HIV Testing & Risky Sexual Behavior

Erick Gong*

October 2011

Abstract

HIV testing is one of the key policy responses to the HIV/AIDS epidemic in sub-Saharan Africa, yet there is little rigorous evidence on how testing affects sexual behavior. Using data from a study that randomly assigns offers of HIV testing in two urban centers in East Africa, I examine the effects of testing, taking into account people's beliefs of their HIV status prior to testing. I objectively measure risky sexual behavior using gonorrhea and chlamydia infections (sexually transmitted infections or "STIs") contracted during the 6 month study as proxies. I find large behavioral responses to HIV tests when tests provide new information to individuals. Individuals surprised by an HIV-positive test are over nine times more likely to contract an STI compared to a similar untested control group, indicating an increase in risky sexual behavior. Individuals surprised by an HIV-negative test are 84% less likely to contract an STI relative to a similar untested control group, indicating a decrease in risky sexual behavior. When HIV tests agree with a person's belief of HIV status there is no change in the incidence of STIs, implying no change in sexual behavior. Using these estimates, I simulate the effects of testing on new HIV infections in urban areas in Kenya, Mozambique, and Zambia, and find that under certain circumstances, the overall number of HIV infections increase when people are tested compared to when they are unaware of their status - an unintended consequence of testing.

JEL Codes: D84, I18, O12
Keywords: HIV/AIDS; risk behavior; information, beliefs

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*Department of Economics, Middlebury College. Author's email: egong@middlebury.edu. I am thankful to Ted Miguel for his insights and constant encouragement and to Betty Sadoulet for her patient guidance. Thanks also to Michael Anderson, Marshall Burke, Steve Buck, William Dow, Fred Finan, Paul Gertler, Susan Godlonton, Kelly Jones, Jeremy Magruder, Rebecca Thornton, and participants at the UC Berkeley Development Seminar, Northeast Universities Development Consortium, ARE Departmental Seminar, Pacific Development Conference, and Midwest International Development Conference for their advice and suggestions. Data for this study comes from The Voluntary HIV1 Counseling and Testing study (which) was sponsored by UNAIDS/WHO, AIDSCAP/Family Health International and the Center for AIDS Prevention Studies, University of California, San Francisco. All errors remain my own.

1 Introduction

HIV Testing is regarded as the gateway to prevention and treatment (WHO, 2009). Learning your HIV status is believed to lead to safer sexual behavior, while the provision of antiretrovirals (ARVs) requires first identifying infected individuals. Under this premise, universal access to HIV testing has been a key policy response to the HIV/AIDS epidemic. In nineteen countries in sub-Saharan Africa (SSA) with reliable data,[1] the number of people tested for HIV increased from 4.6 million in 2007, to 8.3 million by 2008 - a yearly growth rate of 80% (WHO, 2009).[2] Despite this emphasis, a major question remains: how does HIV testing affect risky sexual behavior? Since testing serves two purposes (prevention and access to treatment), it can be a desirable policy intervention if at a minimum testing does not increase the number of HIV infections. However, if testing leads some people to undertake riskier sexual behavior, it could counteract the effect that treatment has on the epidemic.

The two main challenges to empirical research on HIV testing are selection into testing and measuring risky sexual behavior. Previous studies have relied on non-random variation in who is tested and used self-reported sexual behavior, which is subject to bias; there is substantial evidence that people underreport their sexual behavior to conform with social norms (Minnis et al., 2009; Gregson et al., 2002; Palen et al., 2008).[3] The notable exception is Thornton (2008), who uses random assignment of financial incentives for learning one's HIV status and improves on self-reported sexual behavior by using observed condom purchases as the outcome of interest. Changes in condom purchases, however, may not fully capture changes in actual sexual behavior.[4] My paper is the first to simultaneously resolve both selection and measurement problems by using data from a study that randomly assigns offers of HIV testing and uses biological markers (gonorrhea and

[1] The nineteen countries include: Benin, Botswana, Cape Verde, Central Africa Republic, Democratic Republic of Congo, Eritrea, Ethiopia, Gambia, Ghana, Guinea-Bissau, Lesotho, Mauritania, Niger, Sao Tome & Principe, Senegal, Sierra Leone, Somalia, Swaziland, and Uganda.

[2] The number tested in 2008 represents just 5.9% of the 142 million people who live in these countries.

[3] See Weinhard et al. (1999) and Denison et al. (2008) for comprehensive reviews of the HIV testing literature.

[4] Thornton notes that "condom purchases may not reflect the true demand for safe sex. If knowledge of HIV status increases abstinence, the demand for condoms could fall in response to obtaining test results."

chlamydia infections) as objective proxies of risky sexual behavior.

Even when selection and measurement issues are resolved, it is not clear how people will respond to testing. Economic models predict asymmetric behavioral responses to HIV testing. Boozer & Philipson (2000) show theoretically that there will only be a behavioral response when HIV tests provide new information. For example, if someone believed she was unlikely to be infected with HIV, an HIV-negative test result will have little effect on this person's behavior. According to this framework, only people surprised by their test results will change their behavior. Theoretical models, however, must assume the preferences of individuals. Individuals surprised by HIV-positive tests could reduce their risky sexual behavior if they are altruistic (i.e. they don't want to infect others); on the other hand, they could increase their risky sexual behavior if they feel they have "nothing to lose." Ultimately, understanding the effects of HIV testing on risky sexual behavior requires an empirical approach.

I use data from the Voluntary Counseling & Testing (VCT) Efficacy study conducted in Kenya and Tanzania, which randomly assigned people into HIV testing and followed up with them 6 months later (Coates et al., 2000). I construct a measure of people's beliefs about their HIV status before getting tested using questions on the baseline survey. To measure risky sexual behavior, I use biological markers that are not susceptible to self-reporting bias. Data are collected on newly contracted infections of gonorrhea and chlamydia (henceforward known as "sexually transmitted infection" or "STI") that occur during the study.[5] An STI only results from unprotected sex with someone who has an STI and serves as an objective measure of risky sexual behavior. The random assignment of testing enables me to identify the effect that HIV tests have on sexual behavior conditioned on prior beliefs of HIV infection.

My findings suggest that HIV tests have the largest effects on risky sexual behavior when test results provide new information to an individual. I find that people surprised by an HIV-positive test (i.e. those who believed they were at low risk for HIV before testing and learn they are HIV-

[5]HIV is also a sexually transmitted infection. However, in this paper an STI will refer specifically to either a gonorrhea or chlamydia infection.

positive) have a 10.5 percentage point increase in their likelihood of contracting an STI compared to an HIV-positive control group who had similar beliefs of HIV risk but were untested at baseline.[6] I interpret this over nine-fold increase in contracting an STI as an indication that those surprised by an HIV-positive test *increased* their risky sexual behavior. People surprised by an HIV-negative test (i.e. those who believed they were at high risk for HIV before testing and learn they are HIV-negative) have a 5 percentage point decrease in the likelihood of contracting an STI compared to an HIV-negative control group with similar beliefs of HIV risk but were untested at baseline.[7] This 84% decrease in the likelihood of contracting an STI suggests that those surprised by HIV-negative tests decrease their risky sexual behavior. Both of these results indicate that when people make decisions about risky sexual behavior, self-interests dominate altruistic preferences. People who discover they are HIV-positive no longer have any incentive to practice safe sex (i.e. "nothing to lose"), while those who learn they are HIV-negative face greater incentives to avoid risky behavior. Finally, when HIV test results agree with a person's beliefs of HIV status, the effects of testing on STI likelihood are not statistically different from zero. This is consistent with an economic model where there is a behavioral response to HIV tests if they provide new information.

I use the empirical results described above and combine them with a simple epidemiological model to simulate the short-run effect of rolling out HIV testing in an urban setting. I use the distribution of beliefs of HIV risk and actual HIV status from the Demographic Health Surveys in Kenya, Mozambique, and Zambia - all three countries faced with a generalized HIV epidemic. I find that under random matching of sexual partners, HIV testing leads to an increase in the number of HIV infections compared to a case of no testing in all three countries. When assortative matching by HIV status and the provision of antiretrovirals (ARVs) are taken into account, testing leads to decreases in the number of HIV infections in Kenya. For the cases of Mozambique and Zambia, under most scenarios, the overall number of HIV infections increase when people are

[6] The mean STI rate for the control group (not tested at baseline) who believed they were at low risk for HIV at baseline but are actually HIV-positive is 1.06%.

[7] The mean STI infection rate for the control group (not tested at baseline) who believed they were at high risk for HIV at baseline but are actually HIV-negative is 5.90%.

tested compared to when they are unaware of their status - an unintended consequence of testing. This is driven by a larger percentage of people surprised by an HIV-positive test in Mozambique and Zambia compared to those in Kenya. These results suggest that the distribution of prior beliefs and actual HIV status are important to take into account when estimating the effects of HIV testing on risky sexual behavior.

This study makes several contributions. It is the first work that provides empirical evidence that individuals who discover they are HIV-positive through testing increase their risky sexual behavior. This finding is at odds with conventional wisdom that those who learn they are HIV-positive will take steps to prevent infecting others (Potts et al., 2008; Bunnell and Cherutich, 2008; Gersovitz, 2010). My ability to simultaneously resolve the selection and measurement problems is the key methodological contribution, an issue unresolved in the few existing sub-Saharan studies that have exogenous variation in who is tested (Coates et al., 2000; Thornton, 2008). As a result these findings have important policy implications. The first is that given the limited resources available for HIV prevention, interventions known to prevent new HIV infections such as male circumcision and preventing mother-to-child transmission should be emphasized (Potts et al., 2008). In addition, we may need to provide those who receive HIV-positive tests with incentives to reduce their risky sexual behavior. Information that stresses the risks of reinfection with HIV and financial incentives to reduce risky sexual behavior may be potential policies that target those receiving HIV-positive test results (Smith, Richman and Little, 2005; Medlin and de Walque, 2008).

This work also contributes to the emerging empirical literature on the important role that information and beliefs play on an individual's behavior (Manski, 2004; Delavande, Gine and McKenzie, 2010). Dupas (2010) finds that providing teenage girls in Kenya with the relative risk of HIV infection by age leads to a decrease in unprotected sex with older men; the implicit assumption is that these girls did not know what these risks actually were. Both Jensen (2010) and Nguyen (2008) show that providing information on the returns to schooling leads to increased education- both authors attribute this behavioral response to low perceived returns of schooling before information is provided. Goldstein et al. (2010) find that pregnant women with high expectations of being HIV-positive increase their uptake of neonatal services when tested for HIV. This paper shows that HIV testing can have large effects on sexual behavior if the test results provide new information to individuals.

Finally, this work contributes to the growing literature that examines the unintended effects of policies designed to improve health outcomes. In western Kenya, Duflo, Dupas and Kremer (2011) examine the effects of two school interventions designed to improve educational and health outcomes: 1) free school uniforms and 2) an HIV/AIDS curriculum focused on abstinence until marriage. They find that while providing school uniforms increased educational attainment and reduced early fertility, the additional provision of the HIV/AIDS curriculum mitigated both these positive effects. Kohler and Thornton (2010) find that conditioning cash transfers to men in Malawi for maintaining their HIV-negative status did not change HIV infection rates, but did increase the men's risky sexual behavior after receiving the cash rewards. This paper shows that HIV testing which is intended to prevent the spread of HIV can lead to additional infections since those who discover they are HIV-positive optimize their individual behavior (i.e. increase their number of partners) but do not take into account the negative externalities they are generating by this behavior (i.e. infecting others).

The paper is structured as follows. Section 2 outlines a simple model which shows that theoretically HIV testing has ambiguous effects on behavior. Section 3 describes the features of the data. Section 4 provides the empirical strategy and presents the main results. Section 5 discusses the findings and proposes ways they can be reconciled with Thornton (2008) and de Paula, Shapira and Todd (2010), both of whom find that HIV-positive tests (or increases in beliefs of being HIV-positive) lead to decreases in risky sexual behavior. In addition, I discuss how my findings contrast to those from the original paper published in the *Lancet* by Coates et al. (2000). Section 6 does a simple simulation showing the effects of testing on new HIV infections, and Section 7 concludes.

2 Conceptual Framework

In this section, I present a simple model to show: 1) the role that beliefs of HIV infection play in determining risky sexual behavior, and 2) the effects of HIV testing on behavior are, *a priori,* ambiguous. This model is influenced by Boozer and Philpson (2000) and is similar to de Paula, Shapira and Todd (2010). My model does not explicitly show how beliefs of HIV status are updated as de Paula, Shapira and Todd (2010) do, and shows that testing has an ambiguous effect on individual sexual behavior which differs from Boozer and Philpson (2000). An individual chooses a level of risky sexual behavior j to maximize utility $U(j)$

$$U(j) = u(j) - [\pi + (1-\pi)j\lambda(\beta, W)]c$$

where $u(j)$ is utility from risky sex j. While risky sex can take multiple forms, in this model j represents the number of sexual partners. The beliefs of being infected with HIV are $\pi \in [0,1]$, $\lambda(\beta, W)$ is the probability per partner of becoming infected with HIV and is a function of β (HIV transmission rate) and W (prevalence of HIV). Finally, c is the disutility that comes from knowing that you are HIV-positive. I assume $u(j)$ is increasing in j and concave. Intuitively, individuals face a trade-off when choosing their risky sexual behavior; the utility that comes with risky sex vs. the possibility of becoming infected with HIV. The first-order condition equates the marginal benefit of risky sexual behavior with the marginal cost:

$$u_j = (1-\pi)\lambda(\beta, W)c$$

where u_j is the partial derivative of $u(j)$ with respect to j. As beliefs of being HIV-positive increase, the marginal cost of risky sexual behavior decreases, which leads individuals to choose higher levels of risky sex (j). From this model, it is clear that beliefs of HIV infection have an important role when an individual chooses a level of risky sexual behavior.

I now introduce altruism to the model which takes the form of a discount to the utility one receives from risky sex:

$$U(j) = u(j)A(\pi) - [\pi + (1-\pi)j\lambda(\beta, W)]c$$

where $A(\pi) \in [0,1]$ is a function of beliefs of HIV infection and serves to discount the marginal benefit of risky sex. I assume that $A_\pi < 0$ or that as beliefs increase, a greater discount is applied to the utility of risky sex.

How does risky sexual behavior respond to HIV testing? We can think of HIV tests as shocks to beliefs (π), where someone surprised by an HIV-positive (HIV-negative) test has $\Delta\pi > 0$ ($\Delta\pi < 0$). When an HIV test confirms an individual's beliefs prior to testing, beliefs are unchanged ($\Delta\pi = 0$).

The comparative statics show how behavior (j) responds to a change in beliefs (π):

$$\frac{\partial j}{\partial \pi} = -\left(\frac{u_j A_\pi + \lambda(\beta, W)c}{u_{jj}A(\pi)}\right)$$

Since by concavity, $u''(j) < 0$, and given a non-zero HIV transmission rate ($\lambda(\beta, W) > 0$), the sign of $\frac{\partial j}{\partial \pi}$ depends on $u'(j)A_\pi + \lambda(B, W)c$. When $|A_\pi|$ is large, or when the utility from risky sex is heavily discounted when beliefs increase (i.e. altruistic preferences) then $u'(j)A'(\pi) + \lambda(B, W)c < 0$ and risky sexual behavior decreases as beliefs increase ($\frac{\partial j}{\partial \pi} < 0$). When $|A_\pi|$ is small, or when the utility from risky sex is not greatly discounted when beliefs increase, then $u'(j)A'(\pi) + \lambda(B, W)c > 0$ and people increase their risky sexual behavior as their beliefs increase ($\partial j/\partial \pi > 0$). If altruistic preferences are not known before testing, then the ex-ante effects of HIV testing on risky sexual behavior are ambiguous. Individuals who receive HIV-positive test results and have strong altruistic preferences will decrease their risky sexual behavior, while those who care only about their own interests will increase their risky sexual behavior.

To summarize, the model shows the role that beliefs of HIV infection play when an individual chooses a level of risky sexual behavior. HIV testing serves as a shock to these beliefs; an HIV-positive test increases these beliefs while an HIV-negative test decreases beliefs of HIV infection.

Without altruism, an increase in the beliefs of HIV infection decrease the marginal cost of risky sex and increases risky sexual behavior. When altruism is introduced, the effects of HIV testing on risky sexual behavior are ambiguous.

3 Data

The data are from the HIV Voluntary Counseling and Testing Efficacy study conducted in 1995-1998 (Coates et al., 2000). The study was designed to assess whether HIV testing and counseling is effective at reducing risky sexual behavior. My analysis uses data from the study sites in Nairobi, Kenya and Dar Es Salaam, Tanzania.[8] In both places, a single study site was placed in/near a health center. These sites enrolled, surveyed, and tested participants. A combination of media (flyers, radio and TV advertisements) and recruiters were used to recruit study participants; those participating in the study did not represent a random sample from their communities. Recruitment and enrollment at both study sites occurred from June 1995 to March 1996. Individuals who previously tested positive for HIV were ineligible for the study. Over 90% of participants reported never receiving an HIV test before the study. The initial sample consists of approximately 2,900 people who were seeking HIV-related services, with 1/3 of them enrolling as a couple (see Kamenga et al.(2000) for an in-depth description of the study's design and methods).

Figure I presents the study design. A baseline survey was conducted and urine samples were taken of all individuals. These urine samples were frozen and used during the 6 month follow up survey. Study participants were then classified as either individuals or couples. They were then randomly assigned into either a treatment or control arm. People assigned into the treatment arm were offered counseling and an HIV test, of which 93% accepted the test.[9] Test results were available 2 weeks after testing; 78% of those in the treatment arm returned to the clinic to receive their HIV test results. Participants enrolled as a couple were strongly encouraged to share their

[8] Port of Spain, Trinidad was the third study side. It was excluded from the analysis since the focus of this paper is on the effects of HIV testing in sub-Saharan Africa.

[9] Of the 1477 in the treatment arm, 1385 opted to take an HIV test.

HIV test results with each other. People in the control arm watched a 15 minute video which described ways to prevent HIV infection and had a question and answer session with a health information officer. Since the treatment and controls arms differ not only due to HIV testing, but different information interventions (counseling in the treatment arm and a video in the control arm), there may be differences between arms in what people learn about HIV. I compare changes in HIV/AIDS knowledge and awareness between the treatment and control arms during the study and find no differences (see section 8.1 in appendices).

Six months after the baseline, a follow up survey was given. Everyone who participated in the follow up round was resurveyed, asked to gave a urine sample, and offered an HIV test. The urine sample was tested for two sexually transmitted infections (STIs): gonorrhea and chlamydia. For people who tested positive for an STI, their urine samples from baseline were unfrozen and tested for an STI. By doing this, we are able to determine whether an STI was contracted between the baseline and follow up surveys, and which preexisted before the study. Those in the control arm were offered HIV testing and counseling, and 84% accepted an HIV test.[10] While the acceptance rates for HIV testing between the treatment (93%) and control arms (84%) is different, there do not appear to be any differences in observed characteristics between those accepting an HIV test in the treatment and control arms (see section 8.2 in appendices for further details).

Baseline summary statistics for the treatment and control group are in Table I. Demographic data is presented in rows 1-9, and relationship status is in rows 10-13; the average age is 28, and 39% of study participants are married. Under the HIV/AIDS section (rows 14-17), we see awareness of how HIV is transmitted is high (row 14),[11] but few have been tested (row 16). Self-reported sexual activity during the 2 months prior to the baseline survey is reported in rows 18-26. Slightly over 20% of participants had two or more partners (row 18), and about 12% have engaged

[10] Of the 1223 in the control arm who returned for the 6 month follow up survey round, 1022 accepted an HIV test.

[11] The HIV/AIDS knowledge test asks participants 12 questions about how HIV is transmitted. Examples of questions include: “Can a person get AIDS or the AIDS virus from: working near someone, eating food cooked by someone who has the AIDS virus, using public toilets, having sexual intercourse without a condom with someone who has the AIDS virus?”(CAPS, 2000)

in commercial sex (row 20).[12] Overall the treatment and control groups are balanced across most covariates.

Baseline HIV tests for the treatment group (Column 1, Row 18) reveal HIV prevalence to be at 20%, which is higher than estimated HIV prevalence in urban Kenya (13-14%) and Dar es Salaam, Tanzania (10-12%) (Balmer et al., 2000; Sangiwa et al., 2000). This suggest that those who selected to participate in the study are more sexually active and are a higher risk group than the general population. Given the main intervention (treatment) of the VCT Efficacy study is to offer free HIV testing, the population of interest is sexually active individuals seeking HIV testing services. Since the policy of universal access to HIV testing is focused on expanding the number of sites where HIV tests can be obtained, this population is a relevant one to study when examining the effects of HIV testing on behavior.

Attrition in the study is both high but similar in the treatment and control arms (Figure II). Table II presents summary statistics of those who remain in the study (columns 1 & 4) and those that leave (columns 2 & 5). Individuals that left the study appear to be slightly younger (row 2), a higher likelihood of being Muslin (row 5), and come from wealthier households (rows 8 & 9). When examining HIV/AIDS and self-reported sexual activity (rows 14-26), there are few statistically significant differences at the 5% level between those that remained in the study and those that left it.

In order to see if attrition affects internal validity, I examine if there is evidence of differential attrition.[13] In Table II, column 7, the difference between those that left the treatment and those that left the control arm are calculated (p-values included in column 8). There are very few statistically significant differences across demographic, relationship, and HIV/AIDS variables (rows 1-16). Most importantly, there are no statistically significant differences in self-reported sexual activity. Overall, there isn't evidence of significant differential attrition between the treatment

[12] Commercial sex partners are defined as when money is exchanged for sexual activity.

[13] For example, if people who engage in riskier sex left the treatment arm in greater proportions than the control arm, any decreases in risky sex attributable to assignment into the treatment arm may actually be due to differential attrition

and control arms, and hence attrition should not threaten the internal validity of the research design.

I now discuss three important aspects of how I use the data: 1) measuring risky sexual behavior, 2) identifying people's HIV status, and 3) measuring people's beliefs about HIV infection.

3.1 Measuring Sexual Behavior

Sexual behavior is difficult to measure because it is unobserved and, due to its sensitive nature, self-reports of sexual behavior are subject to a high degree of social desirability bias (Fenton et al., 2001; Weinhardt et al., 1998). When survey participants are asked about their sexual behavior, they may misreport because of social norms, stigma, and to avoid criticism of their behavior (Turner et al., 2009). When biological markers (biomarkers) such as sexually transmitted infections are collected in a study, they typically provide evidence that self-reports underestimate actual sexual activity (Minnis et al., 2009; Gallo et al., 2006).

Given the bias present in self-reported behavior, recent research in measuring sexual behavior has incorporated biomarkers[14] as objective measures of sexual behavior (Mauck and Straten, 2008; Gallo et al., 2006; Minnis et al., 2009; Cleland et al., 2004). Biomarkers act as proxies for risky sexual behavior, as the likelihood of a biomarker is increasing in both acts of unprotected sex and number of partners.

In this paper, the incidence of gonorrhea and chlamydia infections are used as measures of risky sexual behavior. The primary means of transmission for both infections is unprotected sexual contact and nonsexual transmission is extremely rare (Neinstein, Goldenring and CArpenter, 1984). Both infections are sensitive to risky sexual activity: transmission rates are between .20 to .80 per unprotected sexual act with an infected individual (Kretzschmar, van Duynhoven and

[14]Biomarkers range from sexually transmitted infections (gonorrhea, chlamydia, syphilis), residual semen or prostate-specific antigens, and pregnancy - all signs that unprotected sex took place (Fenton et al., 2001; Minnis et al., 2009).

Severijnen, 1996; Chen, Ghani and Edmunds, 2008).[15] [16] Going forward, STIs will refer specifically to gonorrhea and chlamydia infections (and not HIV).

Since the goal of using biomarkers is to measure risky sexual behavior during the course of the study I rely on the incidence of STIs instead of prevalence. What's the difference? Prevalence can be seen as a stock, or the number of STIs at any given point in time, where incidence is a flow and measures new infections over a time period. In the case of this study, incidence measures the number of new STI cases between baseline and the 6 month follow up.[17] Given that the duration of gonorrhea and chlamydia is slightly over 6 months (Chen, Ghani and Edmunds, 2008; Kretzschmar, van Duynhoven and Severijnen, 1996), using the incidence of STIs is a reasonable choice to avoid overestimating the level of risky sexual activity during the study. However, incidence can underestimate risky sexual behavior since those who have an STI at baseline may continue to engage in risky sex during the study; thus I also estimate the effect of HIV testing on prevalence of STIs at 6 months and find results that are very similar to when using incidence as the main outcome (see section 8.4 in appendices for results using prevalence as the outcome of interest).

3.2 HIV Status

The HIV status of everyone in the treatment arm that accepts an HIV test is known at baseline. However, the HIV status of those in the control group at baseline are unknown since they were not offered testing until the 6 month follow up. This is problematic, since I want to compare HIV-positive (negative) individuals in the treatment arm to those in the control arm. In order to create a counter-factual group for testing I use the HIV test results from the 6 month follow up for the

[15]Transmission rates vary by gender. The likelihood of male to female transmission of gonorrhea is .5-.7 per sexual act, and somewhat lower for chlamydia at .5 per sexual act. The likelihood of female to male transmission of gonorrhea is .2-.3 per sexual act, and .25 for chlamydia (Kretzschmar, van Duynhoven and Severijnen, 1996).

[16]Gonorrhea and chlamydia infection rates contrast sharply to HIV transmission rates where are .003 to .001 per unprotected sexual act with an infected person (assuming the infected person is in his/her asymptomatic phase). HIV transmission rates jump to .05 per unprotected sexual act during the acute infection stage which is during the first three months of a new infection (Gray et al., 1999; Cohen and Pilcher, 2005).

[17]Incidence is therefore defined as having no STI at baseline and an STI at the 6 month follow up. Incidence was determined by testing frozen urine samples for STIs for everyone with a positive STI test at the 6 month follow up. This allows one to distinguish preexisting infections from new infections acquired during the study.

control group. For the control group, I assume that an individual's HIV test results at the 6 month follow up would have been their same result at baseline. Clearly those who are HIV-negative at 6 months were also negative at baseline. For people who test HIV-positive at 6 months, I assume that all of these individuals were positive at baseline as well. This assumption relies on evidence which suggests that HIV is not easily transmitted, with estimated transmission rates of approximately .0015-.0007 per coital act when your partner has an established HIV infection (Wawer et al., 2005; Cohen and Pilcher, 2005).[18]

How do new HIV infections that occur between baseline and the 6 month follow up in the control group affect the estimates of HIV testing on behavior? Let Y_i be risky sexual behavior, T_i indicate random assignment into testing, HIV_i be HIV status, and subscript i denotes an individual. The average effect of an HIV-negative test on risky sexual behavior is:

$$\beta_{HIV-} = \mathbb{E}[Y_i|T_i = 1, HIV_i = 0] - \mathbb{E}[Y_i|T_i = 0, HIV_i = 0]$$

Since HIV status for the control group is not observed until the 6 month follow up, I estimate:

$$\beta^*_{HIV-} = \mathbb{E}[Y_i|T_i = 1, HIV_i = 0] - \mathbb{E}[Y_i|T_i = 0, (HIV_i = 0)^*]$$

where $(HIV = 0)^*$ is the HIV status at the 6 month follow up. If any individuals in the control group became HIV-positive during the course of the study, they would not be included in the HIV-negative control group, even though they were HIV-negative at baseline. Thus the average risky sexual behavior of the true counterfactual group will be greater than the behavior in the control arm:

$$\mathbb{E}[Y_i|T_i = 0, HIV_i = 0] \geq \mathbb{E}[Y_i|T_i = 0, (HIV_i = 0)^*]$$

which results in $\beta^*_{HIV-} \geq \beta_{HIV-}$ or that estimates of the effect of an HIV-negative test on risky

[18] Of the 750 individuals who tested HIV-negative at baseline and retested at 6 months, only 12 became infected, an infection rate of 1.6%.

sexual behavior will be biased upwards.

What is the effect of using HIV-positive tests at the 6 month follow up to infer baseline status? The average effect of an HIV-positive test on behavior is:

$$\beta_{HIV+} = \mathbb{E}[Y_i|T_i = 1, HIV_i = 1] - \mathbb{E}[Y_i|T_i = 0, HIV_i = 1]$$

Again, using test results at the 6 month follow up generates this effect:

$$\beta^*_{HIV+} = \mathbb{E}[Y_i|T_i = 1, HIV_i = 1] - \mathbb{E}[Y_i|T_i = 0, (HIV_i = 1)^*]$$

where $(HIV = 1)^*$indicates an HIV-positive test result at the 6 month follow up. This group will consist of people who were HIV-positive at baseline and those who became infected during the course of the study due to risky sexual behavior. The sexual behavior for this control group then will be on average more risky than the behavior for those who were HIV-positive at baseline:

$$\mathbb{E}[Y_i|T_i = 0, (HIV = 1)^*] \geq \mathbb{E}[Y|T = 0, HIV = 1]$$

which results in $\beta^*_{HIV+} \leq \beta_{HIV+}$ or that the estimated effect of a HIV-positive test will be biased downwards.

To conclude, my estimates for the effects of HIV-negative tests on risky sexual behavior will be biased upwards and for HIV-positive tests the bias will be downwards.

Since my main results show that those surprised by an HIV-positive test increase their risky sexual behavior, this estimate becomes a lower bound for the true effect of HIV-positive tests on risky sexual behavior. Correspondingly, my main results also show that those surprised by an HIV-negative test decrease their behavior, and thus these estimates serve as an upper bound to the effect of HIV-negative tests on risky sexual behavior.

3.3 Beliefs of HIV Infection

There are two major challenges faced when measuring beliefs of HIV infection: 1) questions regarding HIV status are extremely sensitive, and 2) actual beliefs cannot be directly verified. Measuring beliefs on HIV infection presents a specific challenge because of the social stigma associated with HIV infection. People who believe they are HIV-positive face strong incentives to not reveal their true beliefs.[19] Direct questions about HIV status may therefore lead to biased responses. I generate a belief measure using both direct and indirect questions about HIV status that reduce this bias. In addition, while actual beliefs of HIV infection cannot be observed, I provide evidence that the belief measures used in this paper are valid following guidelines established by Manski (2004) and Delavande, Gine and McKenzie (2010) on subjective expectations. If beliefs of HIV status are used by individuals when making decisions about risky sex, then a valid belief measure should predict this behavior.

A set of four questions that were all designed to measure perceived HIV risk are used to measure beliefs of HIV infection. All four questions were included on the baseline survey but removed from the 6 month follow up survey because, "Interviewers needed to be blinded to the baseline serostatus of participants during the follow-up interview;" (Grinstead et al., 2001). The questions are as follows:

Question	Survey Question
A	What are the chances that you will get the AIDS virus?
B	What are the chances that you already have the AIDS virus?
C	How worried are you that you will get the AIDS virus?
D	How worried are you that you already have the AIDS virus?

The responses for the questions use the following Likert scale:

[19] Manski (2004) notes that "An absence of incentives (to honestly respond to survey questions) is a common feature of all survey research, not a specific attribute of expectations questions. (Manski) is aware of no empirical evidence that responses to expectations questions suffer more from incentive problems than do responses to other questions commonly asked in surveys." When considering questions about HIV status however, the incentive problem changes dramatically because of the costs involved of disclosing an HIV+ status.

Response for A & B	Response for C & D	Value
Almost certainly will not happen	Not at all or hardly worried	1
It could happen	A little bit worried	2
It probably will happen	Quite a bit worried	3
It almost certainly will happen	Extremely worried	4

All four questions have been used by economists and demographers to measure beliefs of HIV status; Thornton (2008), Delavande and Kohler (2009), and de Paula, Shapira and Todd (2010) measures beliefs using similar language to questions A and B, while Smith and Watkins (2004), Kohler, Behrman and Watkins (2007), and Boozer and Philpson (2000) use measures similar to questions C and D. Given that the responses use a Likert scale and are not subjective probabilities, interpersonal comparisons warrant some caution.[20]

While question B is the most straightforward means of measuring beliefs of HIV infection, those who believe they are infected may bias their responses downward. The costs of revealing they are HIV-positive, or likely to be, can be high. There are a number of cases documenting that those who reveal they are HIV-positive are subject to employment discrimination, physical violence (including murder), and social stigma (Simbayi et al., 2007; Skinner and Mfecane, 2005; Brown, Macintyre and Trujillo, 2003; Kalichman and Simbayi, 2003).[21] Given the evidence that people misreport their sexual behavior (see section 3.1) due to social desirability bias, it should not be a surprise that people may also misreport their beliefs of HIV infection. The use of questions A,C, and D help resolve this problem. These additional questions are designed to measure perceived HIV risk (Lauby et al., 2006; Smith and Watkins, 2004), and slight changes in language may elicit more accurate responses.

In order to utilize the information from all four questions, I take the average response to

[20] Two people may have identical beliefs about being HIV infected, but one may respond as "not at all or hardly worried" (1) while the other person may respond as "a little bit worried" (2).

[21] By extension, those who reveal that they believe they are likely to be infected with HIV face similar costs.

questions A-D. The median of all the average responses is 2, which I use to divide the sample into a high and low belief group (Figure III). Those with an average response of between 1 to 2 are classified as having low beliefs, while those with an average response greater than 2 are classified as having a high belief of HIV infection. In the robustness section (5) I demonstrate that the results in this paper are not sensitive to this cut point for dividing the sample into low and high belief groups.

How can we be sure this measure is an accurate measure of true underlying beliefs of HIV infection? Both Manski (2004) and Delavande, Gine and McKenzie (2010) note that it is impossible to know for sure since true beliefs are unobserved. However, if individuals take into account their beliefs of HIV infection when making decisions about sexual activity, then any belief measure should be a good predictor of this behavior. To test this, I examine whether the belief measure at baseline predicts STI incidence (the proxy for risky sexual behavior) at the 6 month follow up. I restrict this analysis to the control group since the HIV tests in the treatment arm would change beliefs of HIV infection. The estimating equation is:

$$STI_{ij} = \alpha + \beta_1 High\,Belief_i + X_i'\delta_1 + \gamma_j + u_{ij} \tag{1}$$

where STI_{ij} is an indicator for STI incidence at the 6 month follow up for individual i in country j, $High\,Belief_i$ is an indicator if someone has high beliefs of HIV infection, X_i' is a vector of individual characteristics (i.e. gender, age, religion), and γ_j is a country fixed effect. In addition, since the response to any of these belief questions might depend on the identity of the interviewer, a set of interviewer fixed effects are included as well. Estimates are presented in Table III. Columns 1 and 2 present the correlation between the belief measure relying only on question B (the most direct question), while columns 3 and 4 use the belief measure that takes the average response to questions A-D.[22] The belief measure using all four questions is strongly associated with STI

[22] The $High\,Belief_i$ indicator using only question B takes a value of 1 if someone responds to question B with a "3" or "4" and a zero otherwise.

incidence and statistically significant at the 1% level, while the belief measure using question B is not. This suggests that the belief measure using responses from questions A-D are a better measure of underlying beliefs than relying on question B alone.

Another useful exercise is to examine whether beliefs of HIV infection are accurate. I estimate equation 1 but replace STI_{ij} with $HIV\,Status_{ij}$ which is an indicator for being HIV-positive at baseline. The belief measure using all 4 questions has a slightly stronger correlation with HIV status (Table III; columns 7-8) than the belief measure using only question B (columns 5-6). Given that the transmission risk of HIV is very low (about 1/1000 per coital act), it is not surprising that there is only a weak association between beliefs and actual HIV status.

In section 8.3 in the appendices, I compare how other individual questions (A,C,D) do in predicting behavior (STI incidence) and baseline HIV status; I find that the belief measure incorporating all four questions performs better at predicting both behavior and HIV status. It should be stressed that the results in this section should not be interpreted as causal. What this section does is provides evidence that the preferred belief measure (using all four questions) is a valid measure of beliefs of HIV infection.

4 Empirical Analysis

4.1 Identification Strategy

This paper has argued that risky sexual behavior is a function of beliefs of HIV infection, and HIV tests update beliefs only if test results are different from prior beliefs. Using the measures of prior beliefs described in the previous section, there are two groups where HIV tests should update beliefs: 1) low priors receiving HIV-positive tests, and 2) high priors receiving HIV-negative tests. In these two groups, HIV tests should also have an effect on risky sexual behavior. Testing should not change beliefs or behavior in the other two groups, 3) low priors receiving HIV-negative tests, and 4) high priors receiving HIV-positive tests. The following table presents the four groups and the predictions of the effects of testing in each group.

Four Groups for Analysis: Effect of Testing in Each Group		
	HIV-Negative	HIV-Positive
Low Prior Beliefs	Tests have no effect on beliefs or behavior	Tests increase beliefs => Change in behavior
High Prior Beliefs	Tests decrease beliefs => Change in behavior	Tests have no effect on beliefs or behavior

The goal is to identify the effect of HIV testing conditional on prior beliefs. The estimating equation is a linear probability model:

$$\begin{aligned} STI_{ij} &= \alpha + \beta_1 Test_i + \beta_2 High\,Priors_i + \beta_3 HIV_i + \beta_4 Couple_i + \beta_5(Test_i \times High\,Priors_i) \\ &\quad + \beta_6(Test_i \times HIV_i) + \beta_7(Test_i \times High\,Priors_i \times HIV_i) + I_i'\omega_1 + X_i'\delta_1 + \gamma_j + u_{ij} \quad (2) \end{aligned}$$

where $STI_{ij} = 1$ if individual i in country j contracts an STI during the study, $Test_i$ indicates assignment into the HIV testing arm, $High\,Priors_i$ indicates if the individual has high prior beliefs, $HIV_i = 1$ for those who are HIV-positive, and $Couple_i$ indicates if the individual enrolled in the study with his/her partner. The vector I_i includes all the interactions of $Test_i$, $High\,Priors_i$, HIV_i, $Couple_i$ that are not explicitly specified, X_i' is a vector of individual level characteristics, and γ_j is a country fixed effect.

Assignment into the testing arm is randomly assigned, however not everyone in the testing arm receives their test results (there is a two week delay between testing and availability of results). I therefore employ intent to treat estimators. The random assignment of testing implies that $\mathbb{E}(u_{ij}|Test_i) = 0$ allowing the OLS estimate of β_1 to be unbiased. Since prior beliefs and HIV status were determined before testing occurred they are not affected by the intervention. Therefore, β_5 estimates the causal impact of testing conditioned on high prior beliefs and β_6 is the causal impact of testing conditioned on being HIV-positive.

Using the predictions from the previous table, we should expect $\beta_1 = 0$ (low priors receiving HIV- test), $\beta_1 + \beta_6 \neq 0$ (low priors receiving HIV+ test), $\beta_1 + \beta_5 \neq 0$ (high priors receiving HIV- test), and $\beta_1 + \beta_5 + \beta_6 + \beta_7 = 0$ (high priors receiving HIV+ test).

4.2 Results

Table IV presents OLS estimates of equation 2. STI incidence across the whole sample is 3.91%. Column 1 includes each covariate of interest, while columns 2 and 3 include the full set of interactions. Column 3 also includes a set of controls such as gender, age, education, religion, martial status, number of children, assets, the language of the survey, and both interviewer and country fixed effect. The upper panel of Table IV presents estimates for each of the individual covariates of interest. Since the effect of HIV-testing depends on prior beliefs, the lower panel of Table IV shows the pertinent linear combinations with the standard errors adjusted for the covariance between the variables.[23]

I estimate the effects of HIV-positive and HIV-negative tests by each prior belief group. Individuals with low prior beliefs who receive HIV-negative tests have little change in STI incidence (row 8). The point estimate across both specifications is virtually zero, and standard errors are relatively small. This finding is consistent with a model where HIV-negative tests don't provide any new information to those with low prior beliefs. If beliefs of HIV infection remain unchanged, then behavior will as well.

To examine the effect of an HIV-positive test on individuals with low prior beliefs, I estimate the linear combination $Test + (Test \times HIV+)$ (row 9).[24] The effect is very large and statistically significant; those with low priors have about a 10.5 percentage point increase in STI incidence

[23]Since the variance of the sum of two random variables X, Y is $Var(X + Y) = Var(X) + Var(Y) + 2Cov(X, Y)$ then the standard errors of the linear combination of $\beta_1 + \beta_6$ would be $se(\beta_1 + \beta_6) = \left([se(\beta_1)]^2 + [se(\beta_6)]^2 + 2Cov(\beta_1, \beta_6)\right)^{1/2}$.

[24]I exclude the HIV indicator because I compare HIV-positive individuals with low prior beliefs who get tested vs. HIV-positives with low prior beliefs who are not tested.

after receiving an HIV-positive test. Given that the STI incidence for the low prior/HIV-positive control group is 1.06%, this represents an over nine-fold increase in STI incidence after an HIV-positive test. This result is consistent with a model where people with low prior beliefs update them after receiving an HIV-positive test. The increase in beliefs in this case leads to an increase in risky sexual behavior. This suggests that self-interests have a larger effect on sexual behavior than altruism; once people revise their beliefs upwards the marginal cost of risky sex decreases and they face far less incentive to engage in safe sex.

Now I turn to the group with high prior beliefs of HIV infection. The effect of an HIV-negative test for individuals with high priors is the linear combination $Test + (Test \times High)$ (row 10). STI incidence decreases by 5 percentage points after an HIV-negative test. The effect is statistically significant and the magnitude is large; the mean STI rate of the high prior belief control group is 5.90%, thus testing reduces STI incidence by 84%. Those who update their beliefs of HIV infection downward appear to be reducing their risky sexual behavior. This is consistent with people having greater incentives to protect themselves when they learn they are uninfected. Finally, the effect of HIV-positive tests on high prior types is the linear combination $Test + (Test \times HIV) + (Test \times High) + (Test \times High \times HIV)$ (row 11). There is no statistically significant effect on STI incidence, as predicted, but given the wide confidence intervals, inference warrants caution.

Overall, these results provide strong evidence that HIV testing only affects people's behavior if it changes beliefs about HIV infection. Is it possible to see how people actually change their behavior? There are a few types of behavior that are of interest. The first is how does risky sexual behavior change. Are the types with higher STI rates after testing (low prior beliefs/HIV+) having more partners or reducing condom use? Another behavioral change of interest is if there is assortative matching by HIV status (Dow and Philipson, 1996). If those who receive HIV-positive tests seek out partners who are also HIV-positive, this will mitigate the adverse effects of any increase in risky sexual behavior by these types.[25] Finally, there is another behavioral change that could explain the STI results: those receiving HIV tests might change the way they treat STIs. For example, those in the high prior belief group who receive HIV-negative tests are less likely to have an STI; this result could be explained by these types seeking treatment for their STIs instead of any change in sexual behavior. To examine these various behavioral changes, I look at the self-reported behavior from the six month follow up survey.

I first look at changes in self-reported sexual behavior. I estimate equation 2, but this time I replace the STI outcome with self-reported sexual behavior. The three outcomes used are: 1) an indicator if an individual is sexually active 2) number of sexual partners, and 3) an indicator if they had unprotected sex with a commercial or casual partner (Table V; columns 1-3).[26] I focus the analysis on the group where testing leads to increases in STI incidence: the low prior belief group receiving HIV-positive tests (row 2). Individuals with low prior beliefs who receive HIV-positive tests report having fewer partners and are less likely to have unprotected sex (row 2; columns 2-3). This result is puzzling, given these types are more likely to have an STI. What explains this? One explanation is that low prior types who receive HIV+ tests change their sexual behavior in a way that is not captured by any of these self-reported responses. A more likely explanation is that self-reported sexual behavior is inaccurate due to social desirability bias (Fenton et al., 2001). Individuals who learn they are HIV+ might simply be telling enumerators the "correct" sexual behavior that counselors have instructed them to do. These results suggest that we are unable to use the self-reported sexual behavior for inference.

Another behavior that might be changing is the decision to seek medical treatment for STIs. Groups with higher STI incidence might be choosing to forgo STI treatments. I look at whether an individual went for STI treatments during the course of the study (Table V; column 4). In the

[25]Specifically, when HIV-positive types increase their risky sexual behavior they make it more riskier for HIV-negative types to engage in risky sexual behavior since they increase the likelihood that an HIV-negative individual will match with an HIV-positive individual.

[26]These outcomes are generated from a set of questions on sexual behavior that use a two month time window (i.e. At the 6 month follow up survey, the questions ask about sexual behavior over the past two months).

two groups where HIV testing did lead to changes in STI incidence (rows 2 and 3), there is no evidence that this type of behavior changed.

The type of sexual partner you have is also relevant. Individuals who receive their HIV test results may match with partners with the same HIV status. This has important implications if HIV-positive types match with HIV-positive partners; this type of behavior at the extreme will effectively shut down new HIV infections. While data does not exist for the HIV status of sexual partners that are not enrolled in the study, the follow up survey asks study participants if their most recent sexual partners have tested for HIV. If assortative matching on HIV status is occurring, those tested for HIV should be more likely to have partners who have tested. I create an indicator if an individual's sexual partner has been tested for HIV and estimate equation 2 (Table V; column 5).[27] Those with low priors who receive HIV-positive tests are actually less likely to have a partner that has tested (row 2; column 5).

Even in the absence of an HIV test, it is still possible to infer a partner's HIV status by their behavior. Someone who is a commercial sex worker or has multiple sexual partners will be more likely to be HIV-positive. HIV-positive individuals who match up with higher risk partners will mitigate the spread of HIV. Indicators for whether an individual matched with a commercial partner, casual partner, or someone with multiple partners are used as outcomes to examine whether this type of matching is occurring. In the low prior belief/HIV-positive group, it looks like there is *less* matching with higher risk individuals (Table V; row 2, columns 6-8). Overall, using self-reported behavior, there is no evidence of HIV-positive individuals matching with higher risk partners.

Given the conflicting results between STI outcomes and the self-reported sexual behavior (i.e. groups with higher STI incidence reporting less sexual activity), I rely solely on the STI outcomes as the basis of my inference. In Section 6, I use a simple epidemiological model of STI & HIV transmission to estimate changes in risky sexual behavior based on the STI results. These estimated

[27] This specification is only estimated on individuals enrolled in the study. Couples enrolled in the study always have their sexual partners tested. This is why the number of observations is 916.

changes in sexual behavior will then be used to calculate the change in HIV infections as a result of testing.

5 Discussion

5.1 Are beliefs the channel through which HIV testing is affecting behavior?

While offers of HIV testing were randomly assigned, the research design did not stratify by prior beliefs and randomize within each belief group. There are two possible issues that could affect inference. The first issue concerns whether there are preexisting differences between treatment and control in each of the four groups analyzed, while the second issue is whether prior beliefs are correlated with other variables that might be driving the results.

Regarding the first issue of preexisting differences, if within each of the four groups analyzed: 1) Low Priors/HIV-, 2) Low Priors/HIV+, 3) High Priors/HIV-, and 4) High Priors/HIV+ (see section 4.1), there were differences between the treatment and control group before treatment assignment then the effect I am inferring from testing might be driven by preexisting differences. For example, for those with low priors who are HIV-positive, if the treatment arm had a higher proportion of males and if males engage in riskier sex, than the testing effect I find for this group might be due to the higher proportion of males and not to HIV testing.

To show that preexisting differences between the treatment and control arms are not a concern, I present comparisons of baseline characteristics for the treatment and control arms in each of these four groups (Table VI). The two groups that I focus on are the ones where testing has an effect. The first group, the low prior/HIV-positive (testing increases risky sexual behavior), is presented in columns 4-6. For the most part, there are no major differences in demographics, HIV/AIDS awareness, or self-reported sexual behavior. The two differences to note are: 1) the control arm has a higher proportion of Muslims (row 5; p-value=.09), and 2) the treatment arm has a higher proportion who are married (row 11; p-value $< .01$). Could these two differences explain away the main results? When both of these characteristics are included as covariates, the main results remain (Table IV; Column 3). In the next section, I interact both of these characteristics with all combinations of the testing and HIV status indicators, and show that the main results are remarkably stable. Finally, it should be noted that the marriage variable was generated through self-reported responses, and not verified by marriage certificates. The definition of marriage can be somewhat ambiguous in East Africa; if cohabiting partners is included, the percentage who cohabit in the treatment and control arms is much more similar (row 12; columns 4-6).

The second group where testing has an effect is the high prior/HIV- group (testing decreases risky sexual behavior), is presented in columns 7-9. There are no statistically significant differences on any demographics except for the number of children (Row 13; p-value=.07), and this difference is small. Focusing on self reported sexual behavior, the control group has a lower proportion reporting unprotected sex with a non-primary partner (row 22; p-value=.06). If you recall from section 3.2, the HIV-negative control group should be on average more likely to practice safer sexual behavior. This is because the HIV-status of the control arm was measured at the 6-mo followup; and HIV-negatives in the control arm at baseline who became infected with HIV would be excluded from this group. This difference in self-reported unprotected sex is consistent with this notion .

Overall, across 56 tests of difference of means (2 groups X 28 variables), I find only 1 statistically significant difference at the 5% level. This suggests that the main results are not driven by pre-existing differences between the treatment and control arms.

The second issue is whether prior beliefs are correlated with other individual characteristics. Using a similar example as before, if there were more males in the low prior belief group and females in the high prior belief group, the effects of testing maybe due to differential responses in gender and not beliefs. Comparing observed characteristics at baseline between the low and high belief groups, I find that the members of the low belief group are more likely to be married, have more children, and were less aware about HIV/AIDS.[28] Since marriage rates are different in the low prior/HIV-positive group where I find major behavioral changes due to testing, it is pertinent to see if the behavioral response to testing is due to marriage and not through an updating of beliefs. I estimate the main equation (2) and interact test and HIV status with marriage and the number of children (Table VII; Column 1). I find that the changes in STI rates for those surprised by an HIV test remain intact and statistically significant (Column 1; Rows 9 & 10). In addition, I find that the results are robust to interactions with HIV/AIDS awareness (Column 2), religious characteristics (Column 3), and the full set of interactions (Column 4). Overall, these robustness checks suggest that testing is changing behavior through a change in beliefs and not through an alternative channel.

5.2 Are results sensitive to how belief groups are specified?

The low and high prior belief groups used in the main analysis were determined by taking the average response of four questions designed to measure HIV risk perception and dividing the sample by the median response. One potential concern is that the results are sensitive to using the median response as the cut point to determine low and high priors. To examine how sensitive the results are to this cut point, I estimate the effects of HIV testing when varying this cut point (Figure IV). For example, with a cut point of 1.25, all responses below this are grouped into low priors, while those equal or above the point are grouped into high priors. The effects of testing on STI incidence is then estimated using these 6 different cut points to classify low and high prior groups (Table VIII). The results remain fairly stable across all six specifications. Those surprised by an HIV-positive test show an increase in risky sex in all specifications, and the estimate is statistically significant in four of the six (row 2). The attenuation of the effect makes sense as the cut point increases; a high cut point implies a smaller percentage of people will be surprised by an HIV-positive test since they believe they are at higher risk for HIV. The same pattern is

[28] Specifically those in the low belief group were less likely to have sought HIV/AIDS counseling in the two months prior to the baseline survey.

found with those surprised by an HIV-negative test (row 3). All cut points show a decrease in risky sex, with the effect becoming attenuated as the cut point decreases. Again the attenuation is consistent with the notion that a smaller percentage of people are surprised by an HIV-negative test with a lower cut point (since they will believe they are at low risk for HIV). Finally the effect of testing where test results confirm priors is never statistically significant (row 1 & 4). Overall, the main results in this paper are not sensitive to how the sample was divided into low and high prior belief groups.

5.3 Are results consistent with previous work?

Two main findings of this paper are: 1) individuals surprised by HIV-positive tests increase their risky sexual behavior, and 2) the behavioral response to HIV testing depends on prior beliefs of HIV status. The first result contrasts with the findings of Thornton (2008) and de Paula, Shapira and Todd (2010) both of whom find that when individuals learn they are at higher risk for HIV they *reduce* their risky sexual behavior. Specifically, Thornton (2008) finds that individuals receiving HIV-positive tests buy more condoms in a follow up survey, while de Paula, Shapira and Todd (2010) find that married men are less likely to engage in extra-martial affairs when their beliefs of being HIV-positive increase. Clearly the degree of altruism towards others determines the behavioral response to an HIV-positive test (see Section 2). If married individuals are more likely to be altruistic towards another person (their spouse) than unmarried types, then difference in marriage rates and altruism may reconcile the results. While de Paula, Shapira and Todd (2010) focus exclusively on married men and Thornton (2008) uses a sample where over 70% are married, in this paper, less then 40% are married. To test the hypothesis that married types act differently than singles following an HIV-positive test, I estimate the effects of testing separately on individuals who are single and married (Table IX). Individuals who are single have a statistically significant change in STI incidence (Column 1; Rows 8-9), while married types have no significant change in STI incidence (Column 2: Rows 8-9). In addition, I estimate the effects of testing conditioning on whether someone tests as an individual or couple (i.e. people who test with their partner). Making the effort to test as a couple may signal a higher level of altruism towards your partner, and the results are consistent with this notion. People who test alone have a much stronger response to testing (Column 3; Rows 8-9) compare to those who test as a couple (Column 4). In fact, for those who test as a couple and are surprised by an HIV-positive test, the point estimate is negative (Column 4; Row 8), although it is not statistically significant. Overall, the effect of being surprised by an HIV-positive test does not have a significant effect on behavior for married types or those who test as a couple.

The finding in this paper that the behavioral response to testing depends on a subject's prior beliefs of HIV status is consistent with previous work done in the United States and sub-Saharan Africa. Boozer and Philpson (2000) using non-experimental data, find that HIV testing elicits a differential response depending on a person's priors using a sample in San Francisco. Goldstein et al. (2010) find a differential response in health-related behavior by pregnant women in Kenya to health worker absenteeism depending on their prior beliefs of HIV status. One of the empirical challenges to conditioning a test response on both prior beliefs and HIV status is that cell sizes can become quite small. The data in this paper is unique: over 19% of the sample is HIV-positive which generates 465 individuals who are HIV-positive. This provides sufficient statistical power, even when conditioning on both prior beliefs and HIV status. In comparison, Thornton (2008) has 52 HIV-positive individuals in her sample and does not reject the null hypothesis that there is a differential response to an HIV-positive test depending on priors.

Finally, the results in this paper contrast sharply to the results of the orignal paper by Coates et al. (2000) published in the *Lancet*, a leading medical journal. Coates et al. (2000) compares the self-reported sexual behavior at the follow up round between those randomly assigned into HIV testing to the control group; they find that those assigned into the testing arm were less likely to report unprotected sex with a casual (non-primary) partner.[29] There are three important

[29] A causal or non-primary partner is defined as a sexual partner who is not your spouse if married or boyfriend/girlfriend if unmarrried.

distinctions between my paper and Coates et al. (2000). First, the original paper does not take into account prior beliefs of HIV status. Second, the original paper relies on self-reported sexual behavior which I have previously discussed as being subjected to social desierability bias (see section 3.1). Moreover, as Beegle and de Walque (2009) note, self-reports are limited in that they may not capture all aspects of risky sexual behavior. For example, the simple comparison between the testing and control arms also shows that those assigned into the testing arm increase their likelihood of sexual activity with their primary partners. There maybe different changes in sexual behavior on both the extensive and intensive margin that the self-reports may not be capturing. Third, the orignal paper actually shows that amongst those in the testing arm, HIV-positives are much more likely to contract an STI than HIV-negatives during the study (see Figure 3 in Coates et al. (2000)), yet this very same figure shows that HIV-positives are also *reducing* their self-reported risky sexual behavior. What explains this? It maybe that despite the protective measures that HIV-positive types are taking, their weaken immune system may make them more susceptible to contracting an STI. Since, I take HIV-status into account, and effectively compare HIV-positives who are tested versus HIV-positives who are not tested, I show that this increase in STI outcomes is likely due to an increase in risky sexual behavior and not due to biological reasons.

6 Short-Term Effect of Testing on the Epidemic

What are the effects of testing on new HIV infections? This question has important implications for public policy. There are two challenges to answering this question. The first is that we cannot go directly from the main empirical STI results to estimating new HIV infections. Transmission rates between gonorrhea/chlamydia and HIV differ by a large order of magnitude (see footnote 16), and to the best of my knowledge, no work exists which translates how changes in STI rates change HIV infectivity. The second challenge is that the effects of testing depend on the distribution of beliefs and HIV status in the population. For example, if no one is surprised by an HIV-test, then testing will have minimal effects on behavior. To estimate this distribution, I use the latest round of Demographic and Health Surveys (DHS) that measure both subjective beliefs and actual HIV status. I limit the analysis to countries in SSA with high HIV prevalence and where surveys were conducted over the past 4 years. The surveys used are the Kenya 2008, Mozambique 2009, and Zambia 2007 DHS. I limit the sample in each country to the urban population to make it most comparable to the population used in this study. I therefore make predictions on the effects of HIV-testing for urban populations in Kenya, Mozambique, and Zambia.

I undertake the following steps: 1) estimate the effects of testing on STI incidence, 2) using these STI outcomes to estimate changes in sexual behavior, 3) compare how HIV transmission rates change due to changes in sexual behavior, and finally, 4) estimate new HIV infections in a base case without testing and in a case where everyone is tested. Step 1 comes from the main empirical results (Table IV), while steps 2-3 use a simple epidemiological model. Step 4 relies on the distribution of beliefs of HIV infection and actual HIV prevalence from the DHS. A simple diagram outlines the 4 steps:

$$\text{HIV Testing} \xrightarrow{1} \text{STI Incidence} \xrightarrow{2} \text{Sexual Behavior} \xrightarrow{3} \text{HIV transmission} \xrightarrow{4} \text{New HIV Infections}$$

Before introducing the epidemiological model, some intuition is helpful. The key challenge is that the empirical findings show certain groups changing their STI incidence after testing, but we do not know to what degree behavior is changing. For example, if a group has more STIs after testing, how many more sexual partners does this imply? What is required is translating STI outcomes into actual sexual behavior (step 2). Once this is done, we can see how changes in the number of partners affects the likelihood of HIV transmission (step 3). The model described below helps us in both steps.

The AVERT epidemiological model (Rehle et al., 1998) is used to estimate both changes in sexual behavior and HIV transmission rates (steps 2 & 3). It has been used in the public health literature to estimate the effects of testing on new HIV infections (Sweat et al., 2000). The major difference is that I use the model to translate the STI outcomes to sexual behavior (step 2), which previously was not done. The model predicts the likelihood of infection from HIV or an STI, and is driven by the probability of matching with someone who is already infected, and conditional on this match, the probability of becoming infected. The model is expressed as:

$$\mathbb{P}(Infection) = 1 - \left\{W[1 - R(1 - FE)]^N + (1 - W)\right\}^M \tag{3}$$

where $\mathbb{P}(Infection)$ is the likelihood of becoming infected with either HIV or an STI, W =prevalence, R =infectivity or the probability of infection per unprotected sexual act, F =fraction of sex acts where a condom is used, E = effectiveness of condoms, N =Number of sex acts per partner, and M =number of sexual partners. Parameter estimates for condom effectiveness (E) and infectivity (R) come from epidemiological research (Kretzschmar, van Duynhoven and Severijnen, 1996; Sweat et al., 2000; Gray et al., 2001), while sexual acts per partner N and prevalence of STIs (W) comes from the study (Table X; Panel I).

For step 2, estimating how STI incidence translates into changes in sexual behavior, I focus on M or the number of sexual partners.[30] Solving equation 3 for M results in:

$$M = \frac{log(1 - \mathbb{P}(Infection))}{log(W[1 - R(1 - FE))^N + (1 - W))} \tag{4}$$

Using the parameter values from Table X, and applying the main empirical results (Table IV) for $\mathbb{P}(Infection)$, changes in the number of partners (M) are generated (Table X; Panel II). For example, in the the first row (Low Prior Beliefs) and second column (HIV-positive), the control arm has an average STI incidence of 1.06% which generates an average number of partners of .21. This can be interpreted as the rate of partner turnover, so approximately 1 in 5 from this group changed partners during the 6 month study. The STI incidence in the testing arm is 11.6% (1.06%

[30] The choice of focusing on number of sexual partners and not condom use is not arbitrary. Given the high rates of infectivity for gonorrhea or chlamydia, the most important factor determining likelihood of either of these STIs is the number of partners you have.

+ 10.5%), which translates into 2.36 partners on average during the study period. In the groups where testing had no statistically significant effects, I assume both the control and testing arms had on average a similar number of partners (i.e. low prior beliefs/HIV-negative and high prior beliefs/HIV-positive).

Step 3 converts the sexual behavior (M) into HIV transmission probabilities for HIV-positive types ($\mathbb{P}(HIV\,Transmission)$), and HIV infection probabilities for HIV-negative types ($\mathbb{P}(HIV\,Infection)$) . What I do here is estimate how likely is it for an HIV-positive type to infect someone else or how likely is it for an HIV-negative type to become infected. The probability of infection simply uses equation 3, with HIV parameter values from Table X and sexual behavior estimates from step 2. To calculate the probability of transmitting HIV to another individual requires a trivial modification of equation 3:

$$\mathbb{P}(HIV\,Transmission) = 1 - [W + (1-W)(1-R(1-FE))^N]^{M^*} \tag{5}$$

where M^* are the estimates of sexual behavior from step 2. For example, in the low prior belief/HIV-positive cell of Table X (Panel II), the control arm is estimated to have .21 partners which translates to a .11% chance of transmitting HIV to an uninfected person over a 6 month time frame in urban Kenya. HIV transmission rates vary between countries because of differences in HIV-prevalence.[31]

The final step is to apply these HIV transmission rates to the distribution of prior beliefs and HIV status in urban Kenya, Mozambique, and Zambia (Table XI; Panel I). For example, 39% of urban individuals in Kenya have low prior beliefs and are HIV-negative. I estimate the effects of HIV testing on a population of 100,000 for a six month time frame. In each cell, the number of new HIV infections is determined by multiplying either the transmission rates or infection likelihoods from Table X (Panel II) by the mass in each cell times 100,000. For example, in the low prior

[31] The higher the HIV-prevalence, the lower the likelihood that an individual who is HIV-positive will infect someone. Since the likelihood of infection requires that the HIV-positive match with an HIV-negative, if we assume random matching, then countries with higher HIV-prevalence have fewer HIV-negatives with which to match.

belief/HIV-positive cell in Table XI, the number of new infections in Kenya in the testing case is the mass (3%) times 100,000 and then multiplied by the probability of transmitting HIV to an uninfected individual (1.21%; Table X; Panel II). Base cases (no testing) are compared with testing cases, and differences are shown for each cell. The second part of Table XI (Panel II) reports the changes in HIV infections due to testing in both absolute numbers and a percentage (Panel II, Rows 1-2). We see that in all three countries, HIV-testing leads to an increase in the number of HIV-infections compared to a case without testing. While the magnitude of the percentage changes in Mozambique and Zambia are large, we note that the absolute increases of 64 and 49 are both over a population of 100,000, which amount to much smaller changes in HIV incidence. Also, I am only able to reject the null of zero effect of HIV-testing on new infections for the Mozambique estimate at the 10% significance level[32].

The analysis above assumes both random matching of sexual partners and that ARVs are not provided to those receiving an HIV-positive test. I relax each assumption to see how the effects of testing on new infections changes. I first allow for assortative matching by HIV-status, or that HIV-positives (negatives) are more likely to match with other HIV-positives (negatives). Using HIV-prevalence in the country as the likelihood of matching randomly, I adjust the matching rates by 25 and 50 percent. For example, in urban Mozambique, HIV-prevalence is 16%, and thus random matching would assume that someone has about a 1 in 6 chance of matching with someone who is HIV-positive. Adjusting the match rates by 25%, I assume that HIV-negatives will match with an HIV-positive 12% of the time, while HIV-positives will match with an HIV-positive 20% of the time. Thus, the higher the match rate, the greater the likelihood there is assortative matching by HIV-status. The results for Kenya are most effected by this exercise; HIV-testing now leads to small decreases in new infections(Table XI; Panel II, Rows 3-4). However, the changes in HIV-infections due to testing in both Mozambique and Zambia remain positive under both matching

[32]Confidence intervals for these estimates are calculated using a paired bootstrap with 1000 replications sampling on the couple level. Each replication restimates equation 2 from the sample data, which is then used to estimate changes in HIV infections using the framework in this section.

scenarios.

I also see whether the provision of ARVs for those who are HIV-positive can effect the results. ARVs have been shown to reduce the transmission rates by over 90%, which could mitigate the risk posed by those surprised by HIV-positive tests (Granich et al., 2010, 2009). I compare a scenario where 10% of those testing positive for HIV-positive are immediately given ARVs to scenarios where the percentage is increased to 25 and 50 percent. It is important to note three aspects of this exercise. First ARVs are not typically provided immediately following an HIV-positive test; CD4 counts are monitored and a threshold needs to be crossed before ARVs are administered. Second, if ARVs are provided immediately to those testing positive, testing now also effects those not surprised by an HIV-positive test (high priors/HIV-positive), as ARVs will lower their likelihood of transmitting the infection to another person. Third, the availability of ARVs in itself may lead to an increase in risky sexual behavior as the costs of HIV infection decrease; evidence has been found in the US and sub-Saharan Africa that individuals increase their risky sexual behavior when ARVs are more widely available (Lakdawalla, Sood and Goldman, 2006; de Walque, Kazianga and Over, 2010). With these caveats in mind, I estimate the effects of immediate ARV provision for those testing positive for HIV. I find that in the Kenya case, there are reductions in HIV infections due to testing under all scenarios, while in the Mozambique and Zambia case, testing still leads to increases in HIV-infections unless 50% of all those who test positive are given ARVs (XI; Panel II, Rows 5-7).

Combining a simple epidemiological model with well identified estimates on the effects of HIV testing on sexual behavior, I show that HIV testing in the short term can lead to an increase in the number of new HIV infections. This result is driven by those surprised by an HIV-positive test. The effects of testing depend on the distribution of prior beliefs and HIV status. In the case of Kenya, where there is a small percentage of those surprised by an HIV-positive test (3%) and a large percentage surprised by an HIV-negative test (53%), the effects of testing maybe beneficial under certain assumptions (i.e. assortative matching). However, in countries such as Mozambique and Zambia, where there are larger percentages that are surprised by an HIV-positive test (8%), testing leads to an increase in HIV-infections under a variety of different scenarios.

A few final caveats are in order. First, in the long run, as testing increases the risky behavior of those surprised by an HIV-positive test, the pool of potential sexual partnerships becomes riskier. HIV-negative types may respond to this by decreasing their risky sexual behavior (Kremer, 1996; Mechoulan, 2004). I therefore am unable to say how steady-state HIV prevalence would be changed by HIV testing. Secondly, the population of interest in this study are sexually active urban individuals. The effect of testing maybe different on a rural population that is less sexually active. This remains a topic for further research.

7 Conclusion & Policy Implications

This study is the first to show that HIV testing can lead to adverse outcomes. Empirically, I show that groups surprised by HIV-positive tests (low prior beliefs/HIV-positive), increase their risky sexual behavior after testing. Combining these empirical results with a simple epidemiological model, I find that in the short-run, HIV testing leads to an increase in the number of new HIV infections compared to scenario of no testing.

These results raise concern that HIV testing under some instances may increase the number of new HIV infections. The behavioral response of those surprised by HIV-positive test results is consistent with rational behavior; if there is no longer any benefit of safe sex then individuals no longer practice it ("nothing to lose"). It raises questions about the implicit assumption in HIV testing policies that those who receive HIV-positive tests will behave altruistically and take steps to prevent infecting others.

From a policy perspective, it should be stressed that this paper does not advocate eliminating HIV testing. It does suggest that better targeting of HIV testing might be both feasible and desirable. Using population based surveys, such as ones conducted by the Demographic Health

Surveys (DHS), we may be able to identify populations that overestimate and underestimate their HIV risk. Based on the results from this study, HIV testing may prevent new infections when rolled out in populations that overestimate their HIV risk, such as the case in Kenya (see previous section). It may also be necessary to offer incentives for those who are surprised by an HIV-positive test to reduce their risky sexual behavior. Stressing the dangers of reinfection with HIV and the diminished efficacy of ARV treatments if the HIV virus mutates may be helpful. Providing monetary incentives to practice safe sex may also be a policy consideration, especially given the costs of treating new HIV infections.

HIV testing has been advocated by both international organizations (i.e. UNAIDS) and national governments in sub-Saharan Africa as a means to prevent new infections. There is no rigorous evidence that this is the case. The evidence from this paper and Thornton (2008) suggests that focusing limited resources on other interventions maybe much more cost effective at preventing new HIV infections. For example, preventing mother-to-child transmission of HIV and male circumcision are both interventions that have substantial evidence showing that they reduce HIV transmission. Investing in the prevention of other diseases such as malaria or tuberculosis may also generate a behavioral response to safer sex (see Oster (2009)).

Additional research is needed to understand the incentives that HIV-positive individuals face when making decisions about sexual behavior. Policymakers may also need to take into account people's beliefs and awareness about their HIV risk so that increased access to HIV testing does not lead to unintended outcomes.

8 Appendices

8.1 HIV Knowledge

The key premise in this paper is that HIV testing provided new information to individuals. However, there are additional differences in what was offered to the treatment vs. control arms which might have affected the information set between members of both arms. The control arm received a 15 minute video while the treatment arm also received individual counseling. To see if these differences in interventions beyond HIV testing created differences in information about HIV I compare HIV/AIDS knowledge between both arms. At baseline and the 6 month follow up, 12 questions regarding HIV/AIDS were asked. The questions took the form: "Can you get the AIDS virus from the following? and each question posed a different scenario ranging from: "having sex without a condom" to "using public toilets". For each person in the study, I calculate the change in correct responses between baseline and the 6 month follow up. If people assigned into the testing arm are learning more about HIV/AIDS, then they should have an increase in the number of correct responses. I estimate the following equations:

$$HIV/AIDS\,Knowledge\,6mo_{ij} = \alpha + \beta_1 Test_i + X_i'\delta + \gamma_j + u_{ij}$$

$$\Delta HIV/AIDS\,Knowledge_{ij} = \alpha + \beta_1 Test_i + X_i'\delta + \gamma_j + u_{ij} \tag{6}$$

where $HIV/AIDS\,Knowledge\,6mo_{ij}$ is the total number of correct responses at the 6 month follow up and $\Delta HIV/AIDS\,Knowledge_{ij}$ is the change in the number of correct responses between baseline and 6 months for individual i and country j. The indicator $Test_i$ denotes if the individual was assigned to the testing arm, X_i' is a vector of individual characteristics, and γ_j is a country fixed effect. If there was a differential effect on HIV/AIDS knowledge between the treatment and control arms, then $\beta_1 \neq 0$. Table A.I presents the results. Columns 1 and 2 estimate if there's any difference in HIV knowledge at 6 months, and columns 3 and 4 estimate changes in knowledge. In all four specifications, it appears that there are no differences in either overall knowledge or changes in knowledge between the treatment and control arms. This suggests that there was no differential learning about HIV between the treatment and control arms and that the primary difference between the arms is the information provided by HIV tests.

8.2 HIV Test Uptake in Treatment and Control Arms

The intervention offered HIV tests to study participants - no one was mandated or coerced to take a test. The acceptance rate for HIV tests was 94% at baseline in the treatment arm, and 84% at the 6 month follow up in the control arm. Do differences in the test acceptance rate threaten the validity of the counterfactual groups described above? If test takers in the treatment group have different preferences for risky sexual activity than test takers in the control group it could bias any estimations. To see if there is any evidence of this, a comparison along observables and self-reported activity is made between test takers in the treatment and control arms (Table A.II). Column 1 presents all test takers in the treatment arm at baseline, while column 2 restricts the treatment sample to test takers who participate in the 6 month follow up. A t-test of the difference in means between treatment and controls arms is conducted, and p-values are in columns 4 and 5. Reassuringly, almost all demographic and relationship covariates (rows 1-14) are balanced across test takers in the treatment and control arms. More importantly, there are no differences in HIV/AIDS knowledge, testing, and HIV prevalence (rows 15-18). Self-reported sexual activity also appears virtually balanced between both arms. Thus, despite the differences in HIV testing acceptance rates, there is no evidence that test takers are different across treatment and control arms.

8.3 Beliefs of HIV Infection: Alternative Measures

This section compares belief measures that use individual questions from section 3.3 to the preferred belief measure that uses all four questions. For each question, I create a high and low belief group. For example, using question A, those who respond with a 1 or 2 are placed in the low belief group, and those that respond with a 3 or 4 are placed in the high belief group. I do this for all four questions.

The first validity test is to see how each belief measure predicts risky sexual behavior. I estimate equation 3.3 using each of the individual measures (Table A.III). All four measures are positive correlated (columns 1-4), but the preferred measure using all four questions has more predictive power than any of the individual questions (column 5). I can also examine how accurate the individual questions are in predicting HIV status. All four measures are positively correlated with actual HIV status (columns 7-10), but the preferred measure is more accurate (column 11).

It is worth nothing that the preferred belief measure gives an equal weight to each of the four questions. An alternative is to weight each question by how predictive it is of either behavior or HIV status. To do this, I predict STI incidence for each individual using estimates from each individual measure (Table A.III, Panel 1, column 6). For example, responses to question C (point estimate .03) would count three times as much then question D (point estimate .008) when predicting STI incidence. I then divide the entire study sample by the median of predicted STI incidence which creates a high and low belief group. I perform the same exercise using baseline HIV status instead of STI incidence. Using estimates from each of the four questions to predict HIV status (Table A.III, Panel 2, column 12), I predict HIV status, and then divide the sample using the median of predicted HIV status. This again creates a low and high belief group. Using both of these weighted belief measures, I estimate the effects of HIV testing and find similar results (Table A.IV; columns 1-2). Those surprised by HIV positive tests increase their risky sexual behavior (Row 9), while those surprised by HIV negative tests decrease their risky sexual behavior (Row 10).

Another specification for beliefs is to use a continuous measure. In this specification, I simply use the average response to questions A-D as the belief measure (see Figure III). I estimate the effects of testing and again find similar results: those surprised by an HIV-positive test increase their risky behavior (Column 3, Row 6), while those surprised by an HIV-negative test decrease their risky behavior (Column 3: Row 5).

8.4 Incidence vs. Prevalence

Both incidence and prevalence at the 6 month follow up can be modeled as functions of risky sexual behavior during the study and baseline prevalence. Let $incidence_t = f(risky\, sex_t, prevalence_{t-1})$ and $prevalence_t = g(risky\, sex_t, prevalence_{t-1})$, where t= 6 month follow up and $t-1$= baseline, and suppose that STI tests pick up any risky sexual activity. Then using incidence will underestimate risky sex while prevalence at 6 months will overestimate risky sexual behavior. The following table illustrates these differences:

Incidence as Outcome (underestimate risky behavior)	Prevalence as Outcome (overestimate risky behavior)
$0 = f(0,0)$	$0 = g(0,0)$
$0 = f(0,1)$	$1 = g(0,1)$
$0 = f(1,1)$	$1 = g(1,1)$
$1 = f(1,0)$	$1 = g(1,0)$

To see if the main results are affected by the choice of outcome, I estimate the effects of HIV testing on STI prevalence at 6 months. Results are presented in table A.V. Virtually all of the estimates remain consistent with the main findings. Those surprised by an HIV-positive test increase their risky sexual behavior (row 2). While those surprised by an HIV-negative test reduce their risky sex, although these estimates are attenuated and are no longer statistically significant (row 3). What explains this? Individuals who had a baseline STI infection and decreased their risky sexual behavior during the study may still have that same infection at the 6 month follow up. Finally, when HIV tests confirm prior beliefs, there is no statistically significant effect on behavior (rows 1 & 4).

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Table I: Summary Statistics

	Variable	Treatment Mean (1)	Control Mean (2)	p value (3)
	Demographics			
(1)	Male	0.50	0.50	0.97
(2)	Age	28.3	28.3	1.00
(3)	Primary School	0.62	0.63	0.60
(4)	Secondary School	0.26	0.27	0.85
(5)	Muslim	0.28	0.29	0.46
(6)	Catholic	0.33	0.36	0.10
(7)	Christian	0.35	0.31	0.02
(8)	Tap water in home	0.54	0.54	0.96
(9)	Electricity in home	0.44	0.45	0.49
	Relationship Status			
(10)	Enrolled as Couple	0.33	0.32	0.90
(11)	Married	0.39	0.39	0.94
(12)	Cohabiting	0.49	0.49	0.69
(13)	Number Living Children	1.45	1.48	0.65
	HIV/AIDS			
(14)	HIV/AIDS Knowledge (out of 12)	9.73	9.76	0.75
(15)	HIV/AIDS Counseling	0.19	0.22	0.07
(16)	HIV Testing	0.01	0.02	0.15
(17)	Baseline HIV+	0.20		
	Sexual Activity			
(18)	Two or More Partners	0.22	0.21	0.70
(19)	Unprotected Sex with			
(20)	Commerical Partner	0.12	0.13	0.38
(21)	Non-Primary Partner	0.25	0.24	0.42
(22)	Primary Partner	0.50	0.49	0.35
(23)	Episodes Unprotected Sex with			
(24)	Commerical Partner	6.37	7.32	0.31
(25)	Non-Primary Partner	6.50	7.40	0.21
(26)	Primary Partner	12.52	11.92	0.36
	Sample Size	1477	1465	

P-values are reported from t-tests on the equality of means for each variable within treatment and control arms. A primary partner is either a legal/common-law spouse, boyfriend, or girlfriend. Non-primary partners encompass all other partnership types. Examples include: friends, coworkers, casual dates, and commercial sex workers. Variables under "Episodes Unprotected Sex with" are conditioned on having sex with either a commercial, non-primary, or primary partner (rows 24-26).

Table II: Attrition Analysis

		Treatment Group			Control Group			Attrition		In Study	
		In Study	Attrition		In Study	Attrition		Difference		Difference	
	Variables	Mean	Mean	p value	Mean	Mean	p value	(2) - (5)	p value	(1) - (4)	p value
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Demographics										
(1)	Male	0.51	0.49	0.45	0.50	0.51	0.64	-0.02	0.46	0.01	0.64
(2)	Age	28.7	27.4	0.00	29.0	27.1	0.00	0.35	0.46	-0.22	0.55
(3)	Primary School	0.61	0.63	0.48	0.63	0.62	0.76	0.01	0.77	-0.02	0.41
(4)	Secondary School	0.27	0.25	0.53	0.27	0.27	0.94	-0.01	0.60	0.00	0.90
(5)	Muslim	0.25	0.34	0.00	0.26	0.35	0.00	-0.01	0.76	-0.01	0.61
(6)	Catholic	0.34	0.29	0.05	0.37	0.33	0.08	-0.03	0.27	-0.03	0.18
(7)	Christian	0.36	0.31	0.06	0.32	0.29	0.20	0.03	0.33	0.05	0.03
(8)	Tap water in home	0.53	0.58	0.07	0.51	0.60	0.00	-0.03	0.42	0.02	0.46
(9)	Electricity in home	0.42	0.48	0.04	0.40	0.55	0.00	-0.07	0.03	0.02	0.39
	Relationship Status										
(10)	Enrolled as Couple	0.33	0.31	0.34	0.32	0.33	0.74	-0.02	0.49	0.01	0.54
(11)	Married	0.40	0.37	0.35	0.41	0.36	0.11	0.01	0.68	-0.01	0.80
(12)	Cohabiting	0.48	0.52	0.25	0.49	0.47	0.50	0.04	0.20	-0.01	0.68
(13)	Number Living Children	1.53	1.26	0.01	1.68	1.10	0.00	0.16	0.23	-0.15	0.12
	HIV/AIDS										
(14)	HIV/AIDS Knowledge	9.74	9.71	0.79	9.69	9.88	0.14	-0.17	0.23	0.05	0.65
(15)	HIV/AIDS Counseling	0.19	0.19	0.99	0.20	0.24	0.07	-0.05	0.04	-0.01	0.45
(16)	HIV Testing	0.01	0.01	0.52	0.02	0.02	0.64	-0.01	0.34	-0.01	0.26
(17)	Baseline HIV+	0.19	0.23	0.14							
	Sexual Activity										
(18)	Sexually Active	0.82	0.81	0.68	0.80	0.82	0.23	-0.01	0.60	0.02	0.21
(19)	Two or More Partners	0.22	0.21	0.64	0.21	0.21	0.81	0.00	0.93	0.01	0.69
	Unprotected Sex with:										
(20)	Commerical Partner	0.12	0.11	0.42	0.12	0.14	0.28	-0.03	0.11	0.00	0.96
(21)	Non-Primary Partner	0.26	0.24	0.44	0.23	0.26	0.13	-0.02	0.39	0.03	0.11
(22)	Primary Partner	0.51	0.49	0.61	0.49	0.49	0.99	0.01	0.81	0.02	0.34
(23)	Episodes Unprotected Sex with										
(24)	Commerical Partner	6.62	5.78	0.52	7.78	6.56	0.41	-0.78	0.58	-1.17	0.34
(25)	Non-Primary Partner	6.72	6.01	0.47	7.74	6.86	0.45	-0.85	0.47	-1.02	0.27
(26)	Primary Partner	12.2	13.2	0.29	12.1	11.5	0.52	1.73	0.14	0.06	0.94

P-values are reported from t-tests on the equality of means for each variable between "In Study" vs. "Attrition" in columns (3) and (6) and for differences in attrition between the treatment and control arm in column (8). In the sexual activity section, "primary" refers to a partner that is either a spouse or boyfriend/girlfriend. "NPP" are non-primary partners and refer to commercial and casual sex partners. Variables under "Episodes Unprotected Sex with" are conditioned on having sex with either a commercial, non-primary, or primary partner (rows 24-26).

Table III: Beliefs of HIV Infection

	STI 6mo Mean = .043				HIV+ Baseline Mean = .20			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Belief B	.007	.015			.024	.029		
	(.017)	(.018)			(.026)	(.027)		
High Prior Beliefs (All 4 Questions)			.052	.053			.042	.051
			(.015)***	(.016)***			(.022)*	(.023)**
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Obs.	957	921	957	921	1376	1320	1376	1320
R^2	0	.048	.016	.06	.001	.056	.003	.058

Robust standard errors in parentheses. Disturbance terms are clustered within couple pairings. Significantly different from zero at 99(***), 95(**), and 90(*) percent confidence. Controls include variables for gender, age, marriage, primary school, secondary school, college, Muslim, Catholic, Christian, number of children, number of assets, language of survey interview, and interviewer and country fixed effects.

Table IV: Effect of HIV Testing on STI Incidence (Risky Sexual Behavior)
Dependent Variable: STI Incidence (mean = .039)

	(1)	(2)	(3)
(1) Test	-.009	.002	-.001
	(.009)	(.013)	(.013)
(2) High Prior Beliefs	.023	.056	.053
	(.009)**	(.019)***	(.020)***
(3) HIV+	.042	-.010	-.010
	(.014)***	(.013)	(.014)
(4) Couple	-.012	.005	.020
	(.009)	(.017)	(.017)
(5) Test X High Prior		-.051	-.048
		(.024)**	(.024)**
(6) Test X HIV		.103	.096
		(.042)**	(.043)**
(7) Test X High Prior X HIV		-.096	-.094
		(.059)	(.058)
Interactions	No	Yes	Yes
Controls	No	No	Yes
Obs.	1961	1961	1882
R^2	.013	.029	.054
Linear Combinations: Effect of HIV Tests by Prior Beliefs			
HIV- test on low prior group			
(8) Test		0.002	-0.001
		(0.013)	(0.014)
HIV+ test on low prior group			
(9) Test+(Test X HIV+)		0.105	0.095
		(0.041)***	(0.041)**
HIV- test on high prior group			
(10) Test+(Test X High)		-0.05	-0.049
		(0.02)**	(0.021)**
HIV+ test on high prior group			
(11) Test+(Test X HIV+)+(Test X High)		-0.025	-0.027
+(Test X High X HIV+)		(0.047)	(0.046)

Robust standard errors in parentheses. Disturbance terms are clustered within couple pairings. Significantly different from zero at 99(***), 95(**), and 90(*) percent confidence. Interactions (columns 2-3) include all possible combinations of Test, High Prior, HIV+, and Couple. There are 6 double and 4 triple interaction terms (not all shown). Controls in column (3) include variables for gender, age, marriage, primary school, secondary school, college, Muslim, Catholic, Christian, number of children, number of assets, language of survey interview, and interviewer and country fixed effects. All standard errors on linear combinations are adjusted for covariance between variables.

Table V: Effect of HIV Testing on Self Reported Sexual Behavior

Dependent Variable	Sexually Active (1)	Number Partners (2)	Unprotected Sex (3)	STI Treatment (4)	Partner Tested (5)	Commercial Partner (6)	Casual Partner (7)	Partner Has Multiple Partners (8)
HIV- test on low prior group								
(1) Test	0.06	-0.26	-0.06	-0.05	0.08	0.01	0.01	-0.03
	(0.04)	(0.22)	(.03)*	(.03)*	(.03)**	(0.02)	(0.03)	(0.02)
HIV+ test on low prior group								
(2) Test+(Test X HIV)	-0.12	-0.35	-0.16	-0.04	-0.17	-0.10	-0.11	-0.11
	(0.07)	(0.21)*	(0.06)***	(0.07)	(0.08)**	(0.05)*	(0.07)	(0.05)**
HIV- test on high prior group								
(3) Test+(Test X High)	-0.02	0.03	-0.08	-0.04	0.05	-0.04	-0.04	-0.07
	(0.04)	(0.12)	(0.04)**	(0.03)	(0.03)**	(0.03)	(0.04)	(0.03)**
HIV+ test on high prior group								
(4) Test+(Test X HIV)	-0.13	-0.46	-0.10	0.10	-0.02	-0.05	-0.04	-0.04
+(Test X High)	(0.08)*	(1.04)	(0.06)*	(0.08)	(0.07)	(0.05)	(0.07)	(0.06)
+(Test X High X HIV)								
Observations	1,961	1,961	1,959	1,961	916	1,959	1,959	1,961
R-squared	0.05	0.01	0.03	0.05	0.04	0.02	0.01	0.02
Mean Dependent Variable	0.77	1.13	0.19	0.15	0.09	0.14	0.34	0.18

Estimates of the four linear combinations of interest are presented. Robust standard errors in parentheses and account for covariance between variables. Disturbance terms are clustered within couple pairings. Significantly different from zero at 99(***), 95(**), and 90(*) percent confidence. All specifications include the variables: Test, High Prior, HIV+, and Couple as well as all of their possible combinations which consists of 6 double and 4 triple interaction terms. All standard errors on linear combinations are adjusted for covariance between variables.

Table VI: Comparison of Treatment & Control Arms Stratified by Beliefs and HIV Status

		Low Prior Beliefs						High Prior Beliefs					
		HIV Negative			HIV Positive			HIV Negative			HIV Positive		
	Variable	Treat Mean (1)	Control Mean (2)	p value (3)	Treat Mean (4)	Control Mean (5)	p value (6)	Treat Mean (7)	Control Mean (8)	p value (9)	Treat Mean (10)	Control Mean (11)	p value (12)
	Demographics												
(1)	Male	0.54	0.52	0.57	0.35	0.33	0.76	0.58	0.58	0.82	0.28	0.26	0.76
(2)	Age	29.1	29.3	0.67	29.9	30.1	0.86	27.9	28.0	0.88	29.4	29.1	0.80
(3)	Primary School	0.60	0.64	0.31	0.60	0.62	0.70	0.64	0.61	0.39	0.61	0.69	0.27
(4)	Secondary School	0.29	0.27	0.41	0.23	0.27	0.59	0.25	0.28	0.39	0.25	0.21	0.54
(5)	Muslim	0.25	0.24	0.45	0.21	0.32	0.09	0.26	0.26	0.90	0.20	0.22	0.78
(6)	Catholic	0.33	0.35	0.39	0.37	0.38	0.96	0.33	0.37	0.25	0.41	0.48	0.35
(7)	Christian	0.37	0.35	0.02	0.37	0.28	0.18	0.36	0.32	0.25	0.37	0.22	0.03
(8)	Tap water in home	0.52	0.52	0.08	0.45	0.45	1.00	0.55	0.54	0.76	0.56	0.45	0.15
(9)	Electricity in home	0.44	0.42	0.29	0.34	0.37	0.72	0.43	0.41	0.70	0.37	0.31	0.38
	Relationship Status												
(10)	Enrolled as Couple	0.36	0.39	0.38	0.35	0.29	0.35	0.30	0.25	0.10	0.31	0.27	0.57
(11)	Married	0.45	0.49	0.35	0.52	0.32	0.00	0.35	0.33	0.74	0.29	0.33	0.55
(12)	Cohabiting	0.51	0.54	0.86	0.59	0.51	0.30	0.45	0.43	0.59	0.42	0.47	0.52
(13)	Number Living Children	1.68	1.79	0.58	1.65	1.76	0.67	1.26	1.51	0.07	1.76	1.53	0.36
(14)	Children in near term	0.16	0.13	0.55	0.34	0.26	0.24	0.19	0.18	0.71	0.19	0.20	0.76
	HIV/AIDS												
(15)	HIV/AIDS Knowledge	9.88	9.78	0.48	9.70	9.93	0.50	9.55	9.42	0.48	9.89	10.02	0.68
(16)	HIV/AIDS Counseling	0.18	0.18	0.45	0.13	0.16	0.54	0.21	0.25	0.28	0.20	0.26	0.41
(17)	HIV Testing	0.01	0.02	0.15	0.02	0.01	0.56	0.02	0.03	0.79	0.01	0.03	0.25
	Sexual Activity												
(18)	Sexually Active	0.81	0.78	0.87	0.84	0.83	0.87	0.83	0.80	0.38	0.80	0.83	0.71
(19)	Two or More Partners	0.18	0.17	0.32	0.18	0.26	0.23	0.28	0.25	0.28	0.23	0.28	0.42
(20)	Unprotected Sex with												
(21)	Commerical Partner	0.10	0.09	0.86	0.12	0.18	0.23	0.14	0.13	0.90	0.16	0.15	0.95
(22)	Non-Primary Partner	0.24	0.20	0.79	0.22	0.29	0.26	0.29	0.22	0.06	0.28	0.31	0.72
(23)	Primary Partner	0.53	0.51	0.27	0.52	0.49	0.71	0.49	0.47	0.68	0.47	0.42	0.54
(24)	Episodes Unprotected Sex with												
(25)	Commerical Partner	5.09	7.30	0.06	3.80	4.63	0.62	8.70	6.93	0.39	5.93	15.27	0.04
(26)	Non-Primary Partner	6.17	6.45	0.18	6.00	4.77	0.49	7.26	8.57	0.42	7.22	12.43	0.18
(27)	Primary Partner	11.2	11.6	0.53	14.6	11.4	0.26	12.9	12.3	0.72	12.6	15.3	0.37
(28)	Sample Size	447	455		94	94		365	322		98	86	

P-values are reported from t-tests on the equality of means for each variable between Treatment and Control Groups.

Table VII: Effect of HIV Testing on STI Incidence with Multiple Interaction Terms

	Marriage	HIV Awareness	Religion	All
	(1)	(2)	(3)	(4)
(1) Test	-.002	-.008	-.003	-.026
	(.015)	(.014)	(.014)	(.020)
(2) High Prior Beliefs	.057	.057	.056	.058
	(.020)***	(.019)***	(.019)***	(.020)***
(3) HIV+	-.029	-.011	.008	-.003
	(.023)	(.016)	(.016)	(.034)
(4) Couple	.009	.003	.005	.009
	(.018)	(.017)	(.017)	(.018)
(5) Test X High Prior	-.050	-.052	-.051	-.050
	(.024)**	(.024)**	(.024)**	(.025)**
(6) Test X HIV	.132	.114	.085	.131
	(.047)***	(.045)**	(.044)*	(.061)**
(7) Test X High Prior X HIV	-.113	-.097	-.087	-.104
	(.058)*	(.060)	(.058)	(.058)*
Base Interactions	Yes	Yes	Yes	Yes
Marriage/Children Interactions	Yes	No	No	Yes
HIV/AIDS Awareness Interactions	No	Yes	No	Yes
Religion Interactions	No	No	Yes	Yes
Obs.	1895	1961	1949	1893
R^2	.032	.034	.035	.046
Linear Combinations: Effect of HIV Tests by Prior Beliefs				
HIV- test on low prior group				
(8) Test	-0.002	-0.008	-0.010	-0.026
	(0.015)	(0.014)	(0.018)	(0.020)
HIV+ test on low prior group				
(9) Test+(Test X HIV)	0.130	0.106	0.102	0.105
	(0.045)***	(0.043)**	(0.054)*	(0.059)*
HIV- test on high prior group				
(10) Test+(Test X High)	-0.052	-0.060	-0.061	-0.076
	(0.021)**	(0.021)***	(0.024)**	(0.027)***
HIV+ test on high prior group				
(11) Test+(Test X HIV)+(Test X High)	-0.033	-0.044	-0.036	-0.049
+(Test X High X HIV)	(0.052)	(0.052)	(0.058)	(0.067)

Robust standard errors in parentheses. Disturbance terms are clustered within couple pairings. Significantly different from zero at 99(***), 95(**), and 90(*) percent confidence. Base interactions include all possible combinations of Test, High Prior, HIV+, and Couple. There are 6 double and 4 triple interaction terms (not all shown). Marriage/Children interactions include all combinations of Test and HIV+ with marriage and the number of children. HIV/AIDS awareness interactions include all combinations of Test and HIV+ with an indicator if an individual sought HIV counseling and HIV testing. Religion interactions include all combinations of Test and HIV+ with Muslim and christian. All standard errors on linear combinations are adjusted for covariance between variables.

Table VIII: Effect of HIV Testing on STI Incidence: Alternative Cut Points Beliefs
Dependent Variable: STI Incidence (mean = .039)

	Cut Points					
	1.25	1.50	1.75	2.25	2.50	2.75
HIV- test on Low Prior Group						
(1) Test	-0.02	-0.01	0.00	0.00	-0.01	-0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
HIV+ test on Low Prior Group						
(2) Test+(Test X HIV)	0.13	0.13	0.14	0.08	0.06	0.05
	(0.06)**	(0.05)**	(0.05)***	(0.04)*	(0.04)	(0.04)
HIV- test on High Prior Group						
(3) Test+(Test X High)	-0.02	-0.03	-0.04	-0.05	-0.05	-0.06
	(0.01)*	(0.02)*	(0.02)**	(0.02)**	(0.02)**	(0.03)*
HIV+ test on High Prior Group						
(4) Test+(Test X HIV)+(Test X High)	0.01	0.00	-0.02	-0.05	-0.04	-0.03
+(Test X High X HIV)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Observations	1,961	1,961	1,961	1,961	1,961	1,961
R-squared	0.02	0.02	0.03	0.02	0.02	0.02

Estimates of the four linear combinations of interest are presented. Robust standard errors in parentheses and account for covariance between variables. Disturbance terms are clustered within couple pairings. Significantly different from zero at 99(***), 95(**), and 90(*) percent confidence. All specifications include the variables: Test, High Prior, HIV+, and Couple as well as all of their possible combinations which consists of 6 double and 4 triple interaction terms. All standard errors on linear combinations are adjusted for covariance between variables.

Table IX: Effects of HIV Testing Conditioning on Relationship/Testing Status

	Relationship Status		Testing As	
	Single	Married	Individual	Couple
	(1)	(2)	(3)	(4)
(1) Test	.007	-.005	-.007	.010
	(.017)	(.020)	(.013)	(.020)
(2) High Prior Beliefs	.061	.038	.046	-.006
	(.024)**	(.038)	(.021)**	(.021)
(3) HIV+	-.008	.039	-.024	.006
	(.016)	(.031)	(.012)**	(.039)
(4) Test X High Prior	-.058	-.054	-.037	-.027
	(.030)**	(.045)	(.024)	(.027)
(5) Test X HIV	.077	.068	.128	-.042
	(.050)	(.075)	(.046)***	(.043)
(6) Test X High Prior X HIV	-.054	-.083	-.160	.068
	(.074)	(.069)	(.070)**	(.104)
Obs.	1118	764	1253	629
R^2	.082	.076	.059	.086
Linear Combinations: Effect of HIV Tests by Prior Beliefs				
HIV- test on Low Prior Group				
(7) Test	0.007	-0.005	-0.007	0.010
	(0.017)	(0.020)	(0.013)	(0.020)
HIV+ test on Low Prior Group				
(8) Test+(Test X HIV)	0.084	0.063	0.122	-0.032
	(0.047)*	(0.074)	(0.044)***	(0.037)
HIV- test on High Prior Group				
(9) Test+(Test X High)	-0.051	-0.058	-0.044	-0.017
	(0.025)**	(0.038)	(0.021)**	(0.017)
HIV+ test on High Prior Group				
(10) Test+(Test X HIV)+(Test X High)	-0.028	-0.073	-0.075	0.009
+(Test X High X HIV)	(0.053)	(0.083)	(0.049)	(0.093)

Estimates of the four linear combinations of interest are presented. Robust standard errors in parentheses and account for covariance between variables. Disturbance terms are clustered within couple pairings. Significantly different from zero at 99(***), 95(**), and 90(*) percent confidence. All specifications include all possible combinations of Test, High Prior, HIV+, and Couple. There are 6 double and 4 triple interaction terms (not all shown). Controls in all specifications include variables for gender, age, marriage, primary school, secondary school, college, Muslim, Catholic, Christian, number of children, number of assets, language of survey interview, and interviewer and country fixed effects. All standard errors on linear combinations are adjusted for covariance between variables.

Table X: Estimated Behavioral Change Due to Testing

Panel I

Parameters	Estimate (1)	Source (2)
W (STI Prevalence)	0.06	Dataset
R (STI Transmission per coital act)	0.35	Kretzschmar et. al. (1996); Gray et. al. (2001)
F (Fraction of Acts Condom is used)	0.38	Dataset
E (Condom Effectiveness)	0.95	Sweat et. al. (2000)
N (Sex Acts per Partner)	8.80	Dataset
W (HIV Prevalence) Kenya	8%	DHS
W (HIV Prevalence) Mozambique	16%	DHS
W (HIV Prevalence) Zambia	20%	DHS

Panel II

HIV-negative

		Step 1	Step 2	Step 3 P(HIV Infection)		
		P(STI)	M	KE	MZ	ZM
Low Prior Beliefs	Control + Test	2.42%	0.47	0.02%	0.04%	0.05%
High Prior Beliefs	Control	5.90%	1.17	0.06%	0.10%	0.13%
High Prior Beliefs	Test	0.94%	0.18	0.01%	0.02%	0.02%

HIV-Positive

		Step 1	Step 2	Step 3 P(HIV Transmission)		
		P(STI)	M	KE	MZ	ZM
Low Prior Beliefs	Control	1.06%	0.21	0.11%	0.10%	0.09%
Low Prior Beliefs	Test	11.57%	2.36	1.21%	1.12%	1.06%
High Prior Beliefs	Control + Test	10.33%	2.63	1.4%	1.2%	1.2%

Table XI: Effect of Testing on HIV Infections

Panel I

	HIV-negative				HIV-positive			
		KE	MZ	ZM		KE	MZ	ZM
Low Prior Beliefs	Mass	39%	61%	55%	Mass	3%	8%	8%
	New Infections				New Infections			
	Base	9	25	29	Base	3	8	8
	Testing	9	25	29	Testing	33	93	87
	Difference	0	0	0	Difference	30	85	79
		KE	MZ	ZM		KE	MZ	ZM
High Prior Beliefs	Mass	53%	24%	27%	Mass	6%	7%	10%
	New Infections				New Infections			
	Base	29	25	35	Base	77	85	120
	Testing	5	4	5	Testing	77	85	120
	Difference	-25	-21	-30	Difference	0	0	0

Panel II

	Kenya (KE)	Mozambique (MZ)	Zambia (ZM)
(1) Change in HIV Infections	5	64	49
(2) Percentage Change	4%	44%	26%
Matching Rates			
(3) 25% Change	-3%	37%	18%
(4) 50% Change	-11%	29%	10%
ARVs Coverage			
(5) 10% of HIV-Positives	-4%	33%	16%
(6) 25% of HIV-Positives	-17%	16%	1%
(7) 50% of HIV-Positived	-39%	-13%	-24%

Figure I: Study Design

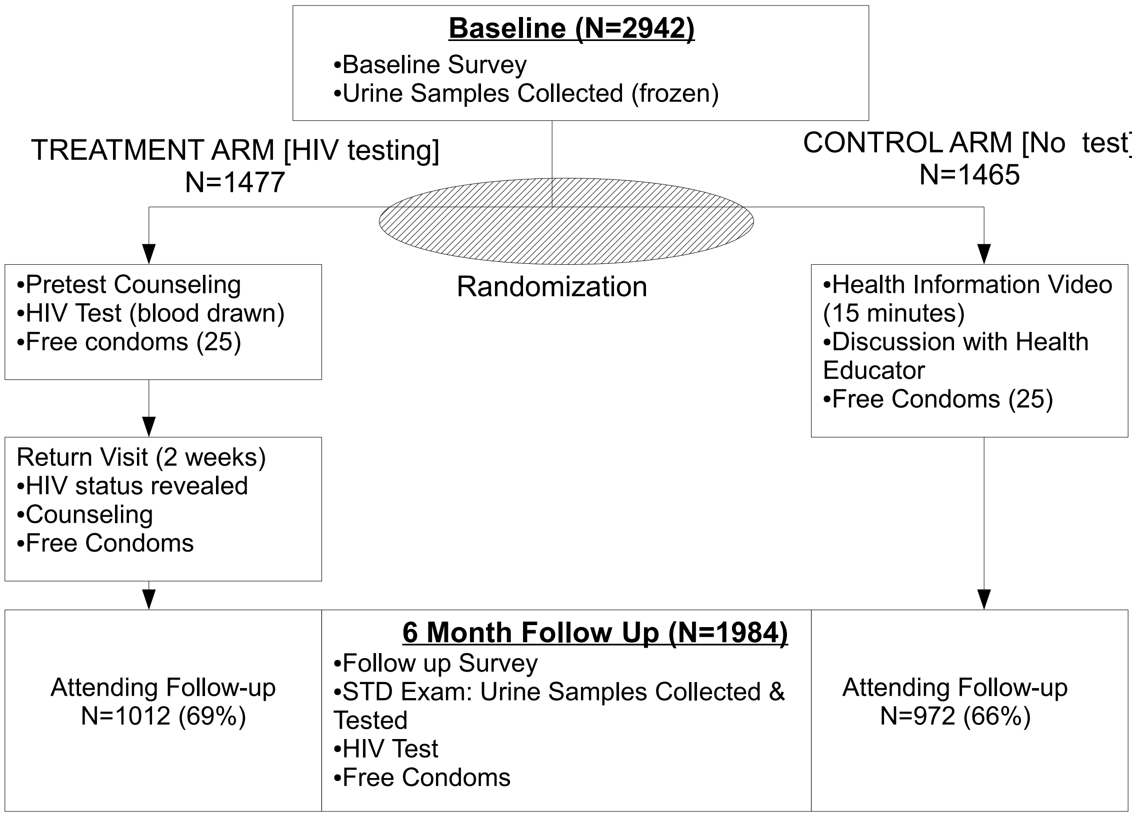


Figure II: Attrition in Study

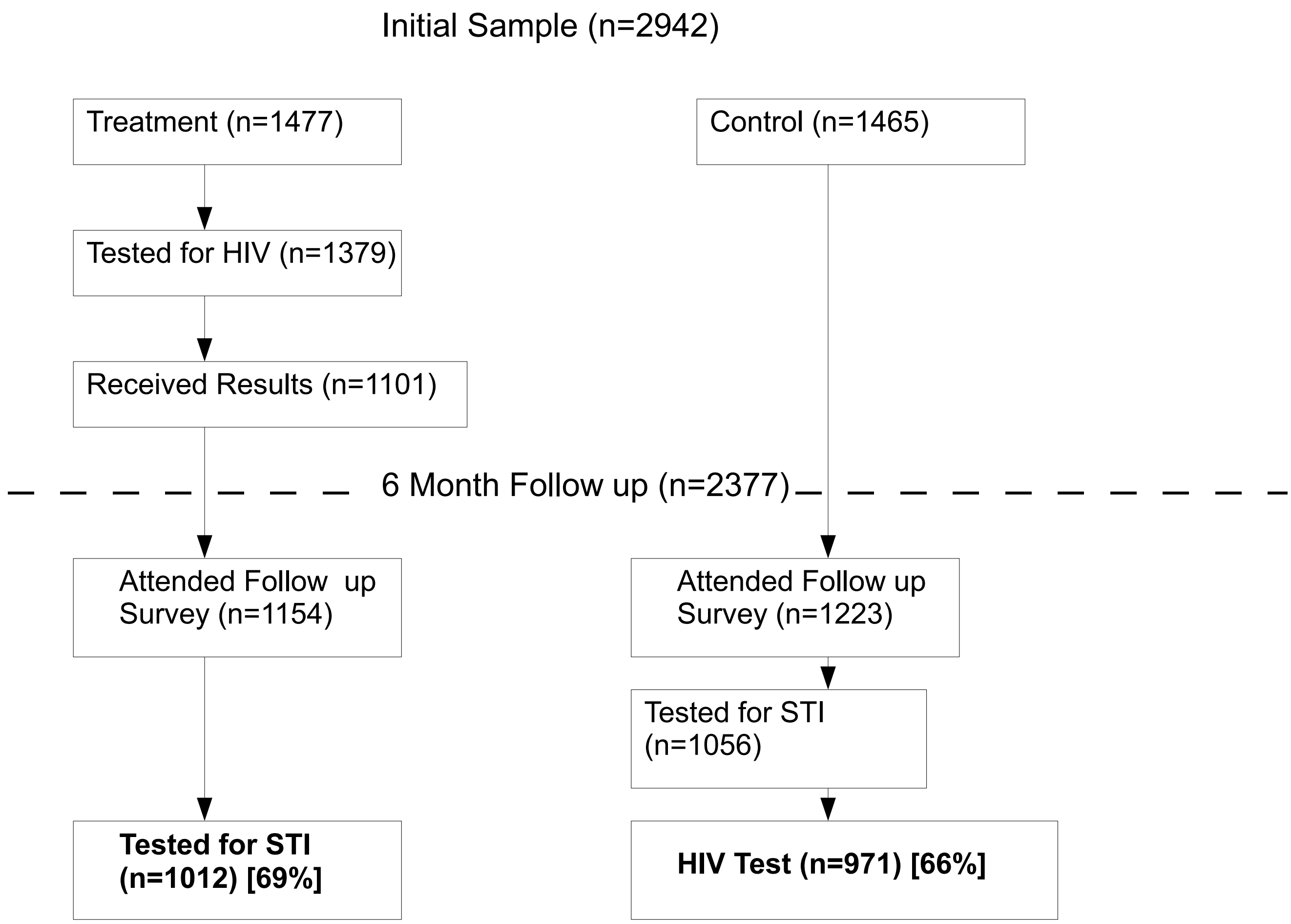


Figure III: Distribution of Average Response to Questions A,B,C,D

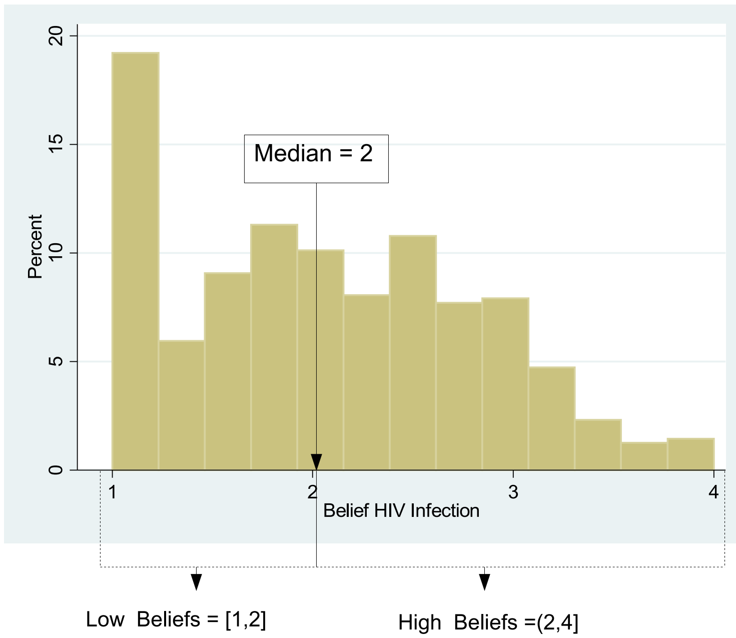
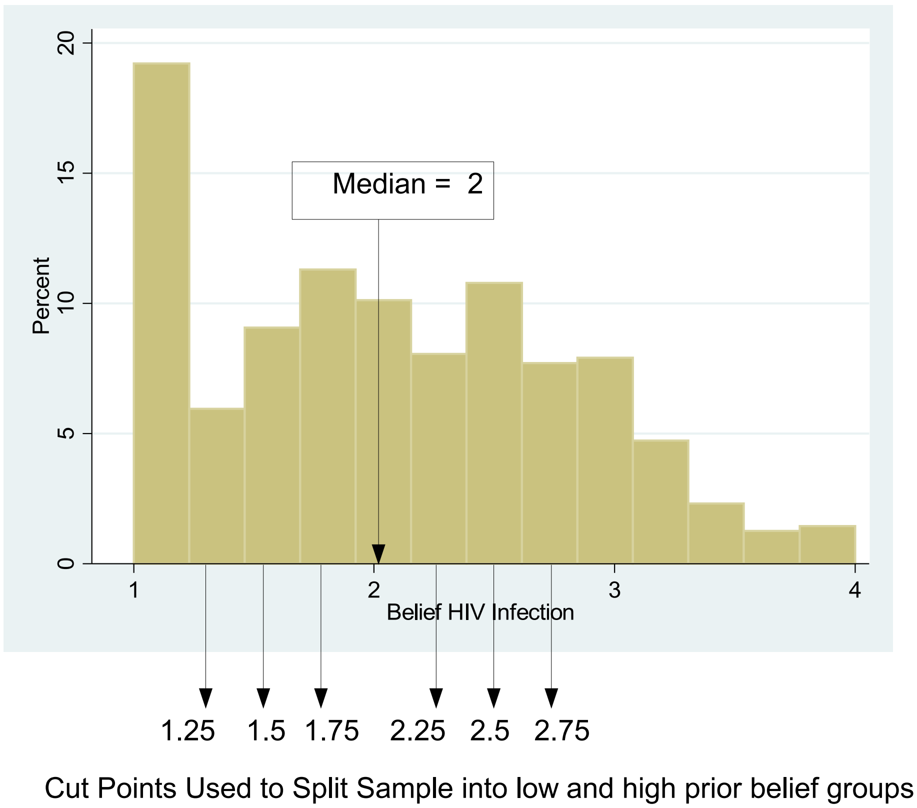


Figure IV: Alternative Cut Points



A Appendix Tables

Table A.I: HIV/AIDS Knowledge by Treatment/Control Arms

	HIV/AIDS Knowledge Followup		HIV/AIDS Knowledge Change	
	(1)	(2)	(3)	(4)
Test	-.005	-.025	-.054	-.027
	(.075)	(.074)	(.094)	(.095)
Obs.	1961	1882	1961	1882
R^2	0	.05	0	.028

Robust standard errors in parentheses. Disturbance terms are clustered within couple pairings. Significantly different from zero at 99(***), 95(**), and 90(*) percent confidence. Controls include: indicator for marriage, primary school, secondary school, college, Muslim, Catholic, Christian, discrete variables for number of children, number of assets, and interviewer and country fixed effects. All standard errors on linear combinations are adjusted for covariance between variables.

Table A.II: Summary Statistics of HIV Test Takers

	Variable	Treatment Mean	Treatment Mean	Control Mean	Diff: (1)-(3) p value	Diff: (2)-(3) p value
	Demographics	(1)	(2)	(3)	(4)	(5)
(1)	Male	0.50	0.51	0.51	0.76	0.91
(2)	Age	28.4	28.7	28.9	0.12	0.64
(3)	Primary School	0.62	0.61	0.64	0.32	0.27
(4)	Secondary School	0.26	0.27	0.26	0.94	0.71
(5)	Muslim	0.27	0.25	0.27	0.69	0.27
(6)	Catholic	0.33	0.34	0.37	0.05	0.28
(7)	Christian	0.35	0.36	0.31	0.07	0.02
(8)	Tap water in home	0.54	0.53	0.51	0.19	0.47
(9)	Electricity in home	0.43	0.42	0.41	0.17	0.59
	Relationship Status					
(10)	Enrolled as Couple	0.33	0.33	0.32	0.46	0.34
(11)	Married	0.39	0.40	0.40	0.60	0.90
(12)	Cohabiting	0.49	0.48	0.49	0.86	0.83
(13)	Number Living Children	1.45	1.53	1.64	0.02	0.24
(14)	Planning for Children in near term	0.20	0.19	0.17	0.09	0.23
	HIV/AIDS					
(15)	HIV/AIDS Knowledge (out of 12)	9.71	9.74	9.69	0.77	0.61
(16)	HIV/AIDS Counseling	0.19	0.19	0.20	0.44	0.46
(17)	HIV Testing	0.01	0.01	0.02	0.14	0.21
(18)	HIV+ Test Result	0.20	0.19	0.19	0.37	0.77
	Sexual Activity					
(19)	Sexually Active	0.81	0.82	0.79	0.20	0.13
(20)	Two or More Partners	0.22	0.22	0.22	0.95	0.78
(21)	Unprotected Sex with					
(22)	Commerical Partner	0.12	0.12	0.12	0.62	0.86
(23)	Non-Primary Partner	0.25	0.26	0.23	0.19	0.17
(24)	Primary Partner	0.50	0.51	0.48	0.26	0.19
	Episodes Unprotected Sex with					
(25)	Commerical Partner	6.39	6.62	7.46	0.32	0.48
(26)	Non-Primary Partner	6.58	6.72	7.40	0.32	0.44
(27)	Primary Partner	12.5	12.2	12.0	0.46	0.80
	Sample Size	1385	1009	1022		

Table A.III: Individual Questions on Beliefs of HIV Status

Panel 1

	STI Incidence: 6mo Follow-up					
	(1)	(2)	(3)	(4)	(5)	(6)
High Belief A	.036 (.019)*					.030 (.021)
High Belief B		.007 (.017)				-.010 (.018)
High Belief C			.038 (.014)***			.030 (.016)*
High Belief D				.025 (.015)*		.008 (.017)
High Beliefs (All 4 Questions)					.052 (.015)***	
Obs.	957	957	957	957	957	957
R^2	.005	0	.008	.003	.016	.012

Panel 2

	HIV Positive at Baseline					
	(7)	(8)	(9)	(10)	(11)	(12)
High Belief A	.015 (.027)					.003 (.029)
High Belief B		.024 (.026)				.022 (.028)
High Belief C			.035 (.022)			.041 (.025)*
High Belief D				.007 (.023)		-.019 (.026)
High Beliefs (All 4 Questions)					.042 (.022)*	
Obs.	1376	1376	1376	1376	1376	1376
R^2	0	.001	.002	0	.003	.003

Robust standard errors in parentheses. Disturbance terms are clustered within couple pairings. Significantly different from zero at 99(***), 95(**), and 90(*) percent confidence.

Table A.IV: Effect of HIV Testing on STI Incidence Using Alternative Belief Measures
Dependent Variable: STI Incidence

	Predicts:		Continuous
	STI 6mo	HIV	Measure
	(1)	(2)	(3)
(1) Test	-0.001	-0.006	0.025
	(0.014)	(0.013)	(0.028)
(2) High Prior Beliefs	0.042	0.048	0.026
	(0.018)**	(0.018)***	(0.013)**
(3) HIV+	-0.018	0.012	0.009
	(0.015)	(0.025)	(0.038)
(4) Couple	-0.000	-0.000	0.039
	(0.020)	(0.019)	(0.037)
(5) Test X High Prior	-0.040	-0.031	-0.023
	(0.023)*	(0.023)	(0.014)
(6) Test X HIV	0.138	0.125	0.205
	(0.048)***	(0.051)**	(0.079)***
(7) Test X High Prior X HIV	-0.139	-0.119	-0.068
	(0.059)**	(0.059)**	(0.031)**
Observations	1961	1961	1961
R^2	0.025	0.026	0.024
Linear Combinations: Effect of HIV Tests by Prior Beliefs			
HIV- test on Low Prior Group			
(8) Test	-.001	-.006	
	(.014)	(.013)	
HIV+ test on Low Prior Group			
(9) Test+(Test X HIV)	.137	.119	
	(.046)***	(.050)**	
HIV- test on High Prior Group			
(10) Test+(Test X High)	-.042	-.038	
	(0.018)**	(.019)**	
HIV+ test on High Prior Group			
(11) Test+(Test X HIV)+(Test X High) +(Test X High X HIV)	-.043	-.032	
	(.041)	(.040)	

Estimates of the four linear combinations of interest are presented. Robust standard errors in parentheses and account for covariance between variables. Disturbance terms are clustered within couple pairings. Significantly different from zero at 99(***), 95(**), and 90(*) percent confidence. All specifications include the variables: Test, High Prior, HIV+, and Couple as well as all of their possible combinations which consists of 6 double and 4 triple interaction terms. All standard errors on linear combinations are adjusted for covariance between variables.

Table A.V: Effects of HIV Testing on STI Prevalence

Dependent Variable: STI Prevalence (mean = .057)

	(1)	(2)
(1) Test	.004	.002
	(.017)	(.018)
(2) High Prior Beliefs	.049	.043
	(.022)**	(.024)*
(3) HIV+	-.009	-.008
	(.025)	(.026)
(4) Couple	.010	.039
	(.022)	(.024)*
(5) Test X High Prior	-.042	-.036
	(.029)	(.030)
(6) Test X HIV	.105	.100
	(.050)**	(.051)**
(7) Test X High Prior X HIV	-.113	-.113
	(.067)*	(.067)*
Interactions	YES	YES
Controls	NO	YES
Obs.	1970	1890
R^2	.017	.049
Linear Combinations: Effect of HIV Tests by Prior Beliefs		
HIV- test on Low Prior Group		
(8) Test	0.004	0.002
	(0.017)	(0.018)
HIV+ test on Low Prior Group		
(9) Test+(Test X HIV)	0.110	0.102
	(0.047)**	(0.048)**
HIV- test on High Prior Group		
(10) Test+(Test X High)	-0.038	-0.034
	(0.023)	(0.024)
HIV+ test on High Prior Group		
(11) Test+(Test X HIV)+(Test X High)	-0.045	-0.047
+(Test X High X HIV)	(0.050)	(0.049)

Robust standard errors in parentheses. Disturbance terms are clustered within couple pairings. Significantly different from zero at 99(***), 95(**), and 90(*) percent confidence. Interactions include all possible combinations of Test, High Prior, HIV+, and Couple. There are 6 double and 4 triple interaction terms (not all shown). Controls include variables for gender, age, marriage, primary school, secondary school, college, Muslim, Catholic, Christian, number of children, number of assets, language of survey interview, and interviewer and country fixed effects. All standard errors on linear combinations are adjusted for covariance between variables.