derives utility from income, w, and that infection is not lethal such that newly infected agents are still alive in the next period as in Geoffard and Philipson (1996), and bear a loss in utility. A state dependent utility approach is proposed in which the utility is conditional upon the individual's status. We use the Viscusi and Evans (1990)'s utility formulation in which the utility of the unhealthy individual is equal to a proportion α of what he would have got if healthy. Formally, the susceptible agent gets $u(w)$ while the infected counterpart gets $v(w) = \alpha u(w)$, where $0 \leq \alpha < 1$. $u(.)$ is assumed to be continuous, increasing and concave. Lastly, assume no discount factor.

Using p as an index for choosing protection and e for exposure to the risk of being HIV-infected, the following expected utilities are derived from the setting: $EU_p = u(w)$, $EU_e = \Delta + \rho\beta v(w) + [1 - \rho\beta]u(w)$. Applying a cost-benefit framework, the susceptible agent maximizes her expected utility and invests in self-protection if the expected utility from protection is higher than that of exposure, i.e. if $EU_p \geq EU_e$.

Then, she buys self-protection if her willingness to pay for it is higher than its cost, i.e. if:

$$\beta\rho(1 - \alpha)u(w) \geq \Delta \tag{1}$$

The left-hand side of this expression measures the expected loss in future utility due to exposure and the right-hand side is the current extra-utility from unsafe sex. Quite obviously, this individual will choose to get protected when the former is larger than the latter, and will choose to be exposed otherwise. Varying the parameters implies that a decrease in the utility loss from infection, in the prevalence rate and in the transmission rate would lead to lower incentives to use self-protective devices, and to an increase in HIV-related risk taking behavior.

endogenous and depends on the expected share of risk takers among healthy agents. However, we argue that the number of agents engaging in unsafe sex whatever their serostatus is approximated by 1.

Deriving condition (1) with respect to income, we find that $\beta\rho(1-\alpha)u'(w) \geq 0$ given that the utility function $u(.)$ is increasing, leading to the following proposition.

Proposition 1 *Assuming an increasing utility function, an increase in income enhances the incentives to use self-protective devices.*

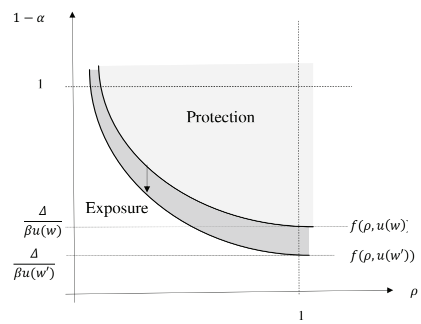

Figure 1: The Decision to Buy Self-Protection

Figure 1 depicts the cut-off line derived from this simple framework. Graphically, an increase in income (from w to w') shifts the cut-off line downward, increasing the set of people choosing self-protection by the area in dark grey. For a given loss in utility, $1-\alpha$, when income increases, a lower prevalence is needed to induce people to self-protect. We find that an increase in income leads to more protection which contradicts with the empirical literature on the HIV/AIDS epidemic in Sub-Saharan Africa where the relation between HIV prevalence and income is shown to be positive. A puzzle emerges. We aim to disentangle this puzzle by introducing a risk on income.

The Case of Income Uncertainty

Now, assume that the income is uncertain in the next period and is a random variable, $\tilde{w}$, that follows a given cumulative distribution function F on a support $[\underline{w}; \overline{w}]$. This assertion is motivated by the magnitude of the fluctuations in most African countries and the vulnerability of both individuals and governments to face such macroeconomic instability.

Denote the expected utility of income by $EU(\tilde{w})$. The expected utilities from protection and exposure are adjusted as follows. When the agent uses a condom, he gets $EU_p = EU(\tilde{w})$ and faces only the exogenous risk on income. On the contrary, when she opts for exposure, she faces both the risk of infection and the exogenous risk, and thus gets $EU_e = \Delta + \rho\beta EV(\tilde{w}) + [1 - \rho\beta]EU(\tilde{w})$, where $EV(\tilde{w}) = \alpha EU(\tilde{w})$. Then, applying the same decision rule as above implies that under income uncertainty, the individual invests in self-protective devices as soon as:

$$\beta\rho(1-\alpha)EU(\tilde{w}) \geq \Delta \tag{2}$$

Certainty vs. Uncertainty

To see how the presence of income uncertainty alters the incentives for self-protection and to compare the two settings, assume that $E(\tilde{w}) = w$. It follows that $u\left[E(\tilde{w})\right] = u(w)$; from the Jensen's inequality, for any random variable $\tilde{w}$, if u(.) is concave, $EU(\tilde{w}) < u\left[E(\tilde{w})\right]$, i.e. $EU(\tilde{w}) < u(w)$. Given that (i) the susceptible agent takes the risk of infection as soon as $u(w) < \frac{\Delta}{\beta\rho(1-\alpha)}$ (under income certainty) and that (ii) $EU(\tilde{w}) < u(w)$, we obtain that for a given average income, people are more likely to adopt HIV-related risky behavior under income uncertainty than under income certainty. Graphically, this increase in risk taking is depicted by the additional dark grey area in Fig. 2. The presence of income uncertainty shifts the cut-off line upwards and extends the set of parameters for which the agent adopts HIV-related risky behavior.

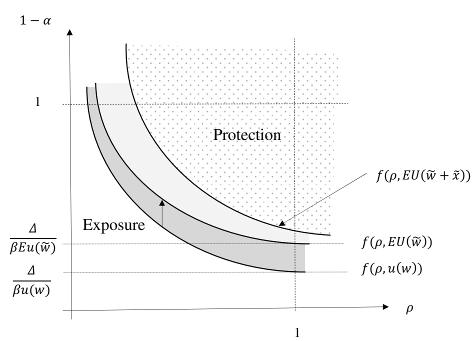

Figure 2: The Decision to Buy Self-Protection
in the presence of income uncertainty

Increased Uncertainty

Of more interest in our context is the effect of increased uncertainty surrounding income on the incentives to adopt self-protective behavior. To analyze this effect, we examine the consequence of a mean-preserving spread of the distribution of income of the type proposed in Rothschild and Stiglitz (1970). A mean preserving spread on the random variable $\tilde{w}$ has the following effect on condition (2) $\beta\rho(1-\alpha)EU''(\tilde{w})$.

This effect is negative given that the utility function is concave. A rise in income risk shifts the condition downwards, meaning that the condition under which people start using condoms is harder to satisfy.

Proposition 2 *For a given average income, an increase in the income risk reduces the incentives to choose protection.*

Fig.2 shows that adding a mean-preserving spread, $\tilde{x}$, on income shifts the cut-off line upwards, implying a rise in risk taking which is represented in light grey. Consequently, for a given loss in utility, the prevalence rate needs to be larger to induce people to buy condoms. Proposition 2 means that the higher the income uncertainty, the higher the HIV-related risk taking behavior. More risk taking implies an increase in the incidence rate because a given proportion of risk takers will become newly contaminated, so that the HIV prevalence in the next period will be higher. In other words, a rise in income uncertainty leads to a faster spread of the epidemic in a country. The empirical counterpart states that for two countries having a similar GDP per capita, the HIV prevalence rate will be greater in the one that exhibits the highest GDP instability. The direct empirical prediction of this proposition is to test the null hypothesis, H_0*: controlling for income, income volatility is positively related to HIV prevalence rate.*

3 The Model and the Data

3.1 The Econometric Model

The paper analyzes the relationship between HIV prevalence, income and income instability by estimating the following dynamic model:

$$HIV_{i,t} = \rho HIV_{i,t-1} + \beta_0 Income_{i,t} + \beta_1 IncomeRisk_i + X'_{i,t}\delta + \alpha_i + \gamma_t + \varepsilon_{i,t} \quad (3)$$

HIV is the HIV prevalence rate in country i in year t. The parameters of interest are the βs that capture whether $Income$ and $IncomeRisk$ influence the dynamics of the epidemic. $Income$ stands for the GDP per capita and $IncomeRisk$ for its variability. The set of control variables, $X_{i,t}$, includes the constant, the literacy rate, the urban population rate and religion. We control for country-specific effects, α_i and time effects, γ_t. The country specific effects capture any country unobserved heterogeneity while the time effects capture the common trend over the period considered, such as a temporal change in HIV/AIDS-knowledge, in the supply of self-protection or in mortality.

The dependent variable stands for the stock of HIV-infected individuals among the adult population. We observe the evolution of the stock over time but we do not observe the new infections nor the number of people who die and leave the stock every year. Nevertheless, estimating the stock of infected people in a dynamic framework consists of predicting the change in the prevalence rate, or, to say it differently, the gross incidence rate in contrast with the net incidence rate that would have taken into account death among HIV-infected people. Controlling for the lagged prevalence rate, our regression coefficients provide insights into the factors that induce risk taking and hence a more or less rapid propagation of HIV in the population.

The presence of both the country-specific effect and the lagged dependent variable in the right-hand side leads to the so-called dynamic panel bias that makes the estimation by Ordinary Least Squares inefficient and the elimination of the specific effects essential. First-differencing of the equation eliminates the country-specific effects but makes appear a correlation between the first-difference of the lagged dependent variable, Δy_{it-1} and the first-difference of the error terms, $\Delta\varepsilon_{it}$, that requires the use of instrumental variables. In a panel data setting, the time series dimension offers the lagged values of the regressors as potential candidates for the instruments. Anderson and Hsiao (1982) propose using Δy_{it-2} or y_{it-2} as instruments for Δy_{it-1} and estimating the model by the instrumental variable method.

Regarding the low efficiency of the Anderson Hsiao estimates, Arellano and Bond (1991) suggest estimating the model by Generalized Method of Moments rather than the IV technique, extending the set of instrumental variables to the entire set of past values and taking into account the heteroskedasticity and autocorrelations of the perturbations. This technique, called the difference-GMM, has some limitations. Firstly, the first differentiation of the equation implies a loss of information. Secondly, the first difference GMM estimator suffers from downward bias and low precision, especially when the value of the autoregressive coefficient ρ increases towards unity (Blundell and Bond 1998).

One alternative approach consists of using both the equations in levels and in first differences in a system of equations. The system-GMM has the advantage over the difference-GMM of identifying the time-invariant regressors and resolving the limitations listed above, especially because it behaves better than the difference-GMM for models where the autoregressive coefficient is high (Blundell, Bond and Windmeijer 2000; Roodman 2006).

3.2 The Data

Our sample consists of 40 countries[4] over the period 1990-2007. The sample size is conditional upon the availability of the data on HIV prevalence, HIV, that is measured as the proportion of HIV-infected people among the population aged 15-49 years old and that comes from UNAIDS (2008) estimates. We exploit the latest UNAIDS dataset that provides a time series of comparable HIV prevalence estimates. These estimates are comparable across time and across countries while the prevalence rates from one annual report to another one were not comparable beforehand. The advantage of this new dataset over the prevalence estimates from the Demographic and Health Surveys is the time series dimension that allows us to use panel data models and to exploit the between and within heterogeneities of the data. Even though UNAIDS estimates are said to be overestimated compared to the population-based estimates from the Demographic and Health Surveys, they are still comparable across all the countries of our sample since the way they are computed are similar across countries. In other words, even though the estimates are upward biased, the country ranking will remain even after correcting for their measurement error. Table 1 in the appendix reports the data description and sources and Table 2 provides some descriptive statistics.

$Income$ is taken from the World Developmeent Indicators and is measured as the gross domestic product per capita in purchasing power parity in constant 2005 international dollars (in thousand). A particular attention has been paid regarding the endogeneity of the GDP per capita in estimating equation (3). Even though previous works suggest that the HIV/AIDS epidemic influences GDP, labor productivity or growth (e.g. Jamison, Sachs and Wang, 2001; Al-Hmoud and Edwards, 2003; Corrigan *et al*, 2005; McDonald and Roberts, 2006), the Hausman test will be in favor of the exogeneity of the variable in each estimation.

[4]UNAIDS (2008) does not provide HIV estimates for Kenya nor for the Democratic Republic of Congo.

To measure the instability in GDP per capita over the period, we apply the Hodrick and Prescott (1981) filter on the GDP per capita series to generate a non linear trend equal to a weighted average of the past, current and future values of the series. The annual cyclical component of the GDP per capita is retrieved by taking the difference between the actual value and the trend. This indicator of GDP fluctuations has two main advantages. Firstly, it is detrended in the sense that it is independent of the mean of the series under consideration. For each country, the mean of the cyclical component over the period is null. Secondly, taking into account both the previous and future values of the series avoids the drawback of the standard coefficient of variation that considers only two periods and may lead to a spurious growth rate[5].

Figure 3 charts the GDP per capita and its fluctuations over the period for a sample of countries where the epidemic is more or less widespread. For illustrative purpose, we use the real gross domestic product per capita in purchasing power parity, expressed in 2005 US dollars from the Penn World Tables, version 6.3 (Heston *et al*, 2009) to have a larger time span. But for the estimation, the GDP series from the World Development Indicators will be used as it is the most appropriate series for the developing world. At the end of the period, in 2007, the HIV prevalence rate is 3.9% in Côte d'Ivoire, 1.5% in Mali, 3.1% in Nigeria and 15.3% in Zimbabwe. We note that the countries differ in two dimensions: rich v.s. poor economies (top chart) and unstable v.s. stable economies (bottom chart).

In the current analysis, we are interested in estimating the impact of GDP volatility and not in estimating the impact of GDP fluctuations. As a consequence we will not use the annual fluctuations as variable of interest that would give some insights into the impact of economic shocks. To capture the GDP volatility over time, the variable $IncomeRisk$ is equal to the standard deviation of the annual deviations from the trend, as suggested in Hodrick and Prescott (1981). This measure allows us to capture both the size of the fluctuations and their frequency[6].

[5] In the sense that if the GDP increases from $t-2$ to $t-1$ by X and then decreases from $t-1$ to t by Y with $Y < X$, the state of the economy in t is worse than in $t-1$ but still better than in $t-2$. The standard coefficient of variation would tell us that the GDP is reduced while the HP fluctuations would not necessarily do so since it would take into account the past and future values of the GDP series.

[6] Note that Equatorial Guinea is excluded from the analysis because it is clearly an outlier in terms of GDP volatility. The index of GDP volatility is equal to to 2.897 for Equatorial Guinea, while the average over the whole sample is of 0.168 when Equatorial Guinea is included and 0.102 when excluded from the sample.

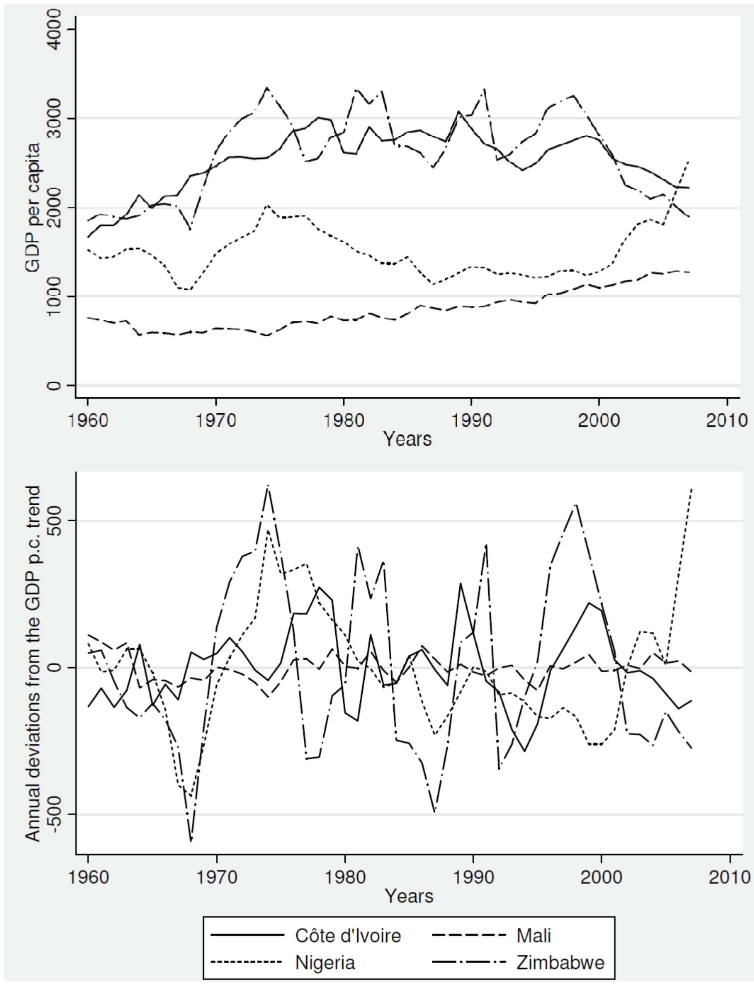

Figure 3: Trend GDP per capita, constant US dollars (PWT 6.3)

The measures of education include the average years of education from Barro and Lee (2001) and the literacy rate extracted from the World Development Indicators 2005 and 2009[7]. The urban population rate comes from the World Development Indicators 2009. From the Center for the Study of Global Christianity, three dummy variables are generated according to the degree of Christianity of the country: (i) less than 50% of the population is evangelized, (ii) over half of the population is evangelized but church members stand for less than 60% of the population, (iii)

[7]Since Barro and Lee (2001) provide measures of education in a 5-year interval basis and given some missing values in the WDI data, both measures are linearly interpolated over the period 1990-2000 and 1990-2007 respectively.

church members represent at least 60% of the population and more than 95% of the population is evangelized.

Before estimating the model, we need to verify that all the variables are stationary. Unit root tests run country by country have low power given the small sample (at most 18 years by country), hence we have used panel unit root tests due to Levin, Lin and Chu (2002) and Im, Pesaran and Shin (2003). These are denoted LLC (2002) and IPS (2003) respectively. Panel unit root tests statistics are reported in Table 3. The evidence is in favor of the stationarity of HIV prevalence, our dependent variable, supporting no evidence in favor of the use of cointegration framework. Accordingly we estimate the HIV prevalence in levels, always controlling for country and time specific effects.

3.3 Primary Results

Table 4 presents the results from estimating Equation (3) through different estimation strategies. Specification 1 estimates the effects of GDP and of GDP instability on HIV prevalence in a dynamic framework. Columns a, b, and d report alternatively the estimates of a pooled OLS, a fixed-effects model, a random-effects model and a system-GMM. As mentioned above, the estimations reported in first three columns should be considered carefully given that they are biased due to the dynamic panel bias. The Hausman specification test favored the fixed-effects model over the random-effects model (results not reported here), but the effect of the GDP instabiliby can be not identified in col.2 since the variable is time-invariant. The empirical results show a positive and statistically significant relationship between GDP volatility and HIV prevalence. When estimating specification 1d, a Hausman test has been performed to know whether GDP per capita should be considered as endogenous or exogenous. The Hausman test has been used to compare two estimations, one in which the GDP per capita is assumed exogenous and another one in which the GDP per capita is assumed endogenous and instrumented by lagged values of the series (not reported here). The Hausman test fails to be rejected, meaning that the GDP per capita should be considered as exogenous. Accordingly the column 1d reports the estimates of the model in which GDP per capita is exogenous.

Specification 2 examines the separated effects of GDP and GDP instability on HIV prevalence by estimating equation (3) with the set of control variables respectively through different estimation strategies. Three main findings are in order.

Firstly, GDP per capita volatility is found to be a statistically significant determinant of HIV prevalence, providing supportive evidence to the prediction of the model presented above. The higher the GDP volatility, the more widespread is the HIV/AIDS epidemic in Sub-Saharan Africa. The positive and significant relationship between HIV prevalence and GDP volatility is robust to the inclusion of control variables such as religion and the rate of urban population. As far as specifications 2b and 2c are concerned, note that a Hausman Test was performed to compare the random-effects and the fixed-effects models and was in favor of the random-effects specification. In the RE model GDP volatility is positively related to HIV prevalence but the relation fails to be statistically significant. Secondly, empirical finding suggests that the GDP per capita can be assumed exogenous in estimating the HIV prevalence in Sub-Saharan Africa over the period 1990-2007. Indeed the Hausman test (test result not reported here) is in favor of the model in which GDP per capita is assumed to be exogenous. Column 2d reports the coefficients for this model. Thirdly, the GDP appears to have no statistical power in predicting the HIV prevalence in our dynamic framework. This finding provides supportive evidence that the second moment of the GDP distribution matters more than its first-moment and that the variance of the GDP should be taken into account when studying the macroeconomic relationship between GDP and the spread of the HIV/AIDS epidemic in Sub-Saharan Africa.

In terms of economic importance of the relationship between GDP volatility and HIV prevalence, the point estimates vary between 2.41 (col. 2d) and 3.27 (col.1d). This means that a one standard deviation increase in the GDP volatility leads to a rise in HIV prevalence by between 0.32 and 0.43 percentage point.

The rate of urban population is included as a control variable and might have two competing effects on the spread of the HIV/AIDS epidemic. Firstly, it could be viewed as a proxy for the access to health care facilities. The rate of urbanization would capture the fact that a higher urbanization may potentially induce a lower cost of self-protection given that living in urban areas offers a larger access to sensitization campaigns and a wider condom availability. Secondly, urbanization might increase sexual promiscuity as it increases population density and probably the opportunities to have sex. The rate of urban population fails to be statistically significant, suggesting that it has no influence on the spread of the epidemic as if neither one of the competing effects dominates.

Religion plays a part in explaining HIV prevalence. By dividing the countries into three groups according to their level of Christianity, the estimations suggest that highly evangelized countries have a higher probability of exhibiting a widespread epidemic than less evangelized countries. More precisely, the highly evangelized countries are more affected than the countries where over half of the population is evangelized but where church members are less than 60% of the population and even more affected than the countries with less than 50% of the population evangelized. This result is in line with previous works such as in Gray (2004). Interpreting the result on religious affiliations is twofold. On one hand, Christian people may be more affected by the HIV/AIDS epidemic because women are more emancipated than in Muslim societies (the age of first sex is lower, the number of lifetime sexual partners is higher). On the other hand, polygyny is more prevalent in Muslim societies than in Christian societies even though in Sub-Saharan Africa polygyny is not only related to religious aspects. But, if the percentage of polygamous marriages is higher among Muslims than among Christians, this would explain why Muslims are less severely affected by the epidemic than Christians since polygyny is associated with a lower number of occasional sexual partners and extramarital sexual intercourses, and hence to a lower risk of HIV-infection.

Table 4 bis re-estimates the benchmark specification 2d using the System-GMM and controlling for education. We did not include education in the benchmark estimation and decided to run separated estimations due to a large number of missing values in the series. Each of the two columns uses different proxies for education. Column 1 uses the literacy rate from the World Development Indicators that responds to the following definition "(The) adult literacy rate is the percentage of people aged 15 and above who can, with understanding, read and write a short, simple statement on their everyday life". Over the 453 observations used to estimate the model, the relationship between HIV prevalence and literacy rate fails to be statistically significant while the relationship between HIV prevalence and GDP volatility remains positive and statistically significant. The positive and statistically significant relationship between HIV prevalence and GDP volatility is also robust when the literacy rate is replaced by the Barro and Lee (2001)'s proportion of people aged 25 and over whose highest educational attainment is the primary school (see col. 2). Note that the coefficient of GDP instability increases in size in the latter specification. This increase could be due to a change in the sample since this estimation is run over 25 countries only. It could be the case that the relationship between GDP instability and HIV prevalence is stronger in this sample of countries than in the whole sample.

4 Robustness of the Results

The evidence found above suggests two novel findings. Firstly, when using a dynamic panel data model and controlling for the second moment of the GDP distribution, the observed relationship between GDP per capita and HIV prevalence is positive but it fails to be statistically significant. Secondly, a more unstable distribution of GDP leads to a more widespread HIV/AIDS epidemic within Sub-Saharan Africa. In this section robustness checks are performed to test whether these previous empirical results are robust to the inclusion of additional control variables and to the definition of income instability. Note that the forthcoming estimations will be compared to the benchmark estimation which is displayed in Table 4 column 2d. Note also that the endogeneity of GDP per capita has been tested for all forthcoming estimations through the Hausman test which was found in favor of the exogeneity of the variable since it fails to be rejected in each case. Accordingly all reported results come from specifications in which the GDP per capita is assumed to be exogenous.

4.1 Omitted Variables

To test for the robustness of our previous results, we add additional control variables that are likely to affect both the spread of the epidemic and the GDP instability and whose omission might lead to biased results.

Degree of Trade Openness

Firstly, we check whether the relationship between HIV prevalence and GDP p.c. and GDP p.c. volatility remain stable and statistically significant when controlling for the degree of trade openness. Openness might be related to both the right- and left-hand side variables. On the one hand, Oster (2008) and Djemai (2009) acknowledge that the degree of openness enhances the HIV incidence and individual risk of HIV-infection, respectively, in Africa. On the other hand, trade openness is known to induce external risk in a country (e.g. Rodrik, 1998). The degree of openness, measured as the sum of exports and imports relative to GDP in 2005 constant prices, comes from the Penn World table, version 6.3. In Table 5, column 1 adds the contemporaneous degree of national trade openness to the set of control variables used in the benchmark equation. Our estimation result claims that the omission of the variable trade openness was not driving the benchmark results since the respective effects of GDP and GDP instability on HIV prevalence are stable in sign and significance. Note that the contemporaneous degree of openness is positively related to HIV but it is not found to be a significant predictor of HIV prevalence in this equation.

Official Development Aid Flows

We argued that the macroeconomic volatility influences the spread of the epidemic through a fall in the incentives to engage in self-protection. Another channel through which the positive association between prevalence and macroeconomic volatility might occur is through aid flows. The argument is that more stable countries could be more likely to receive a large amount of aid flows compared to unstable countries and these aid flows might be targeted or used by the local government to fight the epidemic. If such a scenario prevails, then stable economies are less affected by the epidemic thanks to the aid received and the unstable nations are more affected by AIDS not due to the income risk as such but due to the induced lack of resources. To rule out this possibility, we introduce the contemporaneous amount of official development assistance and aid as a control variable. The official development assistance and official aid in current US dollars comes from the World Development Indicators 2009 and is expressed in million of US dollars. Column 2 in Table 5 shows that (i) the effect of GDP per capita is still not statistically significant, and (ii) its instability remains significantly and positively related to HIV prevalence even after introducing a measure of aid flows. The contemporaneous aid flows fail to explain significantly the HIV prevalence. Note that contemporaneous aid flows are found to be exogenous in our specifications, suggesting that the amount of aid is not allocated in response to the size of the HIV/AIDS epidemic (results not reported here).

Armed Conflicts

The third omitted variable that might lead to biased estimates is armed conflict. There are various open channels through which armed conflicts might have a role in our analysis. Firstly, the conflict might make the economy of the country sluggish, leading to a fall in the income level and a rise in the income volatility; this might be all the more true if the conflict is long-lasting. Accordingly, the occurrence of armed conflict might increase the GDP instability that in turn boosts the spread of the epidemic. If this scenario is validated by the data, one should find that armed conflict increases the HIV prevalence and the effect on the significance of GDP instability is unclear. Secondly, one might argue that income instability has nothing to do with HIV prevalence and gains its significance from the omission of the conflict variable in the sense that armed conflicts have their own impact on prevalence since the bleak prospects due to being in conflict might induce people to be more likely to engage in risky sexual behavior. If this scenario was validated by the data, one would get that income instability is not significant anymore and that the likelihood of experiencing an armed conflict is positively and significantly associated to HIV prevalence. Thirdly, as suggested in Miguel *et al* (2004), economic instability might be considered as a cause of conflict rather than a consequence and this would indicate that income instability leads to conflict that in turn could influence the spread of the epidemic.

The UCDP/PRIO Armed Conflict dataset (Gleditsch *et al*, 2002; Harbom and Wallensteen, 2009) provides very disaggregated data such that we are able to control for whether the sample countries experience an armed conflict for each year over 1990-2007 and to distinguish whether the conflict is against the government in place or due to territory-based issues. Two dummy variables are generated from this dataset, according to whether the country is experiencing a conflict against the government or for territory issues.

Specifications 3 and 4 report the results and suggest that the purpose of the conflict leads to two different conclusions. On the one hand, conflict for territory purposes has no effect on the spread of the epidemic and its inclusion among the set of control variables does not affect the relationships between HIV prevalence and GDP instability. On the other hand, armed conflict against the government leads to a fall in the HIV prevalence and its inclusion implies that GDP instability loses its predictive power. Nevertheless, neither of the proposed alternative channel is validated by the data. Here the relation goes in the opposite direction since we found a negative relation between being in armed conflict against the government and prevalence. This observed relationship suggests that the mechanisms that prevail are either reduced mobility and opportunity to have sex due to conflict, or excess mortality of people living with HIV among the fatalities, or a mixture of the two. Lastly, concerning the connection with Miguel *et al* (2004), we do not find that income instability increases the likelihood of conflict that in turn increases the HIV prevalence for two reasons. Firstly, the two relationships are not consistent, we should have found that the relation between instability and prevalence and the one between conflict and prevalence go in the same direction. Secondly, the results differ according to the conflict purpose and there is no a priori reason why income instability should trigger conflicts against the government more so than conflicts for territory-based issues. Lastly note that the Arellano-bond tests for first- and second- order serial correlation in first differences fail to be rejected in the estimations displayed in col. 3 and 4, suggesting that the conclusions should be taken with caution.

4.2 Different measures of income volatility

This subsection aims at testing whether the relationship between income instability and HIV prevalence remains positive and statistically significant when other proxies for income instability are used. We propose to use another indicator for the GDP per capita instability and to base the measure of income volatility on aggregates other than the GDP per capita.

GDP in constant 2000 US dollars Firstly, we estimate the same model as in Table 4 col. 2d except that we replace the GDP series in the GDP in level and the measure of GDP instability. In the benchmark equation, the GDP per capita in purchasing power parity was used and in the col. 1 of Table 6 we use the GDP per capita in constant 2000 US dollars. Similar results are found since (i) the coefficient of GDP per capita fails to be statistically significant, (ii) GDP instability has a positive and statistically significant impact on HIV growth, and (iii) GDP per capita can be assumed exogenous in this model. Then, we can conclude that our core results were not subject to the estimation of the purchasing power parities.

Normalized GDP fluctuations One might argue that by definition, the richer the country, the greater are its fluctuations. This could be the case with other measures of fluctuations. In the previous sections we used the annual deviations from the trend to compute the indicator of volatility and by definition, the non linear trend is generated given the past and future values of the series and there is no a priori reason why the trend should be further from the actual values for the rich countries compared to the poor ones. Nevertheless we propose to normalize the annual deviations from the trend, to compute the standard deviation of the normalized series for each country of the sample and to estimate its effect on the spread of the HIV/AIDS epidemic in Sub-Saharan Africa. Column 2 in Table 6 displays the empirical results and shows that the coefficient of GDP volatility is robust in terms of sign and statistical significance to this change of definition.

Volatility in agricultural yields

GDP is an indicator of standards of living and gives some insights into the potential public investment. Nevertheless, in most African countries, the majority of the population is working in the fields while agriculture is not very productive, so that it accounts for a small proportion of GDP. For instance, in 2000, in Zambia, 72% of the population was working in agriculture while the share of the agricultural sector in GDP is only 22% (WDI, 2009). The remaining 78% come from other sources and one might guess that their profits do not benefit directly the wide majority of the population. Farmers might have access to these resources through public spending if they are used to finance social programs but they do not constitute individual wealth as such. This example is representative of most countries within Sub-Saharan Africa. In this context, investigating the role of the volatility in agricultural yields provides some additional insights into the relationship between economic instability and the spread of the epidemic. The cereal yields, measured in kg per hectare, come from the World Development Indicators 2009. The measure of volatility in yields is the standard deviation of the annual deviations of the agricultural yields from their trend using the Hodrick Prescott non linear trend.

Col. 3 repeats the benchmark regression replacing the volatility in GDP by the volatility in yields as the independent variable of interest. The evidence shows a positive association between the variance of the fluctuations in yields and the prevalence of HIV. Countries in which yields are highly volatile are much more affected by the epidemic than their counterparts. High and frequent crop shocks discourage people to invest in self-protective behavior, all the more so when the vast majority of the population who works in the agricultural sector has no outside option to avoid crop shocks and their livelihoods are directly affected by these fluctuations in yields. As in the benchmark estimation, GDP per capita turns out to have no predictive power.

Col. 4 and 5 in Table 6 studies the heterogeneous effects of the volatility in yields according to the share of the agricultural sector in GDP. The share of agriculture in GDP comes from the World Development Indicators 2009. We compute two types of median from this series. The first measure is computed yearly and is used to generated a dummy variable, $below1$, equal to one if the country share is below the median and zero otherwise. This measure takes into account the fact that the share of agriculture in GDP varies a lot over the studied period for some sampled countries. The greatest amplitudes are found in Uganda (and Liberia) where the minimum value is 24 (51) and the maximum value reaches 57 (94). Accordingly, this measure allows some countries to appear below the median in some years and above in others. The second median is computed from the country share of agriculture in GDP averaged over the whole period and determines two distinct sets of countries: one being below the median over the entire time period and the other being above the median. Likewise the dummy variable, $below2$, will take the value one in the former case and zero in the latter.

Included in the right-hand side variables are not only the volatility in yields but also the interaction between the volatility in yields and the dummy variable for being below the median. The overall coefficient turns out to be statistically insignificant while the coefficient of volatility in yields is statistically significant and positive for the countries below the median. A Wald test tests for the equality between these two coefficients and fails to reject the null hypothesis of equality, indicating that the effect of agricultural risk is homogeneous across countries whether the national wealth is highly based on agriculture or not. A second Wald test shows that the two coefficients are jointly statistically significant, providing additional support to the empirical results displayed in Col. 3.

Lastly, we replace GDP per capita in level by the measure of agricultural yields to control for another type of income (see col. 6). Similar qualitative findings are in order: (i) the effect of agricultural yields is not statistically significant, (ii) the volatility in yields matters in explaining the spread of AIDS in Sub-Saharan Africa.

Volatility in precipitation

Lastly, we propose to construct a measure of income instability based upon rainfall, claiming that rainfall is an exogenous proxy for income and in particular individual wealth given that the large majority of the population is working in the agricultural sector. The rainfall data we use come from Miguel *et al* (2004)'s dataset that ends up in 2001 and comes from the Normalized Difference Vegetation Index dataset. The standard deviation of the annual rainfall index is used as an alternative proxy for income instability. Equation (3) is estimated replacing the volatility in GDP p.c. by the volatility in rainfalls. Note that this specification could be considered as an instrumental variable specification in reduced-form given that rainfall stands for an exogenous source of GDP. The empirical results displayed in Col. 7 confirm the previous findings, as the volatility in rainfall is significantly and positively related to the spread of the HIV/AIDS epidemic in Sub-Saharan Africa. Note that in this specification of the model, the GDP per capita has still no predictive power and is found to be exogenous.

The estimation in Col. 7 is performed on the 1990-2001 time period given the availability of the data on rainfall. If we estimate the effect of the volatility over the period 1990-2001 on HIV prevalence over the whole time period (1990-2007), the effect is still positive and statistically significant (not reported here).

5 Concluding remarks

This paper addresses the issue of the positive observed relationship between income and HIV prevalence in Sub-Saharan Africa. It goes one step further and examines whether volatility of income plays a role in the spread of the epidemic. The answer is yes. The empirical results provide support to the view that a greater spread distribution of GDP per capita leads to faster spread of the epidemic over time. The effect turns out to be huge since empirical findings suggest that a one standard deviation increase in GDP volatility leads to an rise in HIV prevalence by between 0.32 and 0.43 percentage point. The observed pattern is suggested to be driven by the fall in the opportunity cost of HIV-infection resulting from a high macroeconomic instability. The incentives to invest in self-protective devices are the key element of our analysis and are found to decrease with income volatility.

The paper is based on the central hypothesis that nowadays, HIV-infection is a matter of choice and incentives. Of course, not all Africans have perfect knowledge about the risk of HIV-contamination (see among others, Glick and Sahn, 2007), about how to use condoms properly and some individuals, particularly women, have no power to negotiate on sexuality issues. However previous studies show that the acquisition of HIV/AIDS-knowledge and access to condoms are necessary but not sufficient to induce people to use self-protective devices or to engage in safer practices (e.g. Dinkelman *et al*, 2006; Djemai, 2009).

Even though individual data would have been more appealing to predict individual behavior towards the risk of HIV-infection and to test the prediction of the model, macroeconomic data is used for two reasons. Firstly, there is no individual-level data that provide both information about HIV-related behavior and historical information about the household revenues or consumption that would allow us to construct an index of income instability. Secondly microeconomic data would have the disadvantage of suffering from an endogeneity bias in the relationship of interest. Indeed, one's own HIV-status does not influence the gross domestic product while the GDP might influence one's risk taking behavior and one's own status might influence one's revenue due to the loss of productivity and the opportunistic diseases that a HIV-infected individual is likely to develop. Microeconomic data would have the second disadvantage of suffering from large measurement errors and misreporting (e.g. Gersovitz *et al*, 1998; Gersovitz, 2005). The collection of survey data on both vulnerability to risk and on HIV/AIDS-related behavior and prevalence would provide some additional insights about the role of instability on HIV-related risk taking.

Should policy implications have to be drawn from our work, we would say the following. Our findings suggest that a new approach to fight the HIV/AIDS epidemic could be based on providing people more incentives to invest in health care and to use the self-protective devices that are available to them. One way to enhance HIV-related protection is to protect the agents against income risk, either by reducing the probability of facing such a risk or by reducing the amount of damage in the case of risk occurrence. Secondly, our paper suggests that business cycle can have a deteriorating effect on individual health care, that in turn lead to the spread of the HIV/AIDS epidemic in Sub-Saharan Africa. The cost of business cycle was found to be negligible for developed economies while in the context of this paper, we can conclude that it would be worth exploring their effects on African countries and societies, all the more so that the size of the effect is found to be non negligible.

This paper focuses on income risk and is an attempt to open the debate about the role of risk in lowering the incentives to invest in self-protective behavior. This issue could be tackled in a broader perspective. On the one hand, the framework might be applied to other exogenous risks the agents are likely to face in their everyday life and against which they can not protect, such as political instability, new epidemics, massacres or expropriation. On the other hand, the framework is replicable to other self-protective behaviors such as water filtering, the use of mosquito nets or vaccination. These self-protective behaviors have the common particularity that agents do not massively adopt them even though the cost of self-protection is low and the agents are informed about the health risks in case of non-adoption.

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Appendix

TABLE 1

Data description

Variable	*Definition, Unit*	*Source*
HIV prevalence	Rate of the adult population (15-49) who is living with HIV/AIDS, percent	UNAIDS (2008)
GDP per capita	GDP per capita, in thousand, ppp	WDI
Yields	Agricultural yields, in kg per hectare	WDI
Rainfall	Annual rainfall estimates	NDVI
Aid flows	Official development assistance and official aid, in million of current US dollars	WDI
Agriculture over GDP	Share of the agricultural sector in GDP	WDI
Urban	Rate of urban population, percent	WDI
Literacy rate	Rate of the adult population (15 and older) who is literate, percent	WDI
Primary educ.	Adult population (15 and older) whose educational attainment is primary, percent	Barro and Lee (2001)
Trade openness	Sum of imports and exports over GDP	Penn world Table 6.3
$\text{Christianity}_{low}$	DV equals one if low degree of Christianity	Center for the
$\text{Christianity}_{middle}$	DV equals one if intermediate degree of Christianity	Study of Global
$\text{Christianity}_{high}$	DV equals one if high degree of Christianity	Christianity

TABLE 2

Descriptive statistics

Variable	*Obs.*	*Mean*	*Std. dev.*	*Min*	*Max*
HIV prevalence	738	5.23	6.66	0	28.9
GDP per capita	752	2.122	3.305	.151	28.876
GDP risk	738	.102	.129	.015	.590
Yields	756	1,091.74	490.68	111	3,307
Yields risk	756	146.54	93.90	10.56	369.09
Rainfall volatility	501	286.06	143.10	43.02	720.97
Literacy rate	498	55.61	21.03	11.4	91
Primary educ.	299	34.68	13.03	9.6	59
Aid flows (in millions)	771	448.46	639.74	-11.03	11431.76
Trade openness	774	70.86	38.98	1.09	230.19
Agriculture over GDP	728	29.81	16.84	2	94
Rate of urban pop.	774	34.24	16.36	5	87
$\text{Christianity}_{low}$	774	.233		0	1
$\text{Christianity}_{middle}$	774	.419		0	1
$\text{Christianity}_{high}$	774	.349		0	1

TABLE 3

Panel unit root tests

	Levels		*First differences*	
	IPS	*LLC*	*IPS*	*LLC*
HIV	-4.262***	-17.032***	-2.146***	-11.417***
GDP p.c.	1.149	15.176	-1.665*	-1.298
Yields	-1.645*	-1.560*	-2.630***	3.749
Urban pop.	-0.986	-1.809**	-3.311***	-5.064***
Openness	-1.443	-0.236	-2.531***	-1.910**
Aid flows	-0.926	7.798	-1.924***	14.858

Note: IPS and LLC are the $t - bar$ test statistic for the unit root null hypothesis of the Im, Pesaran and Shin (2003) and the Levin, Lin, Chu (2002) $t - star$ for the presence of unit root in the model. Both tests are performed for the variables of the model, expressed either in levels or in first-differences. **, *** signify rejection of the unit root hypothesis at the 5% and 1% level respectively. A lag length of 2 lags is specified and the Augmented Dickey Fuller regression has an intercept only. When the test is performed for the variable in levels and the evidence rejects the null hypothesis, the variable is shown to be stationary and can be used in levels in the estimation. When the evidence fails to reject the unit root null hypothesis, the test is performed for the variable in first differences and if the null is rejected, the variable is said to be integrated of order 1 and will be used in first-differences.

TABLE 4

HIV prevalence and GDP p.c. volatility

Dependent variable: HIV prevalence

	(1)				*(2)*			
	(a) Pooled OLS	*(b)* Fixed-Ef	*(c)* Rand-Ef	*(d)* Syst-GMM	*(a)* Pooled OLS	*(b)* Fixed-Ef	*(c)* Rand-Ef	*(d)* Syst-GMM
HIV_{t-1}	1.019***	0.906***	0.970***	1.016***	1.016***	0.906***	0.962***	1.004***
	(0.006)	(0.015)	(0.007)	(0.009)	(0.007)	(0.015)	(0.008)	(0.012)
GDP pc.	0.202	0.0485	0.0604	-0.365	0.253	0.0469	0.104	0.0725
	(0.166)	(0.137)	(0.144)	(1.085)	(0.173)	(0.137)	(0.148)	(0.910)
GDP pc. risk	0.658***	-	0.938**	3.269**	0.492*	-	0.319	2.410*
	(0.197)	-	(0.406)	(1.532)	(0.274)	-	(0.526)	(1.420)
Urbanpop					0.0077	-0.0078	-0.0034	0.0595
					(0.054)	(0.048)	(0.054)	(0.175)
$\text{Christianity}_{low}$					-0.154	-	-0.617***	-0.570
					(0.105)	-	(0.189)	(0.489)
$\text{Christianity}_{middle}$					-0.0966	-	-0.339*	-0.471
					(0.101)	-	(0.185)	(0.452)
constant	-0.267***	0.537***	0.544***	0.112	-0.155	0.542***	0.930***	-0.0390
	(0.055)	(0.105)	(0.132)	(0.150)	(0.123)	(0.108)	(0.225)	(0.383)
m1				2.19**				2.45**
m2				2.69***				2.60***
N	659	659	659	659	659	659	659	659
Country	39	39	39	39	39	39	39	39
Country effects	yes	yes	yes	yes	yes	yes	yes	yes
Time effects	yes	yes	yes	yes	yes	yes	yes	yes

Note: Robust standard errors (clustered at the country level in the system-GMM) in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Excluded dummy variable: $\text{Christianity}_{high}$

m1 and m2 are Arellano-Bond test for first-order and second-order serial correlation in first differences

TABLE 4 bis

HIV prevalence and GDP p.c. volatility: controlling for literacy

Dependent variable: HIV prevalence

	(1) *Syst-GMM*	*(2)* *Syst-GMM*
HIV_{t-1}	0.967***	0.896***
	(0.030)	(0.037)
GDP p.c.	-1.018	1.926
	(0.926)	(2.776)
GDP pc. risk	4.928*	12.48*
	(2.971)	(6.407)
WDI literacy	0.0165	
	(0.018)	
Barro and Lee literacy		0.0931*
		(0.048)
Urbanpop	-0.0419	-0.0356
	(0.198)	(0.608)
$\text{Christianity}_{low}$	-0.651	-1.165
	(0.660)	(1.589)
$\text{Christianity}_{middle}$	-0.521	-0.664
	(0.669)	(1.327)
constant	-0.919	-2.586
	(1.035)	(2.341)
m1	1.77*	1.88*
m2	2.43**	2.37**
N	453	250
Country	33	25
Country effects	yes	yes
Time effects	yes	yes

Note: Robust standard errors clustered at the country level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Excluded dummy variable: $\text{Christianity}_{high}$. m1 and m2 are Arellano-Bond test for first-order and second-order serial correlation in first differences

TABLE 5

HIV prevalence and GDP p.c. volatility: additional explanatory variables

Dependent variable: HIV prevalence

	With trade openness	*With aid flows*	*With conflict*	
	(1)	*(2)*	*(3)*	*(4)*
	Syst-GMM	*Syst-GMM*	*Syst-GMM*	*Syst-GMM*
HIV_{t-1}	1.004***	1.004***	1.003***	0.974***
	(0.012)	(0.012)	(0.012)	(0.015)
GDP p.c.	0.0759	-0.109	0.144	0.696
	(0.909)	(0.935)	(0.877)	(0.894)
GDP pc. risk	2.435*	2.714*	2.380*	-0.211
	(1.421)	(1.400)	(1.384)	(1.303)
Urbanpop	0.0596	0.116	0.0581	0.0560
	(0.176)	(0.174)	(0.174)	(0.208)
Christianity$_{low}$	-0.566	-0.548	-0.521	-1.312**
	(0.490)	(0.488)	(0.461)	(0.552)
Christianity$_{middle}$	-0.474	-0.449	-0.427	-1.178***
	(0.454)	(0.463)	(0.426)	(0.380)
Trade Openness	0.0031			
	(0.004)			
Aid flows		0.0001		
		(0.0001)		
conflict, territory			-0.297	
			(0.408)	
conflict, government				-1.560***
				(0.365)
constant	-0.0192	-0.128	-0.0589	1.072**
	(0.380)	(0.395)	(0.369)	(0.426)
m1	2.23**	2.09**	-1.07	-1.07
m2	2.53**	2.26**	-1.19	-1.19
N	659	656	659	659
Country	39	39	39	39
Country effects	yes	yes	yes	yes
Time effects	yes	yes	yes	yes

Note: Robust standard errors clustered at the country level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Excluded dummy variable: Christianity$_{high}$
m1 and m2 are Arellano-Bond test for first-order and second-order serial correlation in first differences

TABLE 6

HIV prevalence and GDP p.c. volatility: alternative measures of income volatility

Dependent variable: HIV prevalence

	(1) *Syst-GMM*	*(2)* *Syst-GMM*	*(3)* *Syst-GMM*	*(4)* *Syst-GMM*	*(5)* *Syst-GMM*	*(6)* *Syst-GMM*	*(7)* *Syst-GMM*
HIV_{t-1}	0.996***	1.004***	0.934***	0.901***	0.901***	0.942***	1.010***
	(0.013)	(0.012)	(0.021)	(0.028)	(0.033)	(0.019)	(0.029)
GDP p.c.		0.0725	1.246	0.178	0.343		0.373
		(0.910)	(1.158)	(0.955)	(1.053)		(0.934)
GDP pc risk (normalized)		1.117*					
		(0.658)					
GDP p.c. 2000USD	0.0288						
	(2.896)						
GDP pc. 2000 USD risk	8.563**						
	(3.951)						
Yields						0.00009	
						(0.000)	
Yields risk (*a*)			0.0070***	0.0031	0.0020	0.0063**	
			(0.003)	(0.002)	(0.002)	(0.003)	
$below1 * Yieldsrisk$ (*b*)				0.0060***			
				(0.002)			
$below2 * Yieldsrisk$ (*b*)					0.0066**		
					(0.003)		
Rainfall volatility							0.0032
							(0.002)
m1	2.41**	2.45**	-0.13	-0.85	0.07	0.05	-0.24
m2	2.58**	2.60***	1.81*	1.48	2.10**	2.10**	2.53**
N	659	659	659	635	659	680	427
Country	39	39	39	39	39	40	39
Other controls	yes	yes	yes	yes	yes		
Country effects	yes	yes	yes	yes	yes		
Time effects	yes	yes	yes	yes	yes		
Wald test (pvalue)							
$H_0 : \beta_a = \beta_b$				.367	.268		
$H_0 : \beta_a = \beta_b = 0$				.003	.008		

Note: Robust standard errors clustered at the country level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *below*1 is equal to one if the share of the agriculture over GDP is below the annual median computed over the whole sample and zero otherwise. *below*2 is equal to one if the share of agriculture over GDP is below the median computed over the entire country/year sample.