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# "Know Your Status": The Impact of HIV testing on Time and Risk Preferences and the Implications for Behaviour

Catherine Jury[1]
University of Oxford

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## Abstract

It has been suggested that voluntary counselling and testing (VCT) may help to reduce the transmission of HIV. Although evidence in support of this claim is mixed, little is known about the channels through which VCT may affect sexual decision-making. The purpose of this study is to test whether learning one's HIV status has an impact on risky sexual behaviour through the channel of time and risk preferences. Using data from the Malawi Longitudinal Study of Families and Health (MLSFH), the impact of learning HIV results on these preferences, two years *ex post*, is measured. Secondly, the role of VCT and time and risk preferences in explaining risky sexual behaviour is analysed. Potential endogeneity problems associated with self-selection into learning results and reverse causality between learning results and preferences are overcome by use of an IV strategy. Randomly assigned vouchers to collect results as well as distance to VCT centres are used as instrumental variables for VCT attendance. Difference-in-difference methodology is used to test robustness of the results. Findings indicate little evidence of an enduring impact of VCT on time and risk preferences and risky sexual behaviour. Furthermore, results suggest that preferences are, on average, not a channel through which VCT affects behaviour. Thus, although VCT may affect sexual decision-making in the short-run, as found in some previous studies, such effects may significantly diminish over time and are likely not via the channel of altered preferences for time and risk.

JEL Codes: D83, D90, I12, I18

Keywords: HIV/AIDS, Voluntary Counselling and Testing, Risk Aversion, Time Preference

[1] Contact email: cathjury@gmail.com

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# 1. Introduction

The developing world and Sub-Saharan Africa (SSA) in particular, is at the epicentre of the global HIV/AIDS epidemic. In 2014 SSA accounted for 70% of the worldwide HIV-prevalence (25.8 million people), and although new HIV cases declined by 41% between 2000 and 2014, two-thirds of all new infections still occur in the region (UNAIDS, 2015). While the extensive rollout of antiretroviral treatment has helped to curb potentially devastating effects of HIV/AIDS in SSA, it remains an on-going public health challenge facing the continent's developing countries. In its latest "Fast-Track strategy to end the AIDS epidemic by 2030" UNAIDS (2014), highlighted that "Without scale-up, [of prevention and treatment efforts] the AIDS epidemic will continue to outrun the response, increasing the long-term need for HIV treatment and raising future costs" (UNAIDS, 2014, p. 4).

According to Slaymaker et al., (2004) in SSA more than 99% of the cases of HIV infection prevalent in 2001 were associated with a sexually acquired infection at some point in the chain of transmission[2]. Although this statistic was calculated some years ago, it highlights the fact that, especially in SSA, risky sexual behaviour is a likely cause of most new HIV infections, "If unsafe sex were to cease, most parts of the world would see a substantial drop in the number of new HIV infections" (Slaymaker et al., 2004, p. 1178).

Thus a better understanding of why people engage in risky sexual behaviour, in spite of the very serious consequences, is essential for the tailored design of effective prevention programmes, especially as "without a cure for HIV/AIDS, prevention is by far the most effective strategy against the spread of HIV" (Njororai, Bates, & Njororai, 2010, p. 69). As highlighted by Lammers et al. (2008), if it is ignorance that causes people to behave riskily, increasing their chances of spreading the virus, then education should be the focus of prevention programs. However, if it is innate time and risk preferences that drive risky sexual behaviour then education may not be a sufficient method of prevention. Furthermore, there is increasing evidence of the need and difficulty associated with affecting positive behavioural change so as to reduce HIV transmission, "[B]ehavioural interventions are essential but incompletely efficacious" (De Cock, Gilks, Lo, & Guerma, 2009, p. 7).

Voluntary counselling and testing (VCT) is an intervention which has long been suggested as a potentially effective tool in the efforts to alleviate the spread of HIV (Dieffenbach & Fauci, 2009). In the past many countries and international organisations have invested significant financial and human resources in scaling up the implementation of VCT programmes (Global Business Coalition on HIV/AIDS, 2004). As highlighted by Thornton (2008), the main assumption behind "testing for prevention" is that knowledge of HIV status will empower individuals to either protect themselves in future sexual relationships, if diagnosed HIV-negative, or others, if -positive. This implies that updating of behaviour occurs upon receipt of results. Although evidence in support of this claim is mixed, little is known about the channels through which VCT may affect sexual decision-making. The purpose of this study is to test whether learning one's HIV status has an impact on risky sexual behaviour via the channel of time and risk preferences. In a developing country context, "literature that associates sexual behaviour with quantified risk and time preferences scarcely exists" (Lammers & van

[2] This was compared to figures as low as 25% in Eastern Europe and up to 95% in parts of Latin America (Slaymaker, et al. 2004).

Wijnbergen, 2008, p. 2). With the analysis and research undertaken for this paper I aim to contribute to this gap in the literature.

Expected Utility Theory (EUT) forms the foundation upon which the economic concepts of risk and time are based. An underlying assumption of EUT is the neo-classical view that "preferences are fixed, while constraints change" (Said, Afzal, & Turner, 2015, p. 168). There is a large body of literature contradicting this assumption and presenting the "potential for behavioural learning" or the fact that life experiences can shape preferences in a nature reminiscent of 'Bayesian updating under limited information' (Said, Afzal, & Turner, 2015, p. 168). Thus economists have begun to investigate if tastes respond systematically to economic shocks (Callen, 2015). In the context of HIV, the receipt of results constitutes an external shock that may have an impact on preferences with important implications for behaviour.

Using data from the Malawi Longitudinal Study of Families and Health (MLSFH), I conduct the analysis in two stages. In stage 1 I employ an instrumental variables strategy to test if VCT has an enduring impact on time and risk preferences. Randomly assigned vouchers to collect results as well as distance to VCT centres are used as IVs for VCT attendance (Thornton, 2008). In stage 2, I test if the detected short-term impact of VCT on behaviour is present 2 years later and whether this effect is explained via the channel of time and risk preferences. I do this by controlling for individual discount rates (IDR) and coefficients of relative risk aversion (CRRA) in a model adapted from Thornton (2008). Results indicate little significant evidence of an enduring impact of VCT on time/risk preferences, and risky sexual behaviour 2 years after receipt of HIV results. It also appears that, on average, these preferences are not a significant channel through which VCT affects behaviour. This suggests that post-VCT behavioural change is achieved via some other drivers of behaviour, indicating the need for further investigation of the mechanisms behind effective HIV prevention programmes.

The paper proceeds as follows: Section 2 proposes a conceptual framework of HIV testing and behaviour. The data and the experimental design will be described in Section 3, while section 4 presents the empirical strategy. Sections 5 and 6 present results and discussion respectively followed by concluding remarks in section 7.

## 2. HIV testing and behaviour: a conceptual framework

Despite the emphasis on testing as a key policy response to the HIV/AIDS epidemic, as highlighted by Gong (2015, p. 32), "a major question remains: how does HIV testing affect risky sexual behaviour?" From a policy-maker's perspective, given that VCT serves two purposes (prevention and access to treatment) it may be a desirable intervention if, at a minimum, it does not increase the number of HIV infections. Conversely, the positive effect of treatment on the epidemic, could be counteracted if VCT leads some people to engage in riskier sexual behaviour (Gong, 2015).

The findings of previous studies which have examined the general impact of HIV testing on risky behaviour have been mixed (Eriksson & Sovero, 2015). Some empirical studies, such as Denison et, al. (2008) find only moderate support for VCT as an effective prevention strategy. The authors of this meta-analysis of seven developing country-based studies[3], over the period 1990-2005, found that

[3] These included studies from Rwanda, Kenya, Thailand and Uganda.

although VCT recipients were significantly less likely to engage in unprotected sex than they were before receiving VCT, or when compared to participants who had not received VCT, there was no significant effect on the number of sexual partners post-VCT (Denison, O'Reilly, Schmid, Kennedy, & Sweat, 2008). Thornton (2008) finds a significant short-term impact: individuals who received HIV-positive results, were three times more likely to purchase condoms, two months later, than HIV-positives that did not learn their results. However, the magnitude of the difference in the number of condoms bought is relatively small. On average HIV-positive individuals who attended VCT bought only two more condoms than those who did not (Thornton, 2008). Thornton (2012), finds that in this same cohort of Malawian respondents, two years later, there are relatively few enduring significant differences in economic behaviour between those who learned and did not learn their HIV status. Specifically, "while learning results had short term effects on subjective belief of HIV infection, these differences did not persist after two years. Consistent with this, there are relatively few differences [...] in savings, income, expenditures and employment between those who learned and did not learn their status" (Thornton, 2012, p. 1).

There may be several channels through which VCT affects behaviour. Considering the general findings above and so as to guide discussion of some more 'channel-specific' results below, I propose the following conceptual framework of sexual behaviour in a time of HIV. It also serves to illustrate how time and risk preferences may play a role as a potential channel through which VCT affects risky sexual behaviour. Each channel and its related literature will be discussed in turn.

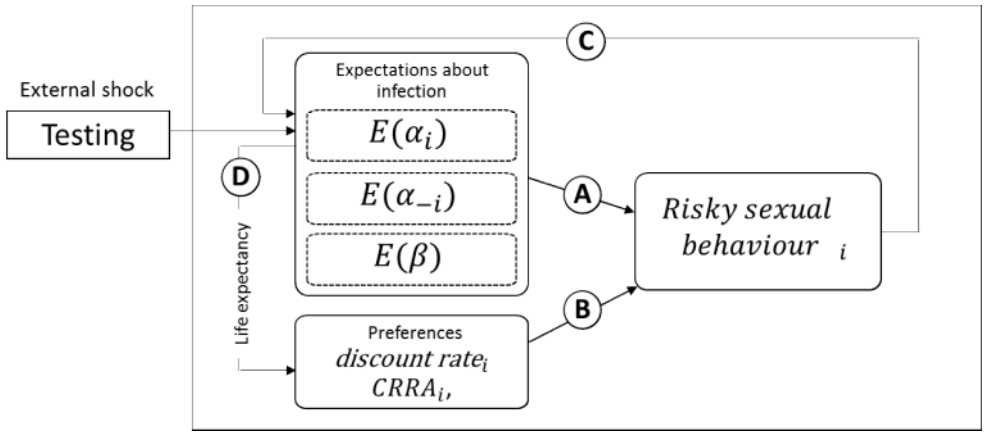


*Figure 1: Channels through which sexual behaviour may be affected*

In figure 1, the main influencers of an individual's risky sexual behaviour are divided into two groups. The first contains expectations about the probability that *I* or *my partner* is infected with the virus, represented by $E(\alpha_i)$ and $E(\alpha_{-i})$ respectively. $E(\beta)$ is the expectation (or subjective belief) of the probability that the virus is transmitted during one unprotected/risky sexual encounter. The impact of expectations on risky sexual behaviour is shown by 'A'.

The dimension of subjective beliefs regarding HIV infection proves to be an important one in a study by Gong (2015). He argues that risky sexual behaviour is a function of these beliefs and that learning one's HIV results may substantially alter such beliefs if the diagnosis is unexpected. This notion introduces the concept of low and high "priors" - individual expectations about the pre-VCT likelihood of being infected. Gong hypothesises that post-VCT risky sexual behaviour will only change for low-priors who receive a positive result or high-priors who receive a negative result. This is a further refinement of Boozer and Philipson's (2000, p.423) theory in which "There is only value of information

when the test is informative and behaviour is information-elastic". Using data from a study based in Kenya and Tanzania which randomly assigns offers of HIV testing and uses biological markers as objective proxies of risky sexual behaviour, Gong (2015, p. 33) finds that respondents surprised by the results of a positive test "have a 10.5 percentage point *increase* in their likelihood of contracting an STI [between testing and follow-up] compared to an HIV-positive control group". Respondents surprised by an HIV-negative test "have a 5 percentage point *decrease* in the likelihood of contracting an STI compared to an HIV-negative control group". These findings are contradictory to the conventional thinking (that VCT will induce HIV-positive people to protect others) and indicate that self-interests dominate altruistic preferences in sexual-decision making. In this case individuals who discover they are HIV-positive have little incentive to practice safe sex, while those who discover a negative result have greater incentives to avoid risky behaviour.

The second group in figure 1 contains preferences, including individual discount rates (IDR) indicative of time preference and coefficients of relative risk aversion (CRRA), showing risk preference[4]. Intuitively, one may hypothesise that those with higher discount rates (myopic) and lower levels of relative risk aversion are more likely to engage in risky sexual behaviour than those with low discount rates (forward-looking) and high levels of risk aversion. Thus channel 'B' represents the potential effect of time and risk preferences on risky sexual behaviour.

In the US Chesson et al. (2006) show that time preferences of a group of adolescents are significantly associated with a range of sexual experiences, including those that may be classified as risky, such as sexual debut before the age of 16. However, they find an insignificant difference between the discount rates of those infected and not infected with a sexually transmitted disease (HSV-2). A UK-based study by Reimers and Maylor (2009), investigates the link between time preference and self-reported behaviours considered as impulsive. While the implications for transmission of sexually transmitted diseases were not specifically discussed, results did reveal that impulsive decision-making choices displayed in hypothetical discounting scenarios can be extended to real-world choices about behaviours relating to sex, smoking and obesity.

As mentioned above, research on the relationship between measured time and risk preferences and their implications for risky behaviour particularly that associated with the transmission of STIs appears to be much less common in the developing country context. Lammers, et al., (2008) report results from an experiment with student participants in South Africa and investigate whether risky behaviours leading to increased perceived HIV contraction risk can be explained by risk and time preferences. Findings point to the fact that "respondents do not continue to practice unsafe sex because of ignorance, but because they are less risk averse and value the future less than those that do not." (Lammers, et al., 2008, p.23). The authors conclude that "risk and time preferences not only have an impact on risky sexual behaviour, but they are also related to perceptions of HIV contraction risk" (Lammers, et al., 2008, p.23).

Channel 'C' represents the feedback which may occur from 'Risky Sexual Behaviour' to expectations about infection. That is, subjective beliefs about infection could be continuously updated based on

[4] The higher the discount rate, the lower the level of patience and the higher the CRRA, the higher the level of relative risk aversion.

risky sexual encounters. In studies based in Burundi and Malawi, respectively, Sterck (2013) and Delavande and Kohler (2012) report general overestimation of HIV transmission rates among non-specialist respondents. Both studies show that on average the *estimated* transmission rate per single act of sexual intercourse with an HIV-positive partner is greater than 80%. In reality this rate of transmission is lower than 1% (Boily, et al., 2009). This highlights the potential risk of reverse causality between behaviour and preferences introduced via channel 'C' which will be discussed as part of the empirical analysis presented below.

If, as suggested by Gong (2015, p.37), VCT is considered as a "shock to beliefs" then its direct effect is shown by the arrow from 'Testing' to 'Expectations about infection'. Furthermore, I propose that this shock to beliefs also has an effect on time and risk preferences via channel 'D' because of the possible effect that learning one's HIV-status has on life expectancy. Although there are studies which examine the effect of measured time and risk preferences on the demand for health screening and tests (Picone, Sloan, & Taylor, 2004) there is little research explaining direct effects of the associated diagnoses on quantified time/risk preferences. As mentioned above, because of important policy implications, the impact of HIV testing on risky behaviour (in general) has received considerable attention (Delavande & Kohler (2012), Thornton (2008), Corbett et, al. (2007)) however, little is known about the role of time/risk preferences as a potential channel through which VCT may affect sexual decision-making. The purpose of this study is to empirically test the importance of this channel ('D') as well as channel 'B'.

This analysis will be carried out via the evaluation of three hypotheses as follows:

> *Hypothesis 1:* VCT decreases the individual discount rate (IDR) and increases the coefficient of relative risk aversion (CRRA) of HIV-negative individuals who learn their status as compared to those who do not (channel 'D')
> *Hypothesis 2:* VCT increases the IDR and decreases the CRRA of HIV-positive individuals who learn their status as compared to those who do not (channel 'D')
> *Hypothesis 3:* The impact of VCT on risky sexual behaviour occurs via the channel of time/risk preferences (channel 'B')

These hypotheses are consistent with the notion that given the implications for life expectancy and the findings of Gong (2015) in opposition to altruism, receiving an HIV-negative result will induce more forward-looking, less risky sexual behaviour (protecting oneself from contraction). Whereas receiving an HIV-positive diagnosis will induce less forward-looking more risky behaviour, due to the associated disincentive to protect others.

# 3. Data description

## 3.1 Malawi Longitudinal Study of Families and Health (MLSFH)

This paper uses data from the nationally representative MLSFH established in 1998 and developed over 6 subsequent rounds (2001, 2004, 2006, 2008, 2010 and 2012) (Kohler, Payne, Bandawe, & Kohler, 2015). The MLSFH includes questions about health, sexual behaviours and household dynamics for up to 4000 individuals randomly selected from approximately 120 villages in the districts of Rumphi, Mchinji and Balaka (see figure 2).

For the empirical analysis in this paper I use the 2004 and 2006 waves of the survey, for three main reasons. Firstly, respondents were offered free home-based counselling and tests for HIV in 2004. 2905 respondents accepted a test out of 3198, from across the three districts, to whom tests were offered. Secondly, Rebecca Thornton implemented an experimental design during the 2004 wave. The randomised components of this design enable the primary method of identification used in this paper. The final reason for the use of these waves of the survey is that both included standard single-delay discounting questions from which I elicit the respondents' discount rates. I also calculate a coefficient of relative risk aversion using ordered lottery selection questions asked in 2006.

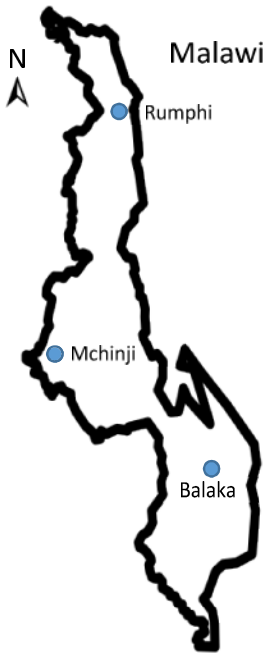

*Figure 2: MLSFH study sites*

## 3.2 Key features of the experimental design

The experimental design was based on two components. The first involved the random allocation of monetary incentives (vouchers), given to respondents by nurses upon completion of an HIV test. Random allocation of voucher amounts was achieved as each respondent was able to draw his/her own token out of a bag which indicated a monetary amount. 82% of those who were tested received any voucher, between zero and three dollars[5]. The average total voucher amount was 1.08 USD, worth approximately one day's wage (Thornton, 2008).

HIV results became available two to four months after the test samples were taken. At this time temporary voluntary counselling and testing (VCT) centres, in the form of small portable tents, were randomly placed throughout the districts. On average respondents who were tested lived two kilometres from the VCT centres with more than 95% living within five kilometres. Respondents were informed of the location and operational hours of their assigned centre and although they were allowed to attend any of the VCT centres, less than 6% attended a centre other than the one to which they were assigned. Upon collection of results all respondents received individual counselling about safe sexual practices. Vouchers were then redeemed and those who received HIV-positive diagnoses were referred to the nearest permanent clinic for further counselling (Thornton, 2008). About two months after the results were available, respondents from Balaka and Rumphi, who had been tested (including those who did and did not obtain their results) were re-interviewed. Interviewers had not been part of the testing process and did not know the respondent's HIV status. Respondents were paid "30 cents as appreciation for participation" at the end of the interview and "offered the opportunity to purchase condoms at half the subsidized retail price", using only the money they had just received (Thornton, 2008, p. 1837). 24% of these respondents purchased any condoms and for those who did the quantity was 3.5 on average.

## 3.3 Eliciting time and risk preferences

### 3.3.1 Time preferences in the MLSFH

Individual discount rates (IDR) serve as a measure of time preference and indicate the rate at which individuals are willing to trade current for future consumption (Coller & Williams, 1999). As pointed

[5] Drawing a zero token meant that the respondent received no voucher.

out by Andreoni and Sprenger (2012, p. 3333), "Understanding and estimating time preferences is obviously of great importance to economists, marketers and policy makers" due to the associated implications for behaviour especially in decision-making of an intertemporal nature. The Multiple Price Listing (MPL) approach is the most commonly used method of elicitation (Andreoni & Sprenger, 2012). Individuals are asked multiple times to choose between two payments, a smaller payment closer to the present versus a relatively larger future payment. The interest rate increases monotonically in the price list. The point at which the respondent switches from preference for the sooner to the later payment indicates the interval within which his/her discount rate lies (Andreoni & Sprenger, 2012).

In the MLSFH, information about time preferences is garnered from three questions which are introduced by a hypothetical situation in which the respondent has earned 500 Kwacha for work done for a "trustworthy neighbour" during the previous week. The first two questions are of the usual MPL format, "Do you prefer to receive 500 Kwacha today, or would you prefer $x$ Kwacha a month from now?" Where $x$ is 600 and 750 respectively. The third question, only posed to those who chose the immediate payment for the two preceding questions, allows respondents to choose their own $x$, revealing individual switching points over a continuous choice set as opposed to those elicited from the binary choice sets in the first two questions.

Assuming expected utility theory (EUT) applies for choices over risky alternatives and that discounting is exponential, then a respondent is indifferent between two income options, $M_t$ and $M_{t+k}$ if the following equation holds:

$$U(M_t) = \frac{1}{(1+\delta)^k} U(M_{t+k}) \quad (1)$$

$U(M_t)$ is the utility of a monetary outcome, $M_t$ at time $t$, $k$ is the horizon for delivery of the delayed monetary outcome, $M_{t+k}$ and $\delta$ is the discount rate that equalizes the present value of utility from the delayed and immediate payments. The standard approach relies on the assumption of risk neutrality. In this case the utility function will be linear and (1) can be rewritten as:

$$M_t = \frac{1}{(1+\delta)^k} M_{t+k} \quad (2)$$

As the two monetary outcomes are observed I am able to calculate a value of $\delta$ for which (2) holds with equality. Respondents are then divided into three groups according to their exhibited levels of patience and assigned the appropriate discount rates as follows:

*Table 1: IDR assignment according to exhibited levels of patience as implied by responses to delay-discounting questions*

| Group | Pattern of choices | Discount rate interval (%) | Assigned discount rate (monthly, %) | Daily discount rate (%) |
|---|---|---|---|---|
| (1) Most patient | Chooses the delayed payment option in the first question (600K) | (0, 20) | 10 | 0.61 |
| (2) Medium patience | Chooses the immediate payment in the first question and the delayed payment in the second | (20, 50) | 35 | 1.37 |
| (3) Least patient | Chooses the immediate payment for both questions. | (50, ∞) | Individual-specific derived from answers to the third question | $\delta = \left(\frac{M_{t+k}}{500}\right)^{\frac{1}{30}} - 1$ |

A few respondents - 63 in 2004 and 13 in 2006 - exhibited irrational switching behaviour in their choices, violating the 'monotone switching rule' implied by EUT. It is not clear from the literature what is best to do about these observations but because they are relatively few it is safe to assume that they can be dropped without significant implications for power or inference. Due to the fact that

respondents in group 3, table 1, were asked to choose their own amount for which they would be willing to wait, some noteworthy outliers are observed, including an amount of 40000 Kwacha (IDR of 7900%) in 2004 and two selections of 100000 Kwacha (IDR of 19900%) in 2006. The decision was thus taken to exclude observations 3 standard deviations above the median (there are no negative IDRs). In 2004 and 2006 this amounted to 24 and 5 observations respectively. Even with the exclusion of outliers, the mean monthly IDRs appear to be high at 81% in 2004 and 191% in 2006. According to Andreoni and Sprenger (2012, p. 3334) this is not an uncommon outcome of the MPL methodology, "A notable feature of MPLs (and other experimental methods) is that they yield high average discount rates. Estimates of annual discount rates over one hundred percent are common". Andreoni and Sprenger (2012, p. 3334) also suggest that "[A] possible explanation […] may lie in experimenters' frequent assumption of linear utility, which leads to upwardly-biased discount rate estimates if utility is concave". In the next section it will be shown that the majority of the sample exhibits risk averse preferences consistent with a concave utility function. Thus the risk neutrality assumption employed in the above calculation, in line with earlier literature, is probably too strict a claim and may be contributing to the upward bias of the measured IDRs.

In an effort to correct for the upward bias Andersen, et al., (2008) focus on the theoretical link between elicited risk attitudes and IDRs. They use structural maximum likelihood methods so as to specify and evaluate a function for the choices that respondents make. This allows for joint estimation of the risk parameter and discount rate in what has been dubbed the "Double Multiple Price List Approach" (Andreoni & Sprenger, 2012, p. 3334). With the "Convex Time Budget Method" (CTB), Andreoni and Sprenger (2012) further develop these frontier techniques by designing an experiment in which they "convexify experimental budgets". In this way the assumption of linearity in the utility function is relaxed at the outset of the experiment. CTB also jointly estimates the curvature and time preference parameters. The MLSFH data is not conducive to the application of these methods. Thus traditional time and risk preference measures will be used in the forthcoming analysis, with particular acknowledgement of the upward bias in the IDRs.

### 3.3.2 Risk preferences in the MLSFH

Three questions involving choice over uncertain prospects, in a format similar to that introduced by Binswanger (1980) are included in the 2006 wave of the MLSFH. These questions allow for elicitation of risk preferences using the standard "Ordered Lottery Selection (OLS) method" outlined below (Jamison, Karlan, & Zinman, 2012, p. 5).

Under EUT, in the standard approach, I assume the utility function is of the constant relative risk aversion functional form:

$$U(M) = \frac{M^{1-\rho}}{1-\rho} \tag{3}$$

For $\rho \neq 1$, where $\rho$ is the individual coefficient of relative risk aversion (CRRA), which captures the respondents' risk-attitudes. With this functional form, $\rho = 0$ indicates risk neutrality, $\rho > 0$ indicates risk aversion and $\rho < 0$ indicates a risk-loving attitude (Andersen, Harrison, Lau, & Rutstrom, 2008). In this specification, utility depends only on consumption and thus ultimately on earnings, which in this experimental design is the monetary outcome from the lottery selection questions. According to Fields (2005, p. 4), this is a reasonable assumption to make in the context of a developing country like Malawi, where "large numbers of people value additional goods greatly compared to leisure, [and thus] the utility-maximization assumption may often be fruitfully replaced by an income-maximization assumption".

Implied bounds of the CRRA are calculated according to the expected utilities of the certain versus risky gambles proposed by each OLS question. For low levels of risk aversion, $\rho$, for each of the three questions:

$$EU(risky\ lottery) > EU(certain\ outcome) \quad (4)$$

And for high levels of $\rho$:

$$EU(certain\ outcome) > EU(risky\ lottery) \quad (5)$$

The level of $\rho$ at which there is a shift from (4) to (5), indicating the change in preference for safety over risk, is identified for each of the three questions. Those who prefer the risky to the safe lottery will have, at most, a level of $\rho$ given by the point of shift in expected utilities. According to EUT one should observe respondents switching from the risky to the safe lottery at most once. This switching point will reveal the CRRA interval within which the respondent's measure of risk aversion lies. For quantitative purposes the midpoint of this interval is assigned to the respondents for whom this is the switching point, and for the two truncated intervals (groups 1 and 4), I have chosen a value that seems reasonable given the distribution of $\rho$ found in other studies (see Falco (2014), Andersen, et al., (2008)). As there are three questions, there will be four groups of respondents, classified according to their risk preferences as follows:

*Table 2: CRRA assignment according to exhibited levels of risk aversion as implied by responses to OLS questions*

| Group | Pattern of choices | CRRA interval | Assigned CRRA coefficient |
|---|---|---|---|
| (1) Risk-loving | Chooses the gamble (risky prospect) for every question | $(-\infty, 0.1)$ | -0.5 |
| (2) Low risk aversion | Chooses the risky prospects for the two questions with the highest $EU(risky\ lottery)$ and then switches to the certain option for the third question | (0.1, 0.2) | 0.15 |
| (3) Medium risk aversion | Chooses the risky prospect for the question in which the $EU(risky\ lottery)$ is highest and then the certain option for the next two questions | (0.2, 0.25) | 0.225 |
| (4) Most risk averse | Chooses the certain (safe) option for every question | $(0.25, \infty)$ | 0.6 |

Group 4 comprises 61% of the sample. A majority risk averse sample is a common finding in experiments of this nature (see Holt & Laury (2002), Binswanger (1980), Falco (2014), Anderson, et. al. (2008)).

## 3.4 Characteristics of the sample

The main sample of 1393 respondents[6], used in this paper, consists of those who accepted an HIV test, for whom there were certain results and basic covariate data (14 respondents' results were indeterminate). At baseline the sample is 47% male and 32 years old on average. 66% of the respondents are married, and have on average 4 living children. Respondents have 4 years of education on average and most are subsistence farmers consistent with the high percentage of land ownership (71%). The HIV prevalence rate is 9.9% (8.7% for males and 11% for females).

Importantly it appears that the MLSFH is a nationally representative sample of the rural population of Malawi, "Comparisons of the 2010 MLSFH study population with the rural samples of the Malawi DHS

[6] This figure is smaller than the 2905 who initially accepted the HIV test. This is largely due to the fact that the variable for 'distance to VCT' was not in the original dataset and had to be merged from Thornton's (2008) publically available dataset from the *American Economic Review* Website. Through the merging process, in which respondents were matched using multiple variables, I unfortunately lost approximately 400 observations, who could not be uniquely identified.

and IHS3 surveys reveal that the MLSFH study population continues to closely match the characteristics of nationally-representative cross-sectional surveys." (Kohler, et al., 2014). 85% of Malawians live in rural areas with the majority participating in home production of crops and a lesser proportion in small-scale market activities (Kohler, et al., 2015). Malawi has a "generalized" HIV/AIDS epidemic, with a prevalence rate of approximately 10.6% among adults between the ages of 15-49 (Malawi National AIDS Commission, 2015). The associated impact of HIV on the country's population has been non-trivial, 65% of deaths among 15-59 year-olds are attributed to AIDS every year (Malawi National Statistical Office, 2011).

*Table 3: Summary Statistics*

| | **Baseline (2004)** | | **Follow-up (2006)** | |
|---|---|---|---|---|
| Observations | 1 393 | | 1 251 | |
| | Mean | SD | Mean | SD |
| *Demographic characteristics* | | | | |
| Male | 0.47 | (0.50) | 0.47 | (0.5) |
| Age | 31.63 | (13.25) | | |
| Education in years | 4.09 | (2.77) | 3.75 | (2.95) |
| Married | 0.66 | (0.48) | 0.75 | (0.43) |
| Number of children alive | 3.98 | (3.02) | 3.71 | (3.58) |
| Owns land | 0.71 | (0.46) | 0.72 | (0.45) |
| *Health indicators* | | | | |
| Self-reported non-zero likelihood of HIV infection | 0.27 | (0.444) | 0.270 | (0.442) |
| HIV-positive | 0.099 | (0.299) | | |
| Had an HIV test before 2004 | 0.174 | (0.379) | | |
| Purchased condoms at 2-month follow-up interview | 0.241 | (0.428) | | |
| Reported purchasing condoms in previous 2 months | | | 0.070 | (0.254) |
| Number of condoms purchased (if >0) | 3.506 | (1.979) | 11.086 | (10.996) |
| *Time and risk preferences* | | | | |
| Monthly discount rate | 0.81 | (1.382) | 1.91 | (3.423) |
| Coefficient of relative risk aversion | | | 0.40 | (0.298) |
| *Instrumental variables* | | | | |
| Received any incentive | 0.82 | (0.38) | | |
| Incentive amount (Dollars) | 1.08 | (0.95) | | |
| Distance to testing centres (kilometres) | 1.98 | (1.21) | | |
| Obtained results | 0.67 | (0.47) | | |
| Obtained results (if incentive = 0) | 0.37 | (0.48) | | |

Notes: The follow-up sample includes those who were tested in 2004 and re-interviewed in 2006. As described in 3.3.1, outliers are excluded in the calculation of mean monthly discount rates. "Number of condoms purchased" pertains to quantity purchased at the 2 month follow-up interview for 2004; and in the 2 months prior to the interview in 2006.

# 4. Empirical strategy

## 4.1 Does VCT have an enduring effect on time and risk preferences?

In order to evaluate whether learning one's HIV status has an impact on time and risk preferences two years *ex post*, I propose the following model:

$$Y_{ij} = \beta_0 + \beta_1 GotResults_{ij} + \beta_2\left(GotResults_{ij} * HIV_{ij}\right) + \beta_3 HIV_{ij} + \beta_4(\boldsymbol{X}_{ij}) + \varepsilon_{ij} \qquad (8)$$

$Y$ is the individual discount rate (IDR) or coefficient of relative risk aversion (CRRA) of individual $i$ in village $j$ measured in 2006. $GotResults$ is a dummy variable indicating whether or not the respondent attended a VCT center to collect their HIV results in 2004. $HIV$ is a dummy indicating an HIV-positive or –negative result. Learning results is interacted with HIV status so as to evaluate the variation in effects on time and risk preferences according to HIV-status. $\boldsymbol{X}$ is a vector of baseline individual control

variables including age, age-squared, gender, years of education, married, number of living children, baseline IDR and regional fixed effects. Inclusion of these control variables is influenced by Bauer and Chytilova (2009). They find that education significantly decreased IDR for men in Uganda. Age (based on the permanent income hypothesis), income and intra-household relations have also been shown to be significant predictors of IDR in this and other settings (Bauer & Chytilova (2009), Tanaka, et al., (2016), Bauer & Chytilova (2009b)). The baseline IDR is included as a control variable considering the benefits for precision of estimators as presented by McKenzie (2012, p. 210). CRRA at baseline is not available and therefore not included as a control.

The estimation of this model serves to test hypotheses 1 and 2 in the conceptual framework. In specification (8) $\beta_1$ represents the difference in outcome for HIV-negative individuals who did and did not learn results. While $(\beta_1 + \beta_2)$ represents this difference in outcome, for HIV-positive individuals. As outlined in the conceptual framework, I hypothesise that for HIV-negative respondents VCT will, on average, decrease $IDR_{2006ij}$ $(\beta_1 < 0)$ and increase $CRRA_{2006ij}$ $(\beta_1 > 0)$ as compared to those who do not obtain their results, all else constant. For HIV-positive individuals, I hypothesise that obtaining results will, on average, increase $IDR_{2006}$ $(\beta_1 + \beta_2 > 0)$, and decrease $CRRA_{2006}$ $(\beta_1 + \beta_2 < 0)$, when compared to those who do not attend VCT, all else constant.

### 4.1.1 Potential sources of endogeneity

#### Omitted variables

The main econometric limitation of testing the above hypotheses using model (8) is that the decision to obtain HIV results is non-random. Due to the fact that sample respondents choose whether or not to learn their HIV status, the variable $GotResults$ will be endogenously determined. In other words, there is selection into learning HIV status based on observables and unobservables. It follows that VCT attendance is not independent of potential outcomes, violating the unconfoundedness assumption required for consistent OLS estimation of the treatment effect of VCT on time/risk preferences. The unobservables will form part of the composite error in (8) and their correlation with the dependent and one or more independent variables could cause omitted variables biases in the OLS estimates.

Possible omitted variables may include employment status, a measure of aspirations for the future and level of household income. As the latter is unobserved in the 2004 wave I attempt to control for wealth in (8) by including an indicator variable for land-ownership at baseline. There are several reasons why this may not be a good proxy for income. In this context ownership of land may imply that the household relies on agricultural means of subsistence. A non-landowner could be someone who works in an urban area and thus has no need for land ownership for agricultural income. Urban employment implies higher earnings than those from subsistence farming. Thus for the Malawian sample used in this paper, land-ownership may not be a good proxy for income which could be one of the omitted variables causing biases in the OLS estimators of $\beta_1$ in (8).

The direction of the potential biases is inconclusive. If one initially just considers HIV-negative respondents, those who are wealthier may have more means to travel to VCT centres (positive correlation between income and $GotResults$). On the other hand, wealthier respondents may perceive the opportunity cost of taking time out of their (work-) day to collect results as sufficiently high enough to deter them from attending a VCT centre (negative correlation). The effect of income on preferences also remains uncertain, "it is a matter of controversy as to how time preference and the discount rate relate to the decision maker's degree of affluence measured by income and/or wealth" (Ikeda, Kiyoshi Kato, Ohtake, & Tsutsui, 2016, p. 330). If discount rates decrease with income while the propensity to obtain results increases with income, then $\beta_1$, the coefficient on $GotResults$

for HIV negative individuals may be biased downwards. Alternatively if discount rates decrease with income and the propensity to obtain results also decreases with income, then $\beta_1$ will be biased upwards. In other words the effect of learning one's results on discount rates will be overstated if income is not controlled for. Similarly the direction of the potential bias on the estimator of $\beta_1$ when CRRA is the dependent variable is also inconclusive due to the fact that there is on-going debate as to whether risk aversion rises or decreases with income.

#### Reverse Causality

The relationship between learning results and time and risk preferences may be subject to reverse causality. On the one hand, as outlined in the conceptual framework, given the implications for life expectancy, receipt of HIV results may have an impact on time/risk preferences. However, such preferences could explain some of the propensity to actively learn results. For example a highly impatient person (high IDR) may lose interest in the wait for results and opt not to learn them (negative correlation between IDR and $GotResults$). Such reverse causation could lead to a downward bias in the OLS estimator of the impact of $GotResults$ on time preference. In the case of risk aversion: it is likely that propensity to learn results increases with risk aversion (positive correlation between CRRA and $GotResults$). This may result in an upwardly-biased estimator of the impact of VCT on CRRA.

### 4.1.2 Identification

#### Instrumental variables (IV)

IV estimation is one way to ensure that the results are not subject to endogeneity biases due to omitted variables and reverse causality. Instruments which satisfy both the relevance and validity conditions would allow for isolation of the exogenous components of $GotResults$ and $GotResults * HIV$ and subsequent measurement of unbiased and consistent estimators of the impact of learning HIV results on time/risk preferences. Due to the fact that there are effectively two endogenous covariates in the structural model (8), two or more excluded instruments will be required for estimation using two-stage least squares (2SLS). This is so as to avoid the problem of under-identification while fulfilling both the order and rank conditions (Wooldridge, 2006).

The implementation of the experimental design in the MLSFH in 2004, allows for the instrumentation of $GotResults$ and $GotResults * HIV$ with randomly assigned incentives and distances to the VCT centres[7]. The impact of these instrumental variables on learning HIV test results is shown in table 4 below. The probability of obtaining results was "highly responsive" to incentives and the distance to the centres (Thornton, 2008, p. 1839). On average those who received any positive-valued voucher were significantly more likely to attend a VCT centre than those who received no incentive, the difference of 35 percentage points is significant at the 1% level (Table 4, column 2). Every additional dollar of incentive increased the probability of obtaining results by 0.13 percentage points which was also significant at the 1% level (Table 4, column 3). A significant, non-linear relationship exists between distance to the VCT centres and the probability of attendance. In this sub-sample it appears that men were more likely to attend than women, while age does not have an impact on attendance. Results are similar when using the probit as an alternative model.

For the purposes of investigation, specification 1 does not cluster or correct for heteroskedastistic standard errors. I conduct a Breusch-Pagan test for heteroskedasticity and the null: 'constant variance' is rejected. Thus there is not enough evidence to suggest that the errors are homoskedastic. We are unable to test for within group (village) correlation in the error term as it is unobserved. The next best

[7]Importantly this instrumentation strategy was designed and utilised by Thornton (2008). I have been in email contact with her regarding my use of the approach with the different dependent variables to which she gave no objection.

option is to test for within group correlation in the dependent variable. Positive intraclass correlation is observed (column 1) indicating that standard errors should be clustered at the village level. Therefore the rest of the specifications in this study have cluster robust standard errors.

*Table 4: The impact of incentives and distance to VCT centres on obtaining HIV results (Dependent variable: GotResults)*

| | OLS | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Any incentive | 0.345*** | 0.345*** | 0.227*** | 0.227*** |
| | (0.0316) | (0.0316) | (0.0434) | (0.0428) |
| HIV | -0.00554 | -0.00554 | -0.0119 | -0.0148 |
| | (0.0398) | (0.0349) | (0.0348) | (0.0345) |
| Value of incentive | | | 0.00128** | 0.00128*** |
| | | | (0.000488) | (0.000480) |
| Incentive^2 | | | -0.0000021 | -0.0000021 |
| | | | (0.0000015) | (0.0000015) |
| Distance in km | | | | -0.0929*** |
| | | | | (0.0334) |
| Distance^2 | | | | 0.0146** |
| | | | | (0.00652) |
| Male | 0.0481** | 0.0481** | 0.0428* | 0.0428* |
| | (0.0236) | (0.0228) | (0.0229) | (0.0228) |
| Age | 0.000497 | 0.000497 | 0.000791 | 0.000800 |
| | (0.000893) | (0.000959) | (0.000953) | (0.000956) |
| District FE | Yes | Yes | Yes | Yes |
| N | 1393 | 1393 | 1393 | 1393 |
| r2 | 0.132 | 0.132 | 0.147 | 0.151 |
| Fstat | 35.08 | 41.45 | 33.41 | 33.21 |
| B-P chi2 | 63.04 | | | |
| Intraclass corr. | 0.0704 | | | |

Notes: Marginal effects; Standard errors in parentheses; *** p<0.01; ** p<0.05; * p<0.10

The highly significant nature of the correlation between $GotResults$, receipt of any incentive, the amount of the incentive, distance and distance-squared suggests that these variables satisfy the relevance condition, $Cov(z_i, x_i) \neq 0$. For use as instrumental variables, they must also satisfy the validity condition, $Cov(z_i, u_i) = 0$, that is there must be no correlation between the instrument and the error term (Wooldridge, 2006). In this case this is a reasonable assumption to make given the randomisation of the allocation of incentives and the distance to the VCT centres. It is thus unlikely that these relatively small incentives (on average only worth about a day's wage) and distances would have an impact on respondents' IDRs and CRRAs. Therefore incentives and distance to the VCT centres are likely valid instruments for the endogenous explanatory variable, $GotResults$.

Since incentives and distance are both uncorrelated with the error term $u$, any linear combination of these two instruments is also uncorrelated with $u$ and is thus also a valid IV. Therefore in an effort to most efficiently use the information available from the two original instruments, and following the recommendation of Thornton (2008), the excluded instruments utilised in the estimation of (8) are a linear combination of the original distance and incentive variables as specified in the first stage regressions shown in table 5 below.

The F-statistics reported in tables 4 and 5 exceed Staiger and Stock's (1997) 'rule-of-thumb' threshold of 10. Thus the instrumental variables' joint significance in the first stage regressions gives an indication that the IVs are relatively strong and further evidence of their relevance. This concept of instrument strength will be revisited in section 5, where more formal tests are applied to the IV specifications.

*Table 5: First stage regressions*

| | GotResults | GotResults*HIV |
|---|---|---|
| Any incentive | 0.325*** | 0.000204 |
| | (0.0507) | (0.00569) |
| Value of incentive | 0.000875 | 0.000000100 |
| | (0.000681) | (0.00000283) |
| Value of incentive^2 | -0.000000725 | 0.0000 |
| | (0.00000229) | (0.000) |
| Distance in km | -0.120*** | 0.000285 |
| | (0.0444) | (0.00796) |
| Distance^2 | 0.0174** | -0.0000501 |
| | (0.00836) | (0.00140) |
| Any incentive*Male | -0.0883 | -0.000384 |
| | (0.0833) | (0.0107) |
| Value*Male | 0.0000414 | -0.000000196 |
| | (0.00102) | (0.00000555) |
| Value^2*Male | -0.000000989 | 0.0000 |
| | (0.00000335) | (0.000) |
| Distance*Male | 0.0903 | -0.000590 |
| | (0.0570) | (0.0165) |
| Distance^2*Male | -0.0191 | 0.000103 |
| | (0.0116) | (0.00289) |
| Male | 0.0501 | 0.00101 |
| | (0.0739) | (0.0283) |
| Any incentive*HIV | 0.00105 | 0.319* |
| | (0.194) | (0.192) |
| Value*HIV | 0.00102 | 0.00190 |
| | (0.00282) | (0.00273) |
| Value^2*HIV | -0.00000402 | -0.00000475 |
| | (0.00000814) | (0.00000795) |
| Distance*HIV | -0.245** | -0.377*** |
| | (0.112) | (0.104) |
| Distance^2*HIV | 0.0412** | 0.0606*** |
| | (0.0204) | (0.0192) |
| HIV | 0.170 | 0.644*** |
| | (0.146) | (0.145) |
| Constant | 0.454*** | -0.000505 |
| | (0.0586) | (0.0141) |
| N | 1393 | 1393 |
| r2 | 0.121 | 0.694 |
| F-stat | 16.34 | . |

Notes: Standard errors in parentheses. Interaction terms included in the estimation of first stage regressions but not shown in table 5 include: *Male*Any*HIV*; *Male*Value*HIV; Male*Value^2*HIV; Male*Distance*HIV and Male*Distance^2*HIV.*

### 4.1.3 Robustness check: Difference-in-difference

Time preference questions were asked in the baseline survey in 2004 - a few months after which time the test results became available - and then again in 2006. Due to this sequence of events the receipt of HIV results (VCT) can be classified as a 'shock' which occurs between the two waves. Thus a diff-in-diff approach enables one to estimate the effect of VCT on discount rates (IDRs) by comparing the average difference in IDRs of those who learnt and did not learn their results before and after the 'shock' of receiving them. Using panel methods in this way allows for elimination of any bias-inducing endogeneity caused by the omission of unobservable, time-invariant fixed effects. Assuming that the parallel trends assumption holds I will conduct difference-in-difference estimation as a robustness check of the results of the above estimation.

## 4.2 Are time and risk preferences a channel through which VCT affects risky sexual behaviour?

As mentioned above, using the MLSFH dataset, Thornton (2008), finds a significant short-term impact of VCT on risky sexual behaviour defined by the purchase of condoms observed at follow-up interviews 2 months after results were obtained. I adapt her model, firstly, to test if there is an enduring effect of VCT on risky sexual behaviour as measured two years after receipt of results. Secondly, in order to evaluate hypothesis 3 (channel 'B') in the conceptual framework above I run the model again, controlling for IDR and CRRA as seen in specification (9). The inclusion of $IDR_{2006ij}$ and $CRRA_{2006ij}$ involves the intentional addition of "bad controls" as defined by Angrist and Pischke (2008), so as to test whether their inclusion takes any explanatory power away from *GotResults* and *GotResults*HIV*. A significant change in the coefficients on these variables, ceteris paribus, would indicate that VCT affects risky sexual behaviour via the channel of time and risk preferences. The IV strategy will also be utilised in estimation of the following specification:

$$NumbCond_{2006ij} = \beta_0 + \beta_1 GotResults_{ij} + \beta_2\left(GotResults_{ij} * HIV_{ij}\right) + \beta_3 HIV_{ij} + \beta_4 IDR_{2006ij} + \beta_5 CRRA_{2006ij} + \beta_6(\boldsymbol{X}_{ij}) + \varepsilon_{ij} \quad (9)$$

$NumbCond_{2006ij}$ is a count variable of the self-reported number of condoms purchased by respondent $i$ in village $j$ in the two months before the 2006 interview. $\boldsymbol{X}$ includes the individual baseline controls described above and the non-zero likelihood of being infected at baseline. It is important to note that $IDR_{2006ij}$ and $CRRA_{2006ij}$ may be endogenous in (9). As explained in figure 1, potential reverse causality may occur via channel 'C': risky sexual behaviour (proxied here by condom-purchase) affects expectations about infection, which would in turn affect time and risk preferences via channel 'D'. Thus inference should proceed with caution.

### 4.2.1 Robustness check: Negative binomial regressions

Due to the fact that $NumbCond_{2006ij}$ is a count variable, as a robustness check of the results obtained from (9) I run negative binomial regressions of the same specification using the 'control function approach' as described by Hilbe (2011). This entails, essentially, a manual implementation of 2SLS in which predicted residuals from the first stage OLS regressions shown in table 5 are included as covariates in the second stage negative binomial regressions, so as to control for endogeneity. The negative binomial regression model is chosen over Poisson because a chi-squared goodness-of-fit test strongly rejects the null that the *NumbCond* data follows a Poisson distribution ($p$=0.000). According to Hilbe (2011, p.2) this indicates that there is "overdispersion […] That is the variance is greater in value to that of the mean" in the dependent variable in which case the negative binomial model in more appropriate.

# 5. Results

## 5.1 Main Results: Does VCT have an enduring impact on time and risk preferences?

The results from estimating model (8) using OLS and IV can be seen in Table 6. Although results are not presented all individual controls, specified in 5.1, were included in each estimation. The output in columns 4 and 8 form the basis of this discussion.

In specifications 1-4 the dependent variable is the 2006 individual discount rate (IDR). Row 1 shows no significant impact of learning HIV-negative results on IDR two years *ex post*. Examining the differences between $\beta_{1OLS}$ and $\beta_{1IV}$, although insignificant, it appears that there may be a downward

bias in the OLS estimator of the effect of *GotResults* on IDR. As suggested above, this might be because we are unable to control for income in the model. Due to the fact that most MLSFH respondents are subsistence farmers in rural areas, it may be safe to assume that they are relatively poor. We may assume that these respondents are more likely to want to attend VCT because there are potential gains to be made in terms of follow-up treatment and care (negative correlation between omitted variable, *income* and explanatory variable, *GotResults*). Based on the findings of studies such as, Tanaka, et al., (2016), Di Falco, et al., (2011) and Bertrand, et al., (2004), we may also assume discount rates are decreasing in wealth (negative correlation between income and dependent variable, $IDR_{2006}$). These negative correlations and the assumption that, on average, HIV-negative individuals are likely to have lower discount rates, could explain the downward bias in the OLS estimator of $\beta_1$.

Examining the interaction between obtaining results and actual diagnosis, it can be seen that, controlling for baseline expectations about HIV-infection, those who received a positive diagnosis, had on average, an $IDR_{2006}$ of 328 percentage points lower than those who are HIV-positive but chose not to learn their results ($\beta_1 + \beta_2$, (4)), although this is insignificant at all commonly used significance levels (bottom row, (4)). The fact that the IDR is lower (although insignificantly), implies increased patience two years later for those who attend VCT. This may be a reflection of the fact that counselling is offered to VCT attendees and additional counselling to those diagnosed HIV-positive. Extra counselling would increase one's knowledge about HIV/AIDS and the life-saving treatment available, and thus may have the effect of promoting a longer-term outlook (than would be the case for HIV-positives who chose not to attend VCT).

Interestingly, in column 1 there appears to be a positive effect on $IDR_{2006}$ of receiving an HIV-positive diagnosis, just significant at the 10% level (bottom row, (1)). This implies that on average, VCT-attendance for HIV-positive individuals results in increased discount rates (decreased patience) two years later. This is more aligned to the original hypothesis, although this effect disappears in the IV (2) and when prior-expectations are controlled for (3 & 4). Although in specifications 1 and 3, it appears that HIV-positive individuals have a significantly lower $IDR_{2006}$ on average than HIV-negative individuals, this result disappears in the IV models. As suggested by McKenzie (2012), the 2004 measure of discount rates contributes significantly to the explanation of the 2006 IDR (at the 5% level).

In columns 5-8, the dependent variable is the coefficient of relative risk aversion ($CRRA_{2006}$). Again row 1 indicates that there is no significant impact of VCT on CRRA for HIV-negative individuals. From column 8, it can be seen that the $CRRA_{2006}$ of an HIV-positive individual who attended VCT two years before is, on average, 0.318 units higher ($\beta_1 + \beta_2$) than one who did not attend VCT, but this difference is not significant at any commonly used significance levels. The self-reported likelihood of being infected at baseline also seems to be important in explaining the level of risk aversion. In column (8), a respondent who has a positive expectation of being infected at baseline has a significantly higher level of risk aversion as compared to one who has no expectation of being infected at baseline.

The *Kleibergen-Paap LM* test statistics are reported in table 6 and in all cases we reject the null of under-identification. However, in some cases there may be concern about the strength of the instruments, given that the *Kleibergen-Paap Wald F* statistics are relatively low and thus result in failure to reject the null of weak instruments in the sense that one may have to be willing to tolerate size distortions of up to as much as 25% in the IV estimators. As highlighted in section 4.1, with the full sample size, there was little concern regarding the strength of the instruments. However, due to the loss of observations that occurs in estimating the models - because of the unbalanced nature of

the panel – the instruments become weaker. As a result the standard errors in the IV models are large and this may contribute to the fact that effects shown as statistically significant in the OLS models disappear in IVs. By nature of the methodology, large standard errors are also a consequence of 2SLS. Therefore both the OLS and IV models tested here have limitations. On the one hand we are faced with potential endogeneity biases when using OLS. While weak instruments may reduce our ability to draw conclusive inferences from the IV results. The fact that the number of HIV-positive respondents is relatively small may explain the somewhat unstable nature of the coefficient on *GotResults*HIV*. With the exclusion of outliers in these tests, only 7.51% of the sample is HIV-positive. Thus given these limitations of the data it is necessary that the results are viewed and interpreted with caution.

*Table 6: Measuring the impact of VCT on time and risk preferences (dependent variables: IDR; CRRA)*

| | (1) OLS | (2) IV | (3) OLS | (4) IV | (5) OLS | (6) IV | (7) OLS | (8) IV |
|---|---|---|---|---|---|---|---|---|
| | Individual discount rate (2006) | | | | Coefficient of relative risk aversion | | | |
| GotResults | -0.160 | 0.329 | 0.161 | 0.844 | 0.0165 | 0.0936 | 0.0251 | 0.170 |
| | (0.296) | (0.816) | (0.227) | (0.736) | (0.0296) | (0.0929) | (0.0327) | (0.112) |
| GotResults*HIV | 1.213* | -1.580 | 1.132 | -4.120 | -0.0265 | 0.101 | 0.0740 | 0.148 |
| | (0.644) | (2.162) | (0.798) | (4.075) | (0.103) | (0.136) | (0.144) | (0.258) |
| HIV | -1.028*** | 0.759 | -0.697** | 2.867 | -0.0151 | -0.0861 | -0.141 | -0.180 |
| | (0.290) | (1.716) | (0.283) | (3.310) | (0.0792) | (0.115) | (0.126) | (0.211) |
| IDR2004 | 0.239* | 0.229* | 0.524** | 0.557** | 0.0210* | 0.0198 | 0.0236 | 0.0224 |
| | (0.132) | (0.134) | (0.228) | (0.217) | (0.0124) | (0.0124) | (0.0173) | (0.0173) |
| Non-zero likelihood infected | | | -0.0405 | 0.000604 | | | 0.0499 | 0.0605* |
| | | | (0.294) | (0.295) | | | (0.0317) | (0.0334) |
| Constant | 0.996 | 0.559 | 0.377 | -0.639 | 0.514*** | 0.476*** | 0.445*** | 0.336* |
| | (0.956) | (1.121) | (1.006) | (1.261) | (0.117) | (0.142) | (0.133) | (0.181) |
| Individual controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 512 | 512 | 415 | 415 | 501 | 501 | 408 | 408 |
| r2 | 0.0241 | 0.00465 | 0.0438 | -0.0198 | 0.0240 | 0.000960 | 0.0380 | -0.0157 |
| Fstat | 3.19 | 1.8 | 2.2 | 1.64 | 6.25 | 7.22 | 5.45 | 5.42 |
| KleibergenPaapLM | | 41.154 | | 33.778 | | 38.399 | | 33.615 |
| KleibergenPaapWaldF | | 7.412 | | 4.905 | | 6.766 | | 4.522 |
| B1+B2 | 1.053* | -1.251 | 1.293* | -3.276 | -0.01 | 0.1946 | 0.0991 | 0.318 |
| p-value (B1+B2) | .09 | .53 | .097 | .41 | .92 | .105 | .46 | .17 |

*p<0.1; **P<0.05; ***p<0.01; Robust standard errors in parenthesis, adjusted for 99 village clusters

### 5.1.1 Robustness check: Difference-in-difference

In the diff-in-diff analysis respondents who had reported having an HIV test before 2004 are excluded (17% of the main baseline sample, 231 individuals). The reason for this is to prevent the potential confounding of selection into treatment (violating the parallel trends assumption). Unlike in the specifications tested above, I am unable to control for expectations regarding HIV infection at baseline in the diff-in-diff. This is because the change in expectations ($E(\alpha_{i2006}) - E(\alpha_{i2004})$) contains the individual's 2006 expectations which are potentially affected by learning results in 2004 (*GotResults*). To avoid this bias-inducing correlation of the covariates, I do not control for the individual's self-reported likelihood of having HIV at baseline, but I do drop the observations who had been previously tested (so that on average, the expectations of those who do and do not end up receiving results are not influenced by previous knowledge of what the result is).

The results presented below are mostly consistent with those shown in table 6 above, except for the fact that ($\beta_1 + \beta_2 = 1.1836$) in column 2, is significant at the 10% level. This indicates that on average, the impact of attending VCT for HIV-positive respondents is an increased IDR, by 118% as compared

to HIV-positive individuals who chose not to learn their results. This is consistent with the findings in the OLS regressions presented in columns 1 and 3, table 6. Also consistent with the OLS output in (1) and (3), is the result presented in column 2 below, that on average, HIV-positive individuals have a lower discount rate than HIV-negative individuals. However, these significant relationships disappear in the IVs. Like both the OLS and IV methodologies above, the diff-in-diff is not free of limitations. Firstly, there are unobserved variables that change over time (such as income) for which I am unable to control, thus omitted variables bias could be a concern. Secondly, the problem of reverse causality between *GotResults* and IDR is not solved in this specification, also leading to potential bias in the estimators. Thus one should be cognisant of the fact that the results are indicative but must be interpreted with care.

*Table 7: Difference-in-difference results*

| | (1) delta_IDR | (2) delta_IDR |
|---|---|---|
| GotResults | 0.121 | 0.0376 |
| | (0.291) | (0.303) |
| GotResults*HIV | | 1.146 |
| | | (0.737) |
| HIV | | -1.069*** |
| | | (0.393) |
| Constant | 1.137*** | 1.216*** |
| | (0.253) | (0.265) |
| N | 754 | 754 |
| r2 | 0.000245 | 0.00205 |
| p-value (GotRes+Gotres*HIV) | | .0961 |

*p<0.1; **P<0.05; ***p<0.01; Robust standard errors in Parenthesis, adjusted for 114 clusters in villages

## 5.2 Are time and risk preferences a channel through which VCT affects risky sexual behaviour?

The lack of evidence of a significant enduring impact of VCT on preferences presented in table 6 suggests that, in the long-term, channel 'D' in figure 1 is relatively unimportant. This also implies that when examining risk and time preferences in this instance, there may not be major concern about the potential feedback from risky sexual behaviour to expectations (channel 'C') as this might affect preferences only indirectly via channel 'D'. Thus the question of whether these preferences actually have a direct effect on risky sexual behaviour via channel 'B' warrants evaluation.

The results from estimating model (9) are reported in table 8 below. The short-term analysis in columns 1 and 2 is adapted from Thornton (2008)[8]. The dependent variable in this case is the number of condoms purchased at follow-up interviews 2 months after results were obtained in 2004. The p-values on *GotResults+GotResults*HIV* in (1) and (2) indicate a significant (short-term) impact of VCT on risky sexual behaviour (as defined here by the quantity of condoms bought). An HIV-positive respondent who chose to learn their results, bought on average, 1.216 more condoms 2 months later, than HIV-positives who did not learn their results ($\beta_1 + \beta_2$, (2)). In (3) and (4) the dependent variable is the self-reported number of condoms purchased by respondents in the 2 months before the 2006 interview. Although self-reported data presents potential limitations (further discussed in section 6), the p-values on $(\beta_1 + \beta_2)$ in (3) and (4) reveal that there is not enough evidence to reject the null that receipt of HIV-positive results has, on average, no enduring effect on risky sexual behaviour 2 years

[8]Results differ from those reported in Thornton (2008) as I have included the extra controls according to specification (9) and the sample size is smaller, primarily due to the merging process explained above.

later. Again results should be interpreted with caution due to the limitations highlighted above, but it appears that, on average, the significance of the impact of VCT on behaviour in the short-run diminishes after two years.

The 2006 measures of IDR and CRRA are included in specifications 5 and 6 so as to assess whether these preferences are a channel through which VCT affects risky sexual behaviour. The sum of $\beta_1$ and $\beta_2$ hardly changes from specifications 3 to 5 and 4 to 6 in both magnitude and significance. This indicates that the inclusion of IDR and CRRA does not, on average, take away any explanatory power from the impact of VCT on condom-purchase, 2 years *ex post*. This evidence suggests that time/risk preferences are not a channel through which VCT affects risky sexual behaviour, ceteris paribus. In column 6, the negative coefficient on IDR is significant at the 5% level suggesting that the number of condoms purchased decreases as IDR (impatience) rises. Specifically, for every 1 percentage point increase in discount rate, the number of condoms purchased in the two months before the interview decreases by 0.07. As highlighted via channel 'C' and 'D' in figure 1, reverse causality may endogenise this variable. Although I am unable to categorically conclude that risky sexual behaviour will not feedback to IDR, because a similar shock (VCT) has no effect, via channel 'D', this concern is somewhat diminished. However, due to the fact that IDR is not randomised or instrumented for, it may still be endogenous in this model. Thus the observed correlation between time preference and condom-purchase requires further investigation in order to understand if a causal relationship exists.

*Table 8: Are time and risk preferences a channel through which VCT affects risky sexual behaviour?*

| | Short term analysis: 2 months after VCT | | Longer term analysis: 2 years after VCT | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | OLS | IV | OLS | IV | OLS | IV |
| | Numcond | Numcond | Numcond | Numcond | Numcond | Numcond |
| GotResults | -0.0920 | -1.549 | -0.751 | 1.596 | -0.763 | 1.662 |
| | (0.289) | (0.999) | (0.495) | (1.169) | (0.503) | (1.159) |
| GotResults*HIV | 1.411** | 2.765** | 1.922* | 2.065 | 1.966* | 1.850 |
| | (0.576) | (1.201) | (1.004) | (2.624) | (1.005) | (2.582) |
| HIV | -0.559 | -1.479* | -1.092* | -1.125 | -1.079** | -0.962 |
| | (0.398) | (0.788) | (0.572) | (1.311) | (0.538) | (1.238) |
| IDR_2006 | | | | | -0.0502* | -0.0704** |
| | | | | | (0.0281) | (0.0347) |
| CRRA | | | | | 0.419 | 0.109 |
| | | | | | (0.358) | (0.330) |
| Constant | -0.535 | 2.013** | -0.402 | -2.204 | -0.569 | -2.279 |
| | (0.556) | (0.981) | (1.281) | (1.793) | (1.254) | (1.758) |
| Individual controls (incl. expectations) | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 244 | 244 | 423 | 423 | 423 | 423 |
| r2 | 0.146 | -0.00633 | 0.0632 | -0.0131 | 0.0652 | -0.0139 |
| Fstat | 7.86 | 6.76 | 2.76 | 1.79 | 2.79 | 1.66 |
| KleibergenPaapLM | | 17.164 | | 29.662 | | 29.089 |
| KleibergenPaapWaldF | | 2.659 | | 3.764 | | 2.766 |
| B1+B2 | 1.319 | 1.216 | 1.171 | 3.661 | 1.203 | 3.512 |
| p-value (B1+B2) | .021 | .088 | .24 | .23 | .23 | .24 |

*p<0.1; **P<0.05; ***p<0.01; Robust standard errors in parenthesis. Standard errors adjusted for 103 village clusters.

### 5.2.1 Robustness check: Negative binomial regressions

As a robustness check, the specifications in table 9 were tested using negative binomial regressions. The IV specifications are conducted using the *control function approach* as explained in section 4.2. The overall results are similar to those presented above. The inclusion of IDR and CRRA does not take any explanatory power away from the impact of learning an HIV-positive result

(*GotResults+GotResults*HIV)* on the number of condoms purchased two years after results were obtained. This suggests further evidence that risk and time preferences may not be the channel through which VCT affects risky sexual behaviour. A significant negative correlation between IDR and number of condoms purchased is again observed in the output of these tests.

# 6. Discussion

There may be several reasons why this analysis finds (i) little evidence of an enduring effect of VCT on time and risk preferences and (ii) that these preferences are, on average, not a channel through which VCT affects risky sexual behaviour.

Firstly, an individual's propensity to engage in risky sexual behaviour, especially in a developing country context, may be influenced more by external factors - societal norms and beliefs - than internal forces such as time and risk preferences. Exogenously determined factors, like culture and norms are difficult to measure, but have been shown to play an important role in shaping human behaviour. Dupas (2011) finds that Kenyan adolescent girls did not realise the danger they were exposing themselves to when becoming sexually active with much older men. Sex with so-called 'sugar-daddies' had been engrained as an acceptable, societal norm, not particularly risky and sometimes even beneficial if the relationship resulted in gifts or financial support. Provision of information regarding the "relative risk of HIV infection by partner's age led to a 28 percent decrease in teen pregnancy, an objective proxy for the incidence of unprotected sex" (Dupas, 2011, p. 1). Such findings present evidence of the substantial influence of societal norms in shaping risky sexual behaviour.

Secondly, the dependent variables in models 8 and 9 may be measured with error. As discussed in section 3, IDRs and CRRAs calculated in the canonical way may not be the most accurate measures of time and risk preference. With suitable data, quantitative measures of these preferences could be better captured by the application of frontier methods, such as the "Double Multiple Price List Approach" or "Convex Time Budget Method" (Andreoni & Sprenger, 2012, p. 3334). It is also important to consider the possibility that condom-purchase may not be a good proxy for risky sexual behaviour especially when such information is self-reported. Mismeasurement of the dependent variable causes decreased precision in estimates, thus lower t-statistics and increased chance of type 2 errors in inference (Hausman, 2001). One way to reduce mismeasurement in the proxy for risky sexual behaviour is to use biological markers indicative of unprotected sex, such as STI contraction, instead of self-reported information which is often subject to reporting biases (Gong, 2015).

Finally, there are limitations to my data in addition to those already mentioned, which have an impact on the strength of the analysis. Although IDRs can be elicited both before and after results were obtained, risk preference data was only collected post-VCT. This limits analysis using CRRA to cross-sectional methods and the benefits, for precision, of including a baseline measure of CRRA in estimation of the main model cannot be realised. A longer panel including both discounting and risk aversion questions and inclusion of these questions at the follow-up, two months after VCT, would have allowed for more robust analysis of both the short- and long-term impact of VCT on preferences. The loss of observations due to the merging process explained in footnote 6 along with the unbalanced nature of the panel, contributed to a reduced sample size in the executed tests. Attrition of this nature may result in biased estimates, if lost observations are significantly different from those which remain, as well as decreased power and weakened instruments. Limitations of this nature could be avoided with a much larger sample of observations or at least minimal missing values per respondent. Although a significant correlation between IDR and condom-purchase is observed, causality cannot be inferred due to the potential endogeneity of IDR as a covariate in model (9). The implementation of a

randomised experiment in which the treatment effect of altered time/risk preferences on risky sexual behaviour could be measured would assist in the determination of the causality of this relationship. However, due to the endogenous nature of such personal preferences, a targeted experimental design may be difficult to achieve, leaving the search for a credible instrument for preferences as the next best option.

# 7. Conclusion

In this study I endeavour to identify if time and risk preferences are a mechanism through which voluntary counselling and testing affects risky sexual behaviour. Although as emphasised above, due to several data limitations, results should be interpreted with caution, they indicate that two years after learning HIV-status, discount rates and coefficients of relative risk aversion are, on average, not significantly different for those who did and did not choose to "know their status". Evidence also suggests that although VCT has a significant short-term effect on risky sexual behaviour, no robust indication of this effect is present 2 years later. Furthermore risk and time preferences do not appear to be an important channel through which VCT affects risky sexual behaviour. The results highlight the inherent complexities of affecting positive behavioural change, especially in the context of HIV. They provide some indication that repeat testing may improve the impact of VCT on risky sexual behaviour and suggest that attempting to affect behavioural change may involve a more nuanced approach. One that not only addresses endogenous individual characteristics but exogenous factors such as societal norms and practices as well. Therefore there is an unequivocal need for further research regarding the channels through which HIV prevention programmes achieve long-term, positive behavioural change. Information which increases our understanding of this inherently complex mechanism, could reduce not only the numbers of lives lost to AIDS in the long-term, but also the hefty expenditure of donor and public health funds on the epidemic[9].

[9]It is predicted that if the "Fast-Track" goals are achieved "US$ 24 billion of additional costs for HIV treatment will be averted." (UNAIDS, 2014)

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