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Love in the Time of HIV: Theory and Evidence on Social Stigma and Health Seeking Behavior

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Abstract

This paper develops a signalling model of HIV testing, and evaluates an information experiment designed to test the theory and reduce stigma. We find that stigma is in part explained by statistical discrimination between potential sexual partners, and that this form of stigma is a significant barrier to HIV testing. Discrimination is based on false beliefs about antiretroviral drugs, the medication used to treat HIV. In our setting, we find that providing precise, new information about the public benefit of antiretroviral drugs reduces stigma and increases HIV testing. The results demonstrate that social stigma can be due to rational behavior by a misinformed public, and that providing new information can be an effective way to mitigate its effects.

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1 Introduction

A surprising number of deaths are caused by preventable or treatable health conditions. Over one million people in sub-Saharan Africa die of AIDS every year, despite the fact that an effective treatment, antiretroviral therapy (ART) is now widely provided to patients free of charge. The medication has large private benefits for those infected with HIV: it prolongs life by decades and reverses the symptoms of AIDS. It has recently been discovered that ART drugs also have a public benefit: they reduce HIV transmission by 96% (Cohen et al., 2011). This discovery prompted the World Health Organization to advocate a "Treatment for Prevention" strategy to bring an end to the AIDS epidemic. Over the past decade, the supply of free ART has increased dramatically in low-income countries, yet demand for HIV testing and treatment remain low.

Social stigma is often blamed for low HIV testing rates. However, the underlying cause of stigma is not well understood. Many policies which increase HIV testing take stigma into account by affording clients more privacy, as in door-to-door testing, or obscuring the signal, for example, by offering monetary incentives to test (Thornton, 2008). Understanding the nature of stigma is important in order to better predict the consequences of any policy, including the long-run impact, the population affected, and the effect on take-up of ART. Depending on the root causes of stigma, it may also be possible to design policies which actually reduce the level of stigma in the community, rather than simply helping people to cope with it.

In this paper, we use a carefully designed information experiment to both detect and reduce one specific type of stigma against those who seek an HIV test: statistical discrimination by potential sexual partners, based on a rational fear of HIV transmission. Those who seek an HIV test are more likely to be infected, and may face rejection from potential partners who fear contracting the virus. The public benefit of ART drugs implies that, in fact, an HIV test should not be viewed as a negative signal, since those who have been tested and treated for HIV are less contagious. We find that providing precise information, at the community level, on the public benefit of ART greatly increases the HIV testing rate within only three months, and we identify a reduction in social stigma as the likely mechanism. These results suggest that stigma is at least in part due to a rational fear of contracting HIV, that this type of stigma is a major barrier to HIV testing, and that correcting wrong beliefs by providing accurate information can mitigate stigma and its effects.

In order to make precise the form of stigma we have in mind, we model HIV testing as a signalling game between potential sexual partners. The first player decides whether to get tested for HIV, either at a clinic near his home village, or far away. He is then matched with a potential sexual partner. She observes his testing decision with some probability, which depends on his choice of testing location. She forms consistent beliefs about the risk of contracting HIV, and decides whether to reject or consent to the match.

Those who are infected with HIV have more to gain from HIV testing, because it allows them to access ART drugs. This causes a signalling equilibrium to emerge, in which some fraction of the population reject matches who have been tested, because they fear contracting HIV. This behavior contributes to the total level of stigma faced by those who choose to get tested. An upward shift in beliefs about the public benefit of ART alleviates stigma if it is based on a fear of HIV transmission, and leaves other potential forms of stigma unaffected. That is, people are more likely to consent to

matches who have been tested and treated, because they know that treatment prevents HIV transmission. This reduction in stigma should, in turn, increase HIV testing.

By mapping the model to an information experiment, we are able to test several theoretical predictions empirically. We randomly assigned 122 villages in Malawi to either treatment or control status. All villages received an intervention in which information about ART was disseminated in public, at community health meetings. In treatment villages, information on both the private and public benefits of ART was provided, in particular, meeting attendees were informed that ART reduces HIV transmission by 96%. In the control group we provided information on only the private benefits of ART.

As the formation of beliefs may depend on endogenous factors such as education and past health seeking behavior, a randomized experiment allows us to measure the causal effect of beliefs. We are also interested in evaluating the information intervention itself, for its potential to inform policy. There is reason to believe that incorrect beliefs might persist in equilibrium. First, ART is under-adopted, which means that first-hand learning is slow. Second, information sharing between social contacts may be strategic and lack credibility; knowledge about ART may be viewed as a signal of HIV status, and a potential sexual partner who claims that ART blocks HIV transmission may have ulterior motives.

Our empirical results are consistent with the theoretical predictions of the signalling model. Survey measures of stigma towards potential sexual partners who are HIV-positive, but treated with ART, were significantly lower in the treatment group. Health seeking behavior also increased significantly. The HIV testing rate, as recorded over three months of administrative data, was 60% higher in treatment villages. Overall, nearly half of HIV tests take place far away from the HIV testing client's home village, but a large shift in beliefs about the public benefit of ART predicts an increase only in the number of tests sought nearby. The individual testing decision is predicted by one's perception of the community's beliefs about ART, and not by one's own beliefs; if the results were driven by altruism, one would expect the opposite.

This paper is a study on the cause and effect of statistical discrimination, and its lessons may apply broadly. We show that a technology which benefits a stigmatized group may be underadopted, and that if stigma is based on statistical discrimination, correcting wrong beliefs may diminish stigma and its effects. Arrow (1973)'s seminal work on statistical discrimination shows that a correlation between individual attributes and productivity results in labour market discrimination. The theoretical and empirical effects of this type of discrimination have been investigated in various contexts[1]. Much of the literature on social stigma, both in the context of HIV and more generally, views stigma as an exogenous cost[2], and investigates the effects of such a social cost. One exception is Besley and Coate (1992), in which the authors model stigma toward welfare recipients as either statistical discrimination or a form of taxpayer resentment, and investigate the theoretical implications of such a model. In this paper we investigate both the source and effect of stigma, theoretically and empirically, by microfounding stigma as statistical discrimination against HIV-infected sexual partners, and using an experiment to investigate the implications for health seeking behavior.

A lack of accurate information may explain the low adoption rates of many health

[1]See for example, Altonji and Pierret (2001), and Coate and Loury (1993).

[2]In the context of HIV, see Thornton (2008) and Ngatia (2011), and in the context of welfare payments, and Moffitt (1983).

measures. Providing new, precise information on health risks has been shown to impact some types of behavior[3]. Within the context of HIV, most papers focus on the effect of information[4] on risk-taking (Dupas, 2011, Kerwin, 2014, Bandiera et al., 2012). However, the type of information which might increase health seeking behavior is not well understood. Information on the protective benefits of circumcision appears to have no effect on demand for the procedure (Chinkhumba et al., 2012, Godlonton et al., 2011). Health seeking behavior may often be stigmatized, and our paper suggests that providing information on the public benefit of health seeking behavior may effectively reduce the level of stigma.

Previous findings by Thornton (2008) show that test-seeking responds strongly to small monetary incentives, which conceal a person's true motivation for testing, and Ngatia (2011) shows that the decision to respond to such incentives carries a social cost, suggesting that stigma still plays a role. These experiments also offer effective policy advice in terms of HIV testing. However, providing monetary incentives for ART take-up may prove infeasible. In order to obscure the signal, the entire community, and not only ART patients, would have to be paid to visit the clinic at regular intervals. An intervention that instead reduces the level of stigma in the community is attractive for several reasons. Such an intervention should increase both HIV testing and treatment, and generate persistent effects for a fixed cost. In addition, we show that stigma is likely to be practiced between potential sexual partners, which has important implications for policy. Stigma imposes a high cost on those individuals most concerned with their sexual prospects, the same individuals who are most at risk of HIV infection. Designing policy to increase HIV testing and treatment among this group should be a priority.

The remainder of the paper proceeds as follows: Section 2 describes the experimental context and design, Section 3 presents the model and its predictions, Section 4 provides a description of the data and results, and Section 5 concludes.

2 Background and Experimental Design

2.1 Antiretroviral Therapy

Antiretroviral therapy, or ART, is a combination of drugs which suppress the HIV virus and reverse the progression of AIDS. The medication dramatically reduces the mortality and morbidity associated with HIV infection.

ART was developed in the late 1980's. However, the price of ART was prohibitively high for the low-income countries most affected by the AIDS epidemic. Around 2000, multiple agreements between governments, international organizations, and pharmaceutical companies led to a large reduction in the price of ART in developing countries. Over the next decade, HIV patients in Africa receiving ART drugs increased from 50,000 to 9.7 million, resulting in an approximate 30% decrease in mortality (WHO, 2013).

While the increased supply of ART has led to a remarkable improvement in outcomes for those infected with HIV, demand for the medication is surprisingly low. In

[3]See, for example Dupas (2011), Kerwin (2014), Bandiera et al. (2012), Madajewicz et al. (2007), and Jalan and Somanathan (2008).

[4]Interventions which provide new, precise information differ sharply from traditional anti-HIV messaging strategies which focus on behavior change directly. Duflo et al. (2012), for example, find that a behavior change program that pushes abstinence fails to reduce risk-taking among adolescent girls in Kenya.

sub-Saharan Africa, half of the population has never been tested for HIV, and only one third of those infected are taking ART drugs (WHO, 2013). There are more than one million AIDS-related deaths in the region every year, most of which could be prevented by ART (WHO, 2013).

In addition to providing large health benefits to HIV-positive individuals, ART reduces HIV transmission between sexual partners by reducing an infected person's viral load. A large randomized controlled trial[5] recently demonstrated that regular ART use by HIV-positive individuals reduces HIV transmission by 96% (Cohen et al., 2011). The World Health Organization and others have called for a "treatment for prevention" strategy, advocating ART use specifically for the purpose of preventing new infections. Epidemiological models suggest that in light of the public benefit of ART, universal testing and treatment could bring an end to the AIDS epidemic within 50 years, and would be cost-effective in the long run (Granich et al., 2009).

2.2 Stigma Against HIV Testing and Treatment

Social stigma, according to the seminal definition by Goffman (1963), is "the phenomenon whereby an individual with an attribute which is deeply discredited by his/her society is rejected as a result of the attribute." There are various potential reasons for such a rejection. Stigma could be based on statistical discrimination, it could be due to a distaste for social interactions with individuals having a particular attribute, or it could arise as an equilibrium of social behavior (Peski and Szentes, 2013).

Because HIV is transmitted through sexual interactions, it is particularly susceptible to many forms of social stigma[6]. This in turn might partly explain why testing levels are low across sub-Saharan Africa, and in Malawi, where our study takes place. For example, an equilibrium may emerge in which individuals wish to disassociate themselves from others who have engaged in sexual behavior that is deemed socially unacceptable (Ngatia, 2011). Stigma may also take the form of pure statistical discrimination: a person might reject sexual partners who are HIV-positive out of a rational fear of infidelity or HIV transmission. The correlation between HIV status and HIV testing implies that any stigma towards those who are HIV-positive may also apply to test-seekers.

In order to obtain ART drugs, a person must first seek an HIV test. While the results of an HIV test are private[7], the decision to test may be observable. The availability of ART drugs induces adverse selection among test seekers; for example, in Malawi, true HIV prevalence is 44% higher among those who report having been tested (DHS, 2010). The fact that seeking an HIV test is associated with HIV infection may generate stigma,

[5]This randomized trial was conducted in the field and in low-income countries. The drug reduced HIV transmission by 96%, measured over a period of a few years, among couples who took the drug at home, unobserved, and in general in a similar manner to most ART patients in the developing world. In particular, this reduction in transmission does not hinge on perfect adherence to the medication. It is accurate to say that ART drugs reduce HIV transmission by at least 96% relative to the absolute transmission rate over any time period up to approximately ten years. The absolute transmission rate is low, so the the total reduction in transmission over repeated interactions is approximately linear.

[6]See Mahajan et al. (2008) for a review of medical and sociological research on the stigmatization of HIV and AIDS.

[7]In Malawi, non-joint HIV tests are confidential, and a person who tests HIV negative does not receive any written proof of the result. The test is conducted twice with different test kits, so an incorrect diagnosis is unlikely.

which in turn discourages HIV testing; in Malawi, 27% of women and 48% of men report never having been tested for HIV (DHS, 2010). In addition, our data shows that 30% of HIV tests do not take place at a nearby health facility, which could be explained by a desire to avoid being seen.

The Malawian Journals Project[8] provides extensive qualitative evidence on the nature of HIV-related stigma. The project has transcribed a vast amount of hearsay data on attitudes towards HIV, and these journals include many examples of stigma towards HIV testing and treatment, especially in the dating market. Many express dismay at the widespread availability of ART, as the medication makes HIV-positive individuals appear healthy and therefore harder to identify. Others report seeking HIV testing and treatment far from home, to avoid being seen and then rejected by potential sexual partners.

2.3 Setting and Randomization

This paper evaluates an experiment which took place in Zomba District, Malawi. Malawi is representative of Southern Africa in terms of its relatively high rate of HIV infection, and recent but widespread access to ART drugs. In Zomba District, HIV prevalence is approximately 14.5% (DHS, 2010), and both HIV testing and antiretroviral therapy (ART) are available for free at more than 20 rural clinics.

The study area covers two areas, TA Chikowi and TA Mwambo (see Figure 1), within Zomba District. We include only villages with unique names in the district, which enables us to identify the study villages in administrative clinic data. From this set, we selected a random sample of 122 villages, which we randomly assigned to either the treatment or control group, stratifying on population and nearest health facility. The sample is balanced on observable village characteristics (see Table 2).

The average village population is 440, with approximately half between the ages of 15 and 49. All villages are within 11 kilometers of a health facility, and the average distance is 5 kilometers. Many villages are very close to one another; 60% have another study village within 1 kilometer. For this reason, accounting for spillovers will be an important part of the analysis in Section 4.

2.4 Intervention

An information intervention took place in each of the 122 study villages, in the form of a community health education meeting sanctioned by the Malawi College of Medicine and the village chief, and conducted by ten community educators[9]. The target population consisted of men and women aged 15 to 49.

Although we use the labels "treatment" and "control" to refer to the two arms of the experiment, we in fact held information meetings in both types of villages in order to isolate the treatment effect of one particular piece of information: the public benefit of ART drugs. In control villages we provided information on the private benefits of ART drugs, while in treatment villages we provided information on both the private and public benefits of ART. In this way, we avoid conflating the effect of beliefs about

[8] http://malawi.pop.upenn.edu/malawi-data-qualitative-journals

[9] These meetings took place in November and December, 2013. The educators had official identification badges from the Malawi College of Medicine which were meant to increase their credibility.

the public benefit of ART with the effect of information on the existence, private benefit, or availability of ART drugs.

In control villages, community educators started the meeting by eliciting a rough measure of initial beliefs: a show of hands to determine whether meeting attendees were aware of the private benefits of ART. 75% of attendees believed that ART allowed HIV-positive individuals to lead a long and healthy life. Educators then informed meeting attendees that ART increases life expectancy, hides the symptoms of AIDS, and is free at local clinics. They emphasized the importance of correct adherence, and that condom use and abstinence were good methods of HIV prevention. They did not discuss the link between ART use and HIV transmission. Educators used an infographic depicting a reduction in viral load to explain how ART alleviates the symptoms of AIDS (Figure 3).

In treatment villages, community educators provided information on both the private and public benefits of ART drugs. First, they provided the same basic information they provided in control villages. Next, they elicited a measure of initial beliefs about the public benefit of ART: a show of hands indicated that the public benefit of ART was initially unknown to most community members; on average, only 5% of meeting attendees believed that ART drugs had any effect at all on HIV transmission. Educators then explained the magnitude of the public benefit: that ART reduces the probability of HIV transmission by 96%. They also used an infographic depicting not only the fact that ART reduces a person's viral load, but that this reduction in viral load leads to a reduction in transmission risk (Figure 4). The community educators emphasized that this reduction in HIV risk was based on correct adherence to ART as prescribed.

A detailed description of the information provided in treatment and control villages is shown in Table 1. Educators followed a carefully worded script, and answered questions only by repeating information already provided. Unanswered questions were referred to the nearest health facility. The meetings were balanced in terms of length (approximately 45 minutes) and community participation; treatment and control villages had different show-of-hands questions and infographics. The information content of the meetings was identical, except for the crucial discussion about ART and HIV transmission.

The community educators first conducted meetings in the control villages, which took place over ten days. At the end of these ten days, training on the treatment village information campaign took place, and the meetings in treatment villages took place over the following ten days. We conducted the control and treatment interventions sequentially in order to prevent information spillovers due to the conduct of the community educators. The team of educators traveled together to a different geographical section of Zomba District on each day, and within that area they were randomly assigned to different villages. Small villages were assigned one educator, while in villages with over 100 households work was done in pairs. Educators disseminated information through a combination of the meeting organized by the village chief and door-to-door campaigning. The educators knew they were to receive large incentives based on knowledge retention in the specific treatment and control villages they had visited, according to data from a survey five months after the intervention[10]. While educators

[10]The maximum incentive was approximately 100 USD. These incentives were paid to community educators in May, 2014, and the size of the incentive was based on the percent of community meeting attendees in treatment villages who believed that ART prevents HIV transmisson, and the percent of

knew the maximum size and timing of the incentive, the exact relationship between the survey questions and the size of the incentive were left intentionally undefined in order to avert any attempt to "teach to the test."

Attendance levels at community health meetings were high. An average of 67% of the target population was reached in each village, and approximately two thirds of attendees were women. It does not appear as though the community educators learned to attract more meeting attendees over time; the average attendance level was insignificantly lower in the treatment group (65%) than in the control group (68%). The topic of the meeting was not announced ahead of time, so the sample of meeting attendees should be similar in treatment and control villages. Village chiefs received small gifts of soap and salt for organizing and advertising the meetings, but attendees did not receive any incentive for attendance.

3 Model of HIV Testing as a Signal

The aim of this section is to provide an economic model of social stigma in the context of HIV testing, and to illustrate a clean empirical test of the underlying mechanism. This empirical test motivates the information experiment described in Section 2.4.

We define HIV-related stigma as a phenomenon whereby individuals who are suspected of having HIV are excluded from social interactions[11]. This paper focuses on one potential source of stigma, and one particular type of social interaction. Individuals who are likely to be HIV positive may be excluded from sexual interactions due to a rational fear of contagion. If HIV testing is a signal of underlying risk, that is, high-risk individuals are more likely to seek an HIV test, then those who do so may face statistical discrimination by potential sexual partners. Other types of stigma, and other barriers to HIV testing[12] may exist, and are included in the model in reduced form[13]. Comparative statics will show that the information experiment reduces stigma if and only if it is due to a fear of HIV transmission; other forms of stigma and costs of testing remain unaffected.

3.1 Environment

We model the HIV testing decision as a one-sided signalling game between two players, over two periods. In the first period, the first player decides whether to seek an HIV test based on his private type, which corresponds to his HIV risk. In the second period, he is matched at random to a potential sexual partner, who might observe whether or not he has been tested for HIV. Based on this signal, the second player decides whether or not to consent to a sexual relationship.

community meeting attendees in control villages who believed that ART had private benefits, as recorded in the survey.

[11]This is derived from the seminal definition by Goffman (1963), who defines stigma as "The phenomenon whereby an individual with an attribute which is deeply discredited by his/her society is rejected as a result of the attribute."

[12]HIV testing has increased significantly over the past decade, in part due to increased supply of HIV testing services and ART. We do not wish to suggest that stigma is the only potential barrier to HIV testing.

[13]For ease of exposition, we include only stigma from potential sexual partners. Allowing for stigma from the general population does not produce a substantially different model or predictions.

Consider a continuum of agents $\mathcal{A} = [0,1]$, and another continuum of equal measure $\mathcal{B} = [0,1]$ which represents potential sexual partners for agents in $\mathcal{A}$. A fraction $\bar{h}$ of individuals $a \in \mathcal{A}$ are HIV positive, while every $b \in \mathcal{B}$ is HIV negative[14]. We denote HIV status by $h_a \in \{0,1\}$.

We assume that individuals possess asymmetric information about their own HIV risk, as they have full knowledge of past risk-taking behavior and current symptoms. In the first period, each agent $a \in \mathcal{A}$ privately observes his type θ_a. This represents his probability of being infected, which takes one of two values:

$$\theta_a \in \{\theta_L, \theta_H\}$$

with $0 < \theta_L < \theta_H < 1$. We refer to these two types as low-risk and high-risk types, respectively.

The agent a then decides whether or not to seek an HIV test, and if so, whether to test at a far away clinic $t_a^F \in \{0,1\}$ or nearby $t_a^N \in \{0,1\}$, such that $t_a^N + t_a^F \in \{0,1\}$ (agents cannot test in both locations). HIV testing is beneficial to those who are infected, as it provides immediate access to ART drugs[15]. ART drugs yield total payoff v every period if the test result is positive, and 0 otherwise.

The cost of traveling to a nearby clinic is c, while traveling to a far away clinic costs $c + d$. These costs are not necessarily monetary: they include the opportunity cost of time, the probability that the clinic is closed, and the psychic cost of learning one's HIV status.

We assume that for low-risk types, the direct cost of HIV testing is higher than the expected benefit of access to medication, as the test result is unlikely to be positive. Meanwhile, for high-risk types, the expected benefit is higher than the direct cost.

$$\theta_L v(1+\delta) < c < \theta_H v(1+\delta) \tag{1}$$

Here δ denotes the discount factor between periods 1 and 2. We also assume that the cost of traveling to a far away clinic is bounded in the following way[16].

$$\frac{d}{1-\phi} < \theta_H v(1+\delta) - c \tag{2}$$

Agents $a \in \mathcal{A}$ receive the following payoff at the end of the first period.

$$u_1^a(n,f) = (t_a^N + t_a^F)(h_a v - c) - t_a^F d \tag{3}$$

In the second period, each agent $a \in \mathcal{A}$ is matched at random with a potential sexual partner $b \in B$. While b is aware of the population HIV prevalence $\bar{h}$, she does not observe a's risk type directly, and she does not observe whether or not he is HIV positive.

Agent b may, however observe a's testing decision. If a tested nearby, he is observed with probability one, while if he tested far away, he is observed with probability $\phi \in (0,1)$. This is modeled by a signal $\sigma_a \in \{0,1\}$ with $\mathbb{P}(\sigma_a = 1) = t_a^N + \phi t_a^F$. Agent b uses

[14] We shall refer to a as "he" and b as "she" for clarity, but the model is not meant to be gender specific.

[15] In this model, if we allowed those who tested positive to forgo ART, a person who knows he would do so would has no motivation to test in the first place.

[16] If this does not hold, then no equilibrium will exist in which agents test far away.

this signal to form beliefs about the probability that her partner a is HIV positive; we denote these beliefs by $\hat{\theta}_b(\sigma_a)$.

Agent b then decides whether to consent to a sexual relationship with her match, $m_b \in \{0,1\}$. If b consents, a and b obtain relationship benefits $y_a \sim G$ and $y_b \sim G$ respectively[17], where the distribution G has positive support.

Consenting to the relationship comes with a cost to agent b; she risks becoming infected with HIV. Because ART drugs reduce HIV transmission, the probability of contracting HIV from an infected partner depends on whether or not he has been tested and treated. The relative reduction in HIV transmission risk associated with ART use is denoted by ρ, and the true value is approximately 0.96 (Cohen et al., 2011). We denote the absolute transmission rate by τ; this is the probability that an infected person transmits HIV to his sexual partner if he is not taking ART. The cost of contracting HIV is s.

We also allow for other forms of stigma. Agent b may experience disutility from a relationship with an HIV-positive person distinct from the possibility of contracting HIV. This could be, for example, because of a's propensity for infidelity, because of social norms, or because of a taste parameter. We capture all of these costs in reduced form, denoted by s_0.

If b chooses to consent, the second-period payoff to agent a consists of the benefit of the relationship and, in the case where he has tested positive for HIV, the value of ART drugs .

$$u_2^a(m_b) = m_b y_a + (t_a^N + t_a^F)(h_a v) \tag{4}$$

The second-period payoff to agent b depends on both the benefit of the relationship and the risk of contracting HIV.

$$u_2^b(m_b) = m_b \left[y_b - h_a \left(s\tau \left(1 - \rho(t_a^N + t_a^F) \right) + s_0 \right) \right] \tag{5}$$

In calculating the payoff to agent b we make use of our assumption that everyone who seeks an HIV test receives ART immediately. This allows agent b to conclude that an HIV-positive individual who has been tested is less contagious, as captured by the term $(1 - \rho(t_a^N + t_a^F))$.

We now make two additional assumptions. First,

$$\mathbb{P}(y_b > \bar{h}(s\tau + s_0)) = 1; \tag{6}$$

the net payoff from a sexual relationship with the average, untreated member of the population is always positive. Second,

$$\mathbb{P}(y_b < s\tau + s_0) = 1; \tag{7}$$

the net payoff from a sexual relationship with an untreated, HIV-positive match is always negative.

[17] We have assumed that a always obtains net benefit from the relationship. We do not model his consent decision.

Heterogeneous beliefs about the effect of ART

In order to illustrate the link between the model of stigma and the experiment we use to test it, we assume that agents differ in their perception of the risk of HIV transmission. Specifically, agents in $\mathcal{B}$ have heterogeneous beliefs about the extent to which ART drugs prevent the spread of HIV. Each agent $b \in \mathcal{B}$ has belief $\hat{\rho}_b \in [0,1]$ about the relative reduction in HIV transmission risk associated with ART. For example, $\hat{\rho} = 0$ corresponds to the belief that ART has no effect on transmission, and $\hat{\rho} = 1$ to the belief that it is impossible to contract HIV from a person taking ART.

We denote by $F_{\hat{\rho}}$ the distribution of beliefs[18] in the population $\mathcal{B}$. We assume that $F_{\hat{\rho}}$ is common knowledge among the population $\mathcal{A}$. This distribution of beliefs forms a key link between the model and our experimental design: our intervention provides information on the true value of ρ, which leads to a shift[19] in the distribution $F_{\hat{\rho}}$.

3.2 Strategies and Equilibria

We solve for the pure-strategy Perfect Bayesian Equilibria of this game.

In the first period, agents in $\mathcal{A}$ choose an HIV-testing strategy $\{t^N, t^F\}$ to maximize their present discounted expected utility

$$\mathbb{E}(u_1^a + \delta u_2^a),$$

taking their private types, the strategies of $\{b \in \mathcal{B}\}$, as well as beliefs $F_{\hat{\rho}}$ and $\{\hat{\theta}_b(\sigma) : b \in \mathcal{B}\}$ as given.

In the second period, agents $b \in \mathcal{B}$ receive the signal σ_a and form corresponding beliefs about a's type $\hat{\theta}_b(\sigma_a)$, which are consistent on the equilibrium path. That is, agents use Bayes' rule to calculate the probability that a person is infected, taking into account whether or not they were observed seeking an HIV test. They then choose whether or not to consent in order to maximize their expected utility, based on their beliefs $\hat{\rho}_b$ and $\hat{\theta}_b$.

Proposition 1. *There are two classes of pure-strategy Perfect Bayesian Equilibria in this game. The first is a "stigma" equilibrium, in which a fraction S of agents in $\mathcal{B}$ reject a match who has been observed seeking an HIV test, and the remaining fraction $1 - S$ of agents consent to any match. The second is a "reverse stigma" equilibrium, in which a fraction P of agents in $\mathcal{B}$ consent if and only if their match has been observed seeking an HIV test.*

We restrict attention to the "stigma" equilibrium, as the "reverse stigma" equilibrium implies universal testing, which is not consistent with the low testing levels observed in the data. Discussion of this second equilibrium, as well as the proof that no other equilibria exist is deferred to Appendix A.

The stigma equilibrium

We begin by characterizing the most important equilibrium for our purposes, in which there is stigma against HIV testing. In this equilibrium, every $b \in \mathcal{B}$ consents to a match

[18] We do not assume any relationship between the distribution of beliefs and the true value $\rho = 0.96$. Indeed, Figure 7 illustrates the extent to which beliefs are incorrect.

[19] The distribution of beliefs, as well as the effect of the intervention are illustrated in Figure 7.

who has not been observed testing, but a proportion S of $\{b \in \mathcal{B}\}$ reject those who have been observed seeking an HIV test.

Given this strategy by agents in population $\mathcal{B}$, the decision to test for HIV is based on the expected impact on present discounted utility, which is equal to

$$\theta_a v(1+\delta) - c - \delta S y_a$$

if the test is sought at a nearby clinic, and

$$\theta_a v(1+\delta) - c - d - \phi\delta S y_a$$

if the test is sought at a far away clinic. In both cases, there is an indirect cost of testing due to the stigma agent a might face in the next period, and this cost is higher if a chooses to test nearby.

By assumption (1), low-risk types will never seek an HIV test in this equilibrium. If $\theta_a = \theta_H$, a will select an action as follows.

$$(t_a^N, t_a^F) = \begin{cases} (0,0) & \text{if } \frac{\theta_H v(1+\delta)-c-d}{\phi\delta S} < y_a \\ (0,1) & \text{if } \frac{d}{(1-\phi)\delta S} < y_a \leq \frac{\theta_H v(1+\delta)-c-d}{\phi\delta S} \\ (1,0) & \text{if } y_a \leq \frac{d}{(1-\phi)\delta S} < \frac{\theta_H v(1+\delta)-c-d}{\phi\delta S} \end{cases}$$

In the absence of stigma, all high-risk types would like to seek an HIV test nearby. However, if $S > 0$, high-risk types will choose to not test, test far away, or test nearby depending on their benefit from a future relationship, y_a. Those who value a future sexual relationship very highly will not seek an HIV test. Agents with intermediate values if y_a will choose far away testing, and those who value the relationship least will test nearby, as they have less to lose by being observed. In any case, the fact that only high-risk types seek HIV testing results in adverse selection.

We now turn our attention to the consent decision. If an agent b does not observe her match seeking an HIV test ($\sigma_a = 0$), she will consent to a sexual relationship. This stems from assumption (6), which states that any agent $b \in \mathcal{B}$ would obtain net benefit from a relationship with the average member of the population $\mathcal{A}$. Because low-risk types do not test for HIV, they generate the signal $\sigma = 0$; meanwhile, some high-risk types generate $\sigma = 0$ and others generate $\sigma = 1$. Therefore, the person b has been matched with cannot be more likely to have HIV than the average member of the population. Formally, maximizing her expected payoff (5), b will consent if

$$y_b > \mathbb{E}\left[h_a\left(s\tau\left(1-\hat{\rho}_b(t_a^N + t_a^F)\right) + s_0\right) | \sigma_a = 0\right]$$

where we have replaced ρ by the belief $\hat{\rho}_b$. The right-hand side of this inequality is always[20] less than or equal to $\bar{h}(s\tau + s_0)$, so by assumption (6), b will consent.

[20]Proof: $\mathbb{E}\left(h_a\left(s\tau(1-\hat{\rho}_b(t_a^N + t_a^F)) + s_0\right) | \sigma_a = 0\right) \leq \mathbb{E}(h_a(s\tau + s_0)|\sigma_a = 0) = \mathbb{E}(\theta_a|\sigma_a = 0)(s\tau + s_0) \leq \mathbb{E}(\theta_a)(s\tau + s_0) = \bar{h}(s\tau + s_0)$

If, on the other hand, b observes that a has tested for HIV ($\sigma_a = 1$), she infers that he is a high-risk type. She will therefore consent if[21]

$$y_b \geq \theta_H \left(s\tau(1 - \hat{\rho}_b) + s_0 \right). \tag{8}$$

Note that she will only consent if her benefit from the relationship (y_b) is sufficiently high, or if she believes that ART is effective at preventing HIV transmission ($\hat{\rho}_b$ is high).

We are now able to provide a formula for the total level of stigma in the population, S, which we previously defined as the fraction of agents in $\mathcal{B}$ who would withhold consent from a match they have observed seeking an HIV test.

$$S = \int_0^\infty \left(\int_0^{1+(s_0/s\tau)-(y/\theta_H s\tau)} f(\hat{\rho}) d\hat{\rho} \right) g(y) dy \tag{9}$$

The functions f and g represent probability densities for $\hat{\rho}$ and y respectively.

3.3 Comparative Statics

This paper evaluates an experiment that was designed to shift beliefs about the ART prevention parameter ρ, by disseminating the information that ART reduces HIV transmission by 96%. In our model, we interpret this as a first-order stochastically dominant shift in the distribution $F_{\hat{\rho}}$. Indeed, we observe empirically that beliefs are biased towards 0 (most are unaware of the preventative effect of ART), and the information intervention appears to have shifted the distribution uniformly towards 1 (see Figure 7).

We now characterize the theoretical implications of such a shift in the distribution of beliefs.

Proposition 2. *If $s = 0$, a change in the distribution of beliefs $F_{\hat{\rho}}$ has no effect on the level of stigma S.*

This comes from (8): if $s = 0$, a change in $\hat{\rho}_b$ has no effect on whether b consents or not. Intuitively, if stigma is based on something other than the risk of HIV transmission, then changing beliefs about the risk of transmission will not affect stigma.

In what follows, we consider the case $s > 0$, that is, there is some cost associated with contracting HIV.

Proposition 3. *If $s > 0$, a first-order stochastically dominant shift in the distribution of beliefs $F_{\hat{\rho}}$ results in a weak decrease in the level of stigma S.*

If the distribution of beliefs shifts upward, each agent is more likely to believe that ART is effective in reducing HIV transmission. For some of these agents, this will imply a change in strategy from not consenting to consenting. In aggregate, stigma will decrease. Formally, the level of stigma can be written as

$$S = \int_0^\infty F_{\hat{\rho}} \left(1 + \frac{s_0}{s\tau} - \frac{y}{\theta_H s\tau} \right) g(y) dy. \tag{10}$$

[21] Here, we make use of the fact that she is certain her match is a high-risk type, and has been tested for HIV: $t_a^N + t_a^F = 1$. In this case, $\mathbb{E}[h_a \left(s\tau \left(1 - \hat{\rho}_b (t_a^N + t_a^F) \right) + s_0 \right) | \sigma_a = 1] = \theta_H \left(s\tau(1 - \hat{\rho}_b) + s_0 \right)$.

Consider a first-order stochastically dominant shift in the distribution $F_{\hat{\rho}}$. For each value of y, the integrand will decrease. Therefore, S will also decrease. It is worth pointing out that if other forms of stigma s_0 are large relative to the cost of contracting HIV, s, a shift in beliefs about ρ will have no effect, as the integrand in (10) will equal 1 for any distribution.

Proposition 3 demonstrates that, by shifting beliefs, the direct effect of the information experiment is to reduce the level of stigma in the community, if that stigma is based on a fear of contracting HIV. We next discuss the implications of this reduction in stigma on HIV testing.

Proposition 4. *A decrease in stigma leads to an increase in the total number of HIV tests, and an increase in the number of tests at nearby clinics.*

These two statements follow from the fact that a cumulative distribution function $G(y)$ always increases in y, and $\lim_{y\to\infty} G(y) = 1$.

Proposition 5. *A moderate decrease in stigma has an ambiguous effect on the number of HIV tests at far away clinics, but as $S \to 0$, the number of far away tests approaches zero.*

The fraction of $\{a \in \mathcal{A}\}$ who choose far away testing equals

$$G\left(\frac{\theta_H v(1+\delta) - c - d}{\phi\delta S}\right) - G\left(\frac{d}{(1-\phi)\delta S}\right)$$

which, depending on the distribution G, may be locally increasing or decreasing in S.

Figure 2 depicts the relationship between stigma, testing levels, and testing location in the case where the distribution G is normally distributed and initial testing levels are low. In this case, a moderate increase in beliefs results in an increase in far away testing, but as stated in Proposition 5, this is not a general result. The effect depends on the distribution G and on initial testing levels.

Finally, it is important to note that the predicted change in HIV testing behavior comes from a decrease in stigma, which is driven entirely by the beliefs of potential sexual partners. This leads to a specific empirical implication: that the decision to test for HIV should depend on the beliefs of the community, and not on one's own beliefs about the preventative nature of ART drugs.

4 Empirical Strategy and Results

4.1 The Effect of the Information Treatment on Beliefs

As a first step, we ascertain whether the information campaign achieved its goal of shifting beliefs about the public benefit of ART, and whether other types of beliefs were affected. We also investigate the effect of the intervention on survey measures of stigma.

Survey data

We conducted a survey approximately five months after the intervention. A total of 1,358 individuals were interviewed[22]. The purpose of this survey was to collect

[22] 12% of observations were dropped due to missing data, 11% in the treatment group and 13% in the control group. This difference is not significant.

individual data on beliefs, attitudes towards HIV, health seeking behavior, and sexual behavior. The survey also provided data on village-level covariates which were not available from census data, such as wealth and education.

The interviewers selected respondents by conducting a random walk within each village[23]. The survey was administered only to those who attended the community health meeting[24].

The interviewers were hired from a pool of candidates who were not socially connected to the community educators employed for the intervention. Interviewers had no information on the purpose of the original intervention, nor the identities of the treatment and control villages. Out of 122 study villages, 119 were successfully surveyed. In one treatment village and two control villages, village authorities denied permission for a survey to take place due to the recent death of a village leader.

Regression equation

In order to investigate the effect of the information treatment on the beliefs of meeting attendees, we regress each belief measure captured in the survey on the treatment status of the village. Because the information treatment was randomly assigned, this allows us to estimate the causal effect of the information treatment on beliefs.

$$Belief_{ij} = \alpha + \beta T_j + \delta^T \chi_{ij} + \epsilon_{ij} \tag{11}$$

Here, $Belief_{ij}$ is a belief measure elicited from respondent i in village j and $T_j \in \{0, 1\}$ is the treatment status of village j. χ_{ij} is a set of individual- and village-level covariates[25]. Standard errors are clustered at the village level. Because T_j is randomly assigned, we expect $\mathbb{E}(\epsilon_{ij}|T_j) = 0$, so the OLS estimate $\hat{\beta}$ is unbiased.

Beliefs about the public benefit of ART increased

Eliciting beliefs about the public benefit of ART was a primary goal of the survey, conducted approximately five months after the intervention. Five different measures were collected. First, respondents were presented with a list of possible HIV prevention methods, including the use of condoms, mosquito nets, circumcision, abstinence, and ART. They were asked to select those which reduce the probability of transmitting HIV. 80% of respondents in the treatment group and only 19% in the control group chose ART as a prevention method (see Column 1 of Table 3).

Next, respondents were asked to agree or disagree (on a Likert five-point scale) with the following statment: *ART reduces the probability that an HIV-positive person will spread the virus to his or her partner*. The information treatment had a significant effect; the average response in the control group was "disagree", while in the treatment group the average response was "agree" (this measure is in Column 2 of Table 3, rescaled).

[23] Two interviewers were assigned to each village; one began the random walk at the center and the other at an outer edge of the village.

[24] This results in selection bias among those interviewed relative to a random sample of the village as a whole, but this selection should be the same in both treatment and control villages.

[25] Individual-level controls include age, gender, whether the person is pregnant, married, has regular partner, employed, primary school educated, secondary school educated, has livestock, and has a brick house. Village-level controls consist of covariates listed in Table 2 and community educator fixed effects.

Respondents then ranked the following two types of potential sexual partners according to HIV transmission risk: a person who has never been tested for HIV, and a person who is HIV positive and taking ART correctly. Column 3 of Table 3 shows that in the control group, respondents said, on average, that a person who has never been tested for HIV is less risky, while in the treatment group, most said that a person taking ART is a safer sexual partner. This suggests that many who attended the community meeting understood an important implication of the information provided: that a partner who has never been tested might in fact be more risky than a partner who is infected but treated.

In order to elicit beliefs about the rate of HIV transmission with and without ART drugs, we took inspiration from the bean-counting subjective beliefs measure advocated by Delevande and Kohler (2009). Respondents were shown ten bottle caps. Each bottlecap was meant to represent a serodiscordant couple: an HIV-positive person and his or her HIV-negative spouse. Respondents removed one bottle cap for each person who they believed would contract HIV within one year, assuming no one was taking ART. The process was then repeated, under the alternative assumption that all HIV-positive individuals took ART drugs as prescribed. Using these two measures of absolute and relative transmission rates, we calculate the beliefs about the relative reduction in risk associated with ART use. In Column 4 of Table 3, we see that based on this measure, individuals in the treatment group believe that the relative reduction in HIV transmission risk is approximately 56%; this is much higher than in the control group (9%) but still well below the true value $\rho = 0.96$.

We also capture beliefs about the ART prevention parameter ρ using an infographic similar to the one displayed at the community health meetings (Figure 6). This measure was elicited last to ensure that respondents were not visually reminded of the information campaign before discussing their beliefs. Histograms in Figure 7 show that the distribution of beliefs about ρ is uniformly higher in the treatment group. In Column 5 of Table 3, we see that average beliefs $\hat{\rho}$ are significantly higher in the treatment group, but below the true value $\rho = 0.96$. It is reassuring that the measures in Columns 4 and 5 are somewhat similar; in the treatment group, they correspond to beliefs $\hat{\rho} = 0.56$ and $\hat{\rho} = 0.70$ respectively.

Beliefs about the private benefits of ART did not change

Both treatment and control villages received basic information about the private benefits of ART drugs, and indeed, Column 3 of Table 4 shows that respondents' beliefs do not differ between the treatment and control groups. Respondents were asked to agree or disagree, on a five-point Likert scale, with the statement *An HIV-positive person can live a long and healthy life if he takes ART.* This statement closely matches the intervention script. In both treatment and control villages, the average respondent strongly agreed with the statement.

Beliefs about HIV transmission and prevalence did not change

The information campaign could have affected several beliefs about HIV. The knowledge that ART reduces HIV transmission may cause individuals to update their beliefs about the overall HIV prevalence in their community. In addition, while the absolute

transmission rate was not mentioned during the information campaign, attendees may have formed some correct or incorrect beliefs about this rate based on the information that was provided. A shift in either of these beliefs may have an effect on HIV testing distinct from the effects predicted by the model described in Section 3. However, Table 4 shows that there were no significant changes in these beliefs.

As mentioned above, we elicited beliefs about the absolute transmission rate using ten bottle caps. We asked respondents how many HIV-negative individuals with infected, untreated partners would contract the virus over the course of one year. The respondent removed one bottle cap for each case of HIV transmission. We also used bottle caps to measure beliefs about prevalence. Ten bottle caps represented ten randomly selected members of the community, and the respondent was to remove one bottle cap for each member who was HIV positive.

Columns 4 and 5 of Table 4 show that neither beliefs about the absolute transmission rate, nor beliefs about HIV prevalence were affected by the information campaign. We might expect beliefs about prevalence to be lower in the treatment group, as respondents are aware that ART should slow the spread of HIV in the population. While this coefficient is negative, it is small and insignificant (Column 5 of Table 4). This may be explained by fact that ART has only been available for the past few years, and adoption has been low, so a reasonable update in beliefs about the spread of HIV might be quite small.

Beliefs about HIV transmission and prevalence are incorrect in both treatment and control villages. In particular, beliefs about the absolute probability of HIV transmission are much higher than the true value, which, according to the Malawi National AIDS Commission, is approximately 10% per year. These beliefs are consistent with the overestimates of HIV transmission rates measured by Kerwin (2012) in Malawi, and may be explained by a health education policy which purposely overstates the risk of contracting HIV in an effort to discourage risk taking behavior.

The information treatment reduced stigma towards ART users

If we are to believe that a reduction in stigma has indeed taken place, we ought to see a change in attitudes towards those taking ART drugs. In the model, stigma is explained by the fact that some people will reject a potential sexual partner who has been tested for HIV, because such a partner is more likely to be HIV positive and taking ART drugs. The survey measures in Columns 1 and 2 of Table 4 directly address this type of behavior, by asking whether the respondent would reject such a partner, and also whether others would do so. The first measure asks respondents whether they would prefer a sexual partner who is taking ART drugs over one who has never been tested. The second measure asks whether a person taking ART drugs would be able to find a new sexual partner. The fact that the information caused a significant change in both of these measures suggests that the specific mechanism outlined in our model of stigma may apply.

4.2 The Effect of the Information Treatment on HIV Testing

The main outcome of interest, both theoretically and from a policy perspective, is HIV testing. The experiment shifted community beliefs about the public benefit of

ART drugs (as observed in Section 4.1). As this reduced stigma, we expect to see a higher number of HIV test seekers from treatment villages. The HIV testing rate is also important for policy, especially in the context of this intervention. The information we provided only addresses the public benefit of ART drugs, so it is likely that any increase in HIV testing will be followed by increased demand for ART. Uptake of ART is important because the medication saves lives and slows the spread of the epidemic.

Administrative data

We use administrative data from the handwritten[26] patient registers of 18 health facilities in Zomba District, including all free clinics whose catchment areas include study villages, and all free clinics and hospitals in Zomba Town.

We photographed and digitized HIV testing registers and outpatient department registers, concealing identifying information due to ethical concerns about privacy. Data on ART use was digitized and provided by Dignitas International, a health care NGO, as a part of their monitoring and evaluation activity.

We collected HIV testing data for the period covering 2.5 months before the start of the intervention and 3 months after the intervention ended. HIV testing registers at each health facility include fields for the date, gender, age, and address or home village (see Figure 5). This last field allows us to link the HIV test to the patient's village, and in particular, to determine whether that village belongs to the study's treatment group or control group. HIV testing registers also indicate whether the patient was pregnant, whether or not the test was a joint test, the time since the client's last HIV test, and the result of the test. The distance traveled to the facility is calculated from GPS coordinates of the clinics and the study villages, as recorded in census data[27].

Regression equation

In the administrative data, we only observe those community members who seek an HIV test, so we are required to use a village-level specification. The primary outcome of interest is the percent of the target population that seeks an HIV test. We construct this outcome measure by first aggregating data on individual HIV tests at the village level, constructing separate variables for tests that took place pre-intervention and post-intervention[28]. The target population for the information campaign consisted of individuals aged 15 to 49, and we restrict the outcome variable to include only HIV tests sought by members of this age group. Pregnant women are excluded, as they undergo mandatory HIV testing as a part of their antenatal health care. Information from the HIV testing register determines whether a given patient belongs to the target group, and census data provides the approximate size of the reference population in each village.

[26] There are two exceptions: Zomba Central Hospital and Matawale Health Facility both have electronic registers. Health facility data was obtained with the permission of the Malawi College of Medicine, as well as the Malawi District Health Office and Zomba Central Hospital

[27] Census data was obtained from the Malawi National Statistics Office

[28] The pre-intervention period covers 2.5 months before the start of the intervention, and the post-intervention period covers 3 months after the intervention ended. We ignore all HIV tests that took place during the intervention period, which lasted 22 days.

In order to identify the causal effect of the information intervention with high statistical power, we perform an ANCOVA regression at the village level, controlling for pre-intervention levels of the outcome variable. This estimator is unbiased in a randomized study, and has lower variance than either a simple regression of post-intervention testing levels on treatment, or a difference-in-difference estimator (McKenzie, 2012).

As stated above, the dependent variable is the percent of the target population who sought an HIV test post-intervention. Covariates include the pre-intervention testing rate, and other village-level covariates determined from the Malawi National Census, GPS coordinates, and the survey. The full set of village-level and pre-intervention covariates is listed in Table 2. We also control for the community educator assigned to the village, and stratification variables: the nearest health center and village population.

This intervention may be subject to spillovers. Indeed, 60% of the villages in the study are within 1 kilometer of another study village. We therefore include a specification which controls for both nearby study villages and nearby treatment villages, considering villages within 1 kilometer (based on GPS coordinates). Because treatment was randomly assigned, including these regressors together should not introduce endogeneity, and will remove the downward bias caused by spillovers from treatment villages to control villages. It will, however increase the risk of multicollinearity. We allow the number of nearby treatment villages to have a heterogeneous effect based on the treatment status of the village itself; for example, it may be that control villages are more strongly impacted by information spillovers than treatment villages, because in treatment villages the information was provided directly.

Our regression specification is as follows:

$$\textit{Percent HIV tested}_j = \alpha + \beta T_j + \gamma_T T_j * N_{Tj} + \gamma_C C_j * N_{Tj} + \gamma N_j + \boldsymbol{\delta}^T \boldsymbol{\chi_j} + \epsilon_j. \quad (12)$$

T_j and C_j are indicators for the treatment group and control group respectively, $\boldsymbol{\chi_p}$ is a vector of village-level covariates including the pre-intervention testing level (see Table 2 for a complete list of village-level covariates), and community educator fixed effects. N_{Tj} is the number of treatment villages within one kilometre, and N_j is the total number of study villages within one kilometer. In regressions which do not control for spillovers, we apply the restriction $\gamma_T = \gamma_C = \gamma = 0$. Standard errors are robust.

Because T_j is randomly assigned, $\mathbb{E}(\epsilon_j | T_j) = 0$, and the OLS estimate $\hat{\beta}$ is unbiased.

The information treatment increased HIV testing

The information intervention caused a significant increase in the total number of HIV tests, as shown in Columns 1 and 2 of Table 5. Controlling for spillovers, the estimated effect size is 60%, measured over a three-month period. This is higher than the estimate without spillovers (37%), but also subject to a larger standard error.

Let us turn to the epidemiological literature to put this magnitude of HIV testing into some context. Granich et al. (2009) provide a mathematical model for the relationship between HIV testing and the spread of HIV, taking into account the fact that ART drugs greatly reduce transmission. The intervention increased annual testing rates among sexually active individuals from approximately 6.4% to 10.4%, which according their model should avert at least two new HIV infections per primary infection. While this is based on a model which abstracts from many behavioral considerations, it is

worth noting that at low levels of HIV testing, a small increase has the potential to have large epidemiological implications.

The information treatment increased total HIV testing rates significantly for both men and women (as shown in the Appendix, Table A1). The magnitudes of the increases are similar, which may at first seem surprising given the fact that women are, in general, more likely to test than men, and attendance at community health meetings was higher among women. However, the model shows that one's HIV testing decision depends on the beliefs of one's potential sexual partners, so the gender split at health meetings should not necessarily match that of HIV testing clients.

HIV testing depends on beliefs about the public benefit of ART

An upward shift in beliefs about the public benefit of ART should lead to a decrease in stigma, and a subsequent increase in HIV testing levels. Beliefs about the public benefit of ART drugs were strongly affected by the information campaign, while other beliefs remained largely unaffected. This makes the information treatment a good candidate for an instrumental variables approach to estimating the effect of an increase in community-level beliefs about ρ, the ART prevention parameter. The village-level average of the measure $\hat{\rho}$, obtained from the infographic in Figure 6, is an endogenous regressor. As instruments, we use village treatment status, as well as the number of nearby treatment villages. This allows us to investigate the effect of community beliefs on HIV testing.

We estimate a two-stage least squares specification, with first stage

$$Beliefs_j = \alpha_0 + \beta_0 T_j + \boldsymbol{\delta_0^T \chi_j} + \nu_j \tag{13}$$

and second stage

$$Percent\ HIV\ tested_j = \alpha + \beta \hat{Beliefs}_j + \boldsymbol{\delta^T \chi_j} + \epsilon_j. \tag{14}$$

where $Beliefs_j$ denotes average beliefs[29] about the ART prevention parameter ρ in village j, and $\hat{Beliefs}_j$ denotes its fitted value from the first-stage regression. $\boldsymbol{\chi_p}$ is a vector of village-level covariates[30] and community educator fixed effects. Standard errors are robust. The identification assumption is $\mathbb{E}(\epsilon_j | T_j) = 0$. Villages were randomly assigned to treatment or control, and we assume that the intervention only affected village-level HIV testing rates through a shift in beliefs about the public benefit of ART, represented by the parameter ρ. Recall that the only difference between the community health meetings in treatment and control villages was the inclusion of information on the public benefit of ART, and Table 4 shows that other beliefs about HIV remained unaffected.

Higher average beliefs about the public benefit of ART lead to a higher rate of HIV testing. In particular, if an entire community were shifted from the belief that ART drugs have no effect on HIV transmission, to the belief that they block transmission completely, the results in Column 3 of Table 5 predict an 77% increase in HIV testing.

[29] This is calculated from the survey measure using the infographic in Figure 6.

[30] See Table 2 for a complete list of village-level covariates.

The choice of testing location is linked to beliefs about the public benefit of ART

Before the intervention, in the average village, 30% of those seeking an HIV test traveled at least four kilometers further than necessary from their home villages. This may be indicative of stigma, because traveling far from home is costly, but reduces the likelihood of being seen by friends and neighbors.

In general, individuals seeking an HIV test may travel to far away clinics for reasons other than to avoid being seen, such as differences in clinic quality or wait time. However, HIV testing is free, and the procedures are identical at all clinics. Wait times do not vary much, especially compared with the time spent traveling to the clinic; those who test far away travel, on average, an extra nine kilometers. Finally, if far away testing is fully explained by reasons other than stigma, we should not observe any link between beliefs about the public benefits of ART and the choice of testing location.

We say that an HIV test takes place *far away* if it takes place at least four kilometers further than the client's nearest health facility[31], and investigate the effect of a shift in beliefs about the public benefit of ART on testing location. We again run a two-stage least squares regression with specifications (13) and (14). The dependent variable is the number of total, nearby, or far away HIV tests; Columns 1 to 3 of Table 6 show the results of these three regressions. A shift in beliefs may cause an increase in nearby testing: the coefficient is large, but imprecisely estimated (Column 2). The increase in far away testing is significant but small (Column 3).

In order to understand the intervention's ambiguous effect on testing location, we turn to the predictions of the model. The model predicts a specific relationship between the choice of HIV testing location and the distribution of beliefs about ART in the community, based on the link between those beliefs and stigma. In particular, a moderate shift in beliefs about the ART prevention parameter ρ, which corresponds to a moderate reduction in stigma, could increase both the number of people who test near their home village and the number who test far away. Meanwhile, a large shift in beliefs, which corresponds to a large reduction in stigma, should only increase the number of nearby tests, as people become less afraid of being seen to seek an HIV test.

We define *high beliefs* as beliefs[32] $\hat{\rho} \geq 0.95$, for the simple reason that this threshold approximately matches the true value of ρ. From a policy perspective, it is useful to know the effects of shifting beliefs to the true value of ρ, and whether this is sufficient to cause a reduction in stigma. As the majority of individuals in control villages hold beliefs $\hat{\rho} = 0$, we define *moderate beliefs* to be $0 < \hat{\rho} < 0.95$.

On average, the information intervention shifted beliefs from low beliefs $\hat{\rho} = 0$ to either moderate or high beliefs, as shown in Figure 7. The distribution of beliefs in a given village can be described by three numbers: the proportion of the population who hold low beliefs, moderate beliefs, and high beliefs.

We analyze the following OLS specification.

$$y_j = \alpha + \beta_1 (\textit{moderate beliefs})_j + \beta_1 (\textit{high beliefs})_j + \boldsymbol{\delta}^T \boldsymbol{\chi_j} + \epsilon_j \tag{15}$$

y_j is set equal to either the percent of the target population in village j that seeks an HIV test nearby, or the percent of the target population in village j that seeks an HIV

[31] See the Appendix for results using other definitions.

[32] These beliefs are elicited in the survey using the infographic in Figure 6. Note that this beliefs measure is discrete, and the selection $\hat{\rho} = 0.95$ is closest to the true value of $\rho = 0.96$.

test far away from their home village. The regressors $(\textit{moderate beliefs})_j$ and $(\textit{high beliefs})_j$ represent the proportion of the village that has moderate or high beliefs, as estimated from survey responses. These regressors are not exogenous, and we must interpret the estimated coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$ as correlations between the level of community beliefs and the number of HIV tests either nearby or far away. χ_p is a vector of village-level covariates[33] and community educator fixed effects. Standard errors are robust.

Consistent with the predictions of the model, high beliefs about the public benefit of ART are associated with an increase in the number of nearby tests, and an (insignificant) decrease in the number of far away tests, as seen in Columns 5 and 6 of Table 6. This suggests that any increase in far away testing is driven by a moderate shift in beliefs (Column 6). In addition, a large shift in beliefs about the public benefit of ART reduces stigma enough that more people feel comfortable seeking an HIV test, and are also willing to risk being observed by attending a clinic near their home village.

Testing is linked to perceived community beliefs about the public benefit of ART

The theory predicts that HIV testing decisions should depend on the level of stigma in the community, which in turn depends on community-level beliefs about the public benefit of ART. This differs sharply from predictions based on a model of social preferences, in which one's own beliefs matter most, or a model of household bargaining, in which one's spouse's beliefs are important.

In order to test this prediction, we measured *perceived* beliefs of the community. That is, we asked respondents what they thought most people in their respective communities believed about the public benefit of ART. Once a respondent had fully understood the infographic in Figure 6, she was asked which option that her spouse would choose, and which option most members of the community would choose.

We regress self-reported HIV testing on this measure of perceived beliefs. We use the specification

$$\begin{aligned}\textit{HIV test}_{ij} = \alpha + \beta_0(\textit{respondent has high beliefs})_i + \beta_1(\textit{spouse has high beliefs})_i + \\ \beta_2(\textit{community has high beliefs})_i + \delta^T \chi_{ij} + \epsilon_{ij} \quad (16)\end{aligned}$$

where the dependent variable is an indicator for respondent i in village j reporting an HIV test post-intervention. The three regressors of interest are the respondent's own beliefs, her perception of her spouse's beliefs, and her perception of the community's beliefs. These three variables are indicators for high beliefs about the public benefit of ART, $\hat{\rho} > 0.95$. The set of covariates χ_{ij} includes individual- and village-level controls[34]. Standard errors are clustered at the village level.

As predicted, Table 7 shows that survey respondents are much more likely to report an HIV test post-intervention if they perceive the community to have high beliefs about the public benefit of ART drugs. The respondent's own beliefs and perceived spouse's beliefs do not play a significant role.

[33] See Table 2 for a complete list of village-level covariates.

[34] Individual-level controls are age, gender, whether the person is pregnant, married, has regular partner, employed, primary school educated, secondary school educated, has livestock, and has a brick house.. Village-level controls are covariates listed in Table 2 and community educator fixed effects.

4.3 Sexual Behavior

A reduction in stigma, as defined in the model, may lead to risk compensation in the context of sexual behavior. We model stigma as the fraction of the population who would reject a potential sexual partner based on his decision to seek an HIV test, and we predict that this fraction should decrease in response to the information intervention. Because HIV testing increases, the overall effect on the level of sexual activity is ambiguous.

Unprotected sex increased for those who sought an HIV test

We regress self-reported measures of sexual behavior on village treatment status, following specification (11). The dependent variables are the number of sex acts and number of condoms used, both recalled by respondents over the past seven days. We estimate the number of unprotected sex acts (Column 3) by subtracting the number of condoms from the total number of sex acts[35].

The number of unprotected sex acts is insignificantly higher in the treatment group, and, consistent with the theory, the increase in risky sexual activity is primarily among those who have been tested for HIV (see Columns 3 and 4 of Table 8). The overall effect comes from an increase sexual activity and a small decrease in condom use, as seen in Columns 1 and 2.

While the increase in unprotected sex is statistically insignificant, the magnitude of the coefficient is not negligible. Before reaching the conclusion that this is a negative effect of the information campaign, it is worth noting that rational agents may be expected to increase their sexual interactions in response to the information. Risk compensation may come with large benefits including, for example, being able to start a family.

Finally, if we assume that the increase in risk taking was among those who either tested negative, or are taking ART, the level of risk compensation we observe is inconsequential in terms of HIV transmission[36] compared with the preventative strength of ART drugs. There would need to be a minimum 25-fold increase in unprotected sexual activity to offset the 96% reduction in HIV transmission associated with ART[37].

4.4 Other Potential Mechanisms

We claim that the effects of the information experiment are due to a reduction in stigma towards HIV testing. However, other models may generate similar predictions. For example, both social preferences and household bargaining would predict an increase in HIV testing in response to new information about the public benefits of ART drugs. We will attempt to rule these out as first order explanations for our results.

[35] In the case where more condoms were used than sex acts performed, we set the number of unprotected sex acts equal to zero.

[36] Risk compensation may be of concern for other reasons, for example, the spread of other sexually-transmitted infections which ART does not prevent. Gong (2014) and Baird et al. (2014) find an increased risk of sexually-transmitted infection after a person tests positive for HIV.

[37] Let τ be the HIV-transmission rate. The probability of avoiding infection in an interaction with an HIV-positive person is $1-\tau$, or, if the person is taking ART, $1-0.04\tau$. We are interested in solving for the proportional increase in sexual interactions x which equalizes risk: $(1-\tau) = (1-0.04\tau)^x$. For any $\tau \in (0,1)$, this is solved by $x > 25$.

Social costs are not the only potential barrier to HIV testing and treatment. For example, the psychic costs of testing may be quite large. Oster et al. (2013) propose an optimal expectations model to explain low uptake of a medical test for Huntington's Disease. This type of model, in which individuals prefer to choose optimistic beliefs about the future rather than learn the truth, may also partly explain low HIV testing rates. However, such behavior is unlikely to be affected by information on the public benefit of ART, conditional on the private benefits being known. For this reason, we restrict attention to mechanisms which are plausibly linked to our intervention through a social component of behavior change.

Social preferences

Altruism is an obvious alternative mechanism by which information on the public benefit of ART might increase HIV testing. People may derive utility from protecting their sexual partners from HIV. If this were the primary mechanism, we would expect to see self-reported testing increase in one's own beliefs about the public benefits of ART, as opposed to the beliefs of others. As shown in Table 7, this does not seem to be the case. Additionally, while altruism may cause either nearby or far away testing to increase, it does not explain the pattern observed in Table 6; high beliefs about the public benefit of ART are linked specifically to nearby testing.

This is not to suggest that individuals are not altruistic, or that altruism does not play a role in HIV testing. It is plausible that a person who is altruistic towards his partner is also less likely to be HIV positive, as he might use condoms and have fewer concurrent partners. In addition, an altruistic person may choose to test even without knowledge of the public benefit of ART, in order to make informed choices about the risk of transmitting the virus.

Household bargaining

Household bargaining has been shown to play a role in family planning decisions (Ashraf et al., 2013). There are many reasons to believe that HIV testing decisions are also subject to household bargaining, and this suggests an alternative explanation for the increase in HIV testing we observed. In particular, a person who is aware of the fact that ART reduces HIV transmission may put greater pressure on her spouse to get tested and treated for HIV. In this case, we would expect the testing decision to be strongly linked to one's spouse's beliefs about the benefits of ART. Table 7 shows that this is not the case.

A model of household bargaining would also predict an increase in joint testing. A person has little to gain by putting pressure on her partner to seek an HIV test if he is not intrinsically motivated to get treated. The results of the test are private, and he can simply report a negative test result. However, if a couple is tested jointly, the results are seen by both, which means that each member of the couple can exert additional pressure on the other to seek ART if necessary. Column 1 of Table 9 shows that the effect of the information campaign on joint testing is insignificant, and does not explain the overall increase in HIV testing. Survey results indicate that treatment villages are similar to control villages in terms of HIV tests reported due to pressure, preference for

joint testing over private testing, and relative willingness to pay for joint and private testing (see Columns 2, 3, and 4 of Table 9).

Household bargaining does not seem to explain the increase in HIV testing we have seen as a result of the information campaign. It may nevertheless play some role in HIV testing decisions. In both treatment and control villages, most respondents report a strong preference for joint testing, and approximately 20% of HIV tests in the clinic data are joint tests. Those with enough bargaining power to pressure their partners to test jointly may have already been motivated to do so before learning that ART would protect them from transmission. For example, joint testing allows couples to make informed decisions about condom use and family planning, and form accurate expectations about the future.

5 Conclusion

This study identifies a particular type of social stigma as a barrier to HIV testing: statistical discrimination between potential sexual partners. HIV testing disproportionately benefits those infected with the virus, and is therefore a signal of underlying risk. An individual's testing decision may be observed by members of the community, and some community members reject potential sexual partners who are known to have been tested.

This example of statistical discrimination is based on misinformation. Most are unaware of the fact that an HIV-positive person who is tested and treated for HIV is much less contagious, due to the public benefit of ART drugs. Providing information about the public benefit of ART reduces stigma, and increases HIV testing by 60%. Villages with high beliefs about the public benefit of ART drugs after the intervention see a large increase in the number of HIV tests sought at nearby clinics, but no increase in HIV testing at far away clinics. In addition, the testing decision appears to be based on perceptions of the community's beliefs about ART, and not one's own beliefs. These results suggest that it is possible to diminish this form of social stigma, by shifting the incorrect beliefs upon which it is based.

If the increase in HIV testing we observed was indeed due to a reduction in stigma, the effect should persist. Uptake of ART drugs should also increase, since the intervention consisted only of providing information on their benefits. Future data will allow us to determine the long run effect of this intervention on HIV testing and demand for ART. In addition, the theory suggests that the intervention targeted those who care most about the number of sexual prospects. Individuals who prefer to have many potential sexual partners are also most at risk of contracting and spreading HIV. Long-run data on HIV incidence will allow us to investigate the effect of the intervention on the spread of the virus.

This work may be relevant to other contexts in which a technology is under-adopted due to stigma. In particular, if a technology disproportionately benefits a stigmatized group, it may be under-adopted, as individuals know it will signal their underlying type. For example, a person who suffers from mental illness may be reluctant to seek psychiatric care, for fear his friends or employer might find out. Stigma, in many contexts, may be explained by statistical discrimination; employers might believe that the mentally ill are less productive workers. This situation leads to a bad equilibrium:

the employee's mental illness goes untreated, and he is less productive than he would be if he were receiving treatment. Of course, one solution is to help the employee obscure the signal, by ensuring privacy of psychiatric care. However, if statistical discrimination is based on incorrect beliefs, providing correct information to the public, or in this example, to employers, should eliminate the stigma equilibrium.

Information as policy

A community-level information campaign on the public benefit of ART drugs is an inexpensive way to reduce stigma and increase HIV testing. A policy which reduces stigma directly is more attractive than one which helps HIV test-seekers conceal their decision to test or their motivation for testing. For example, while monetary incentives increase HIV testing, in order to be effective in the face of stigma, they must be paid repeatedly to the entire community. This might make monetary incentives for ART use infeasible. A reduction in the level of stigma should affect all health seeking behavior, and have permanent effects.

While our experiment took place in Malawi, there is reason to believe its policy lessons apply elsewhere. Southern Malawi is representative of sub-Saharan Africa in many ways. HIV prevalence is high (above 10%), ART drugs are widely available at rural clinics, and the population is concentrated in rural villages, in which health seeking behavior is often observable. Our model of stigma is based on rational behavior and does not depend on cultural norms, therefore it might well apply in communities outside of our study area.

A scaled policy intervention should have two important features: information on the public benefit of ART should be provided at the community-level, to ensure common knowledge, and the information should be provided in a credible way, for example, by trusted health authorities. It is not sufficient to rely on learning and information sharing to shift beliefs over time, because in the presence of stigma, both of these activities will be hampered. Under-adoption of ART drugs means that most people do not learn of their effects first hand, and stigma makes people reluctant to discuss these effects with social contacts. Additionally, those who are infected cannot transmit the information credibly, as they stand to benefit from a shift in community beliefs about ART drugs. In the absence of an information campaign, social stigma allows incorrect beliefs to persist.

Our results suggest that providing precise information on the effect of ART drugs on HIV transmission is an effective way to reduce stigma. Some public health campaigns aim to inflate perceptions of HIV risk by distorting or hiding facts about transmission from the public, in an effort to reduce risk taking. This study suggests that such policies may have unintended consequences; they exacerbate stigma and inhibit health seeking behavior. Informed communities have higher rates of HIV testing and treatment, which improves the lives of those who are infected, and serves the community as a whole by reducing the spread of the virus.

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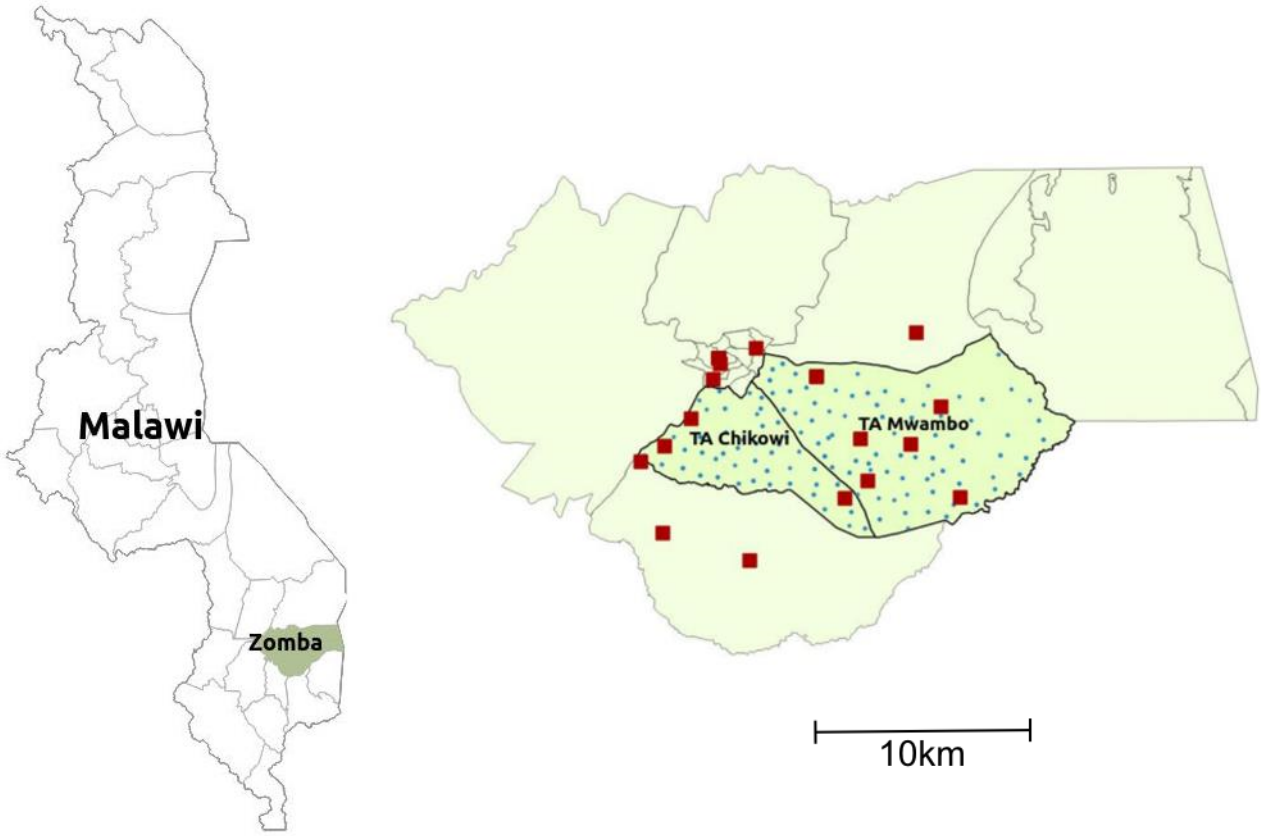
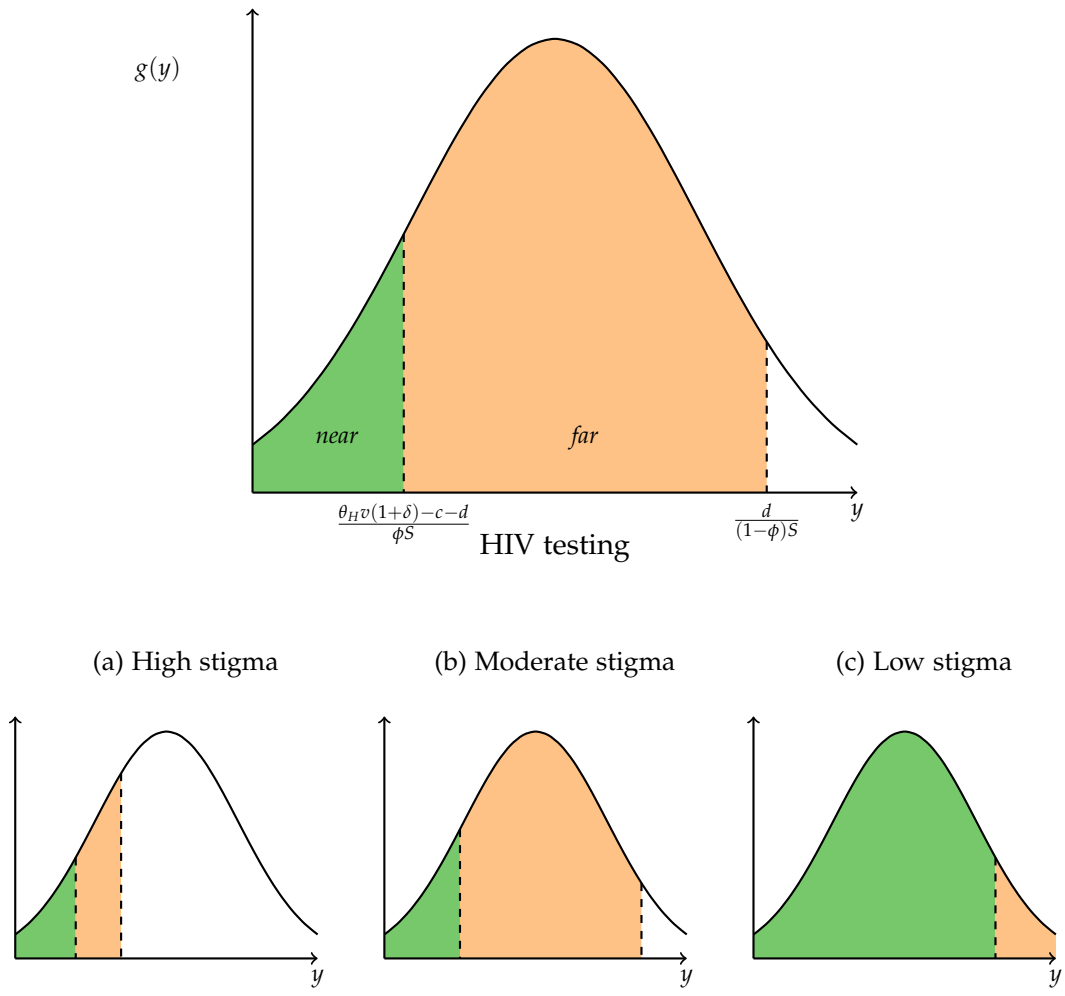
Figure 1: Study area



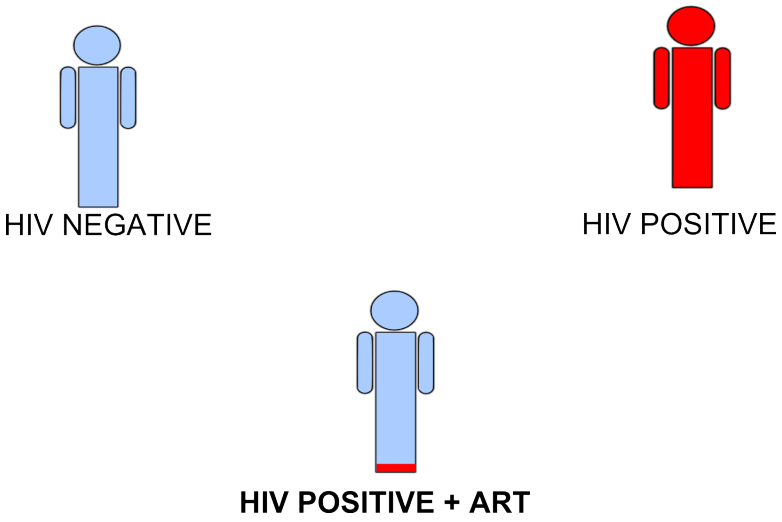
Note: The study included 122 villages in Zomba District, Malawi, represented by blue dots. Administrative data was obtained from 18 health facilities, represented by red squares.

Figure 2: Testing and location depend on stigma



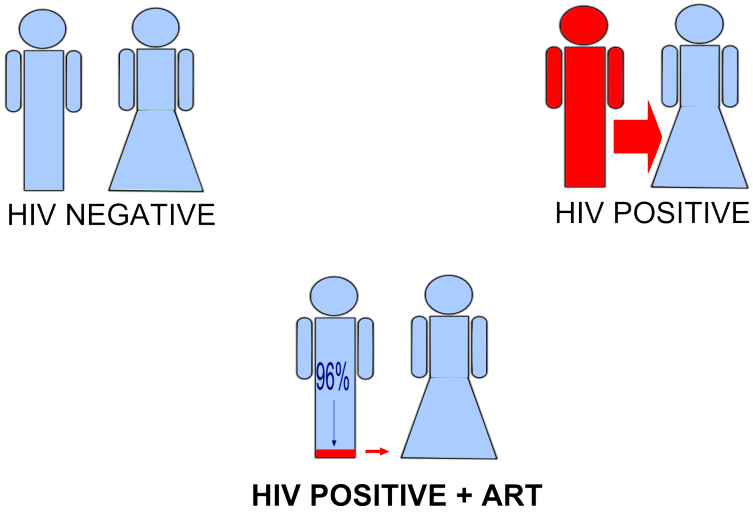
Notes: This figure illustrates the proportion of agents $a \in \mathcal{A}$ who seek nearby and far away testing, respectively. The curve $g(y)$ is the probability density function for the benefit of a relationship, y_a. To the left of the first threshold, agents seek a nearby HIV test. Between the first and second thresholds, agents seek a far away test. To the right of the second threshold no HIV test is sought. These thresholds shift up as stigma S decreases; a lower level of stigma implies a higher total number of tests and a higher number of nearby tests. The effect of a shift in stigma on the number of far away tests is in general ambiguous; in this example far away testing first increases and then decreases. As $S \to 0$, the number of far away tests decreases to 0.

Figure 3: Infographic used during intervention: control



Note: The amount of red represents the viral load. Equivalent infographics with an HIV-positive woman were also shown at each meeting.

Figure 4: Infographic used during intervention: treatment

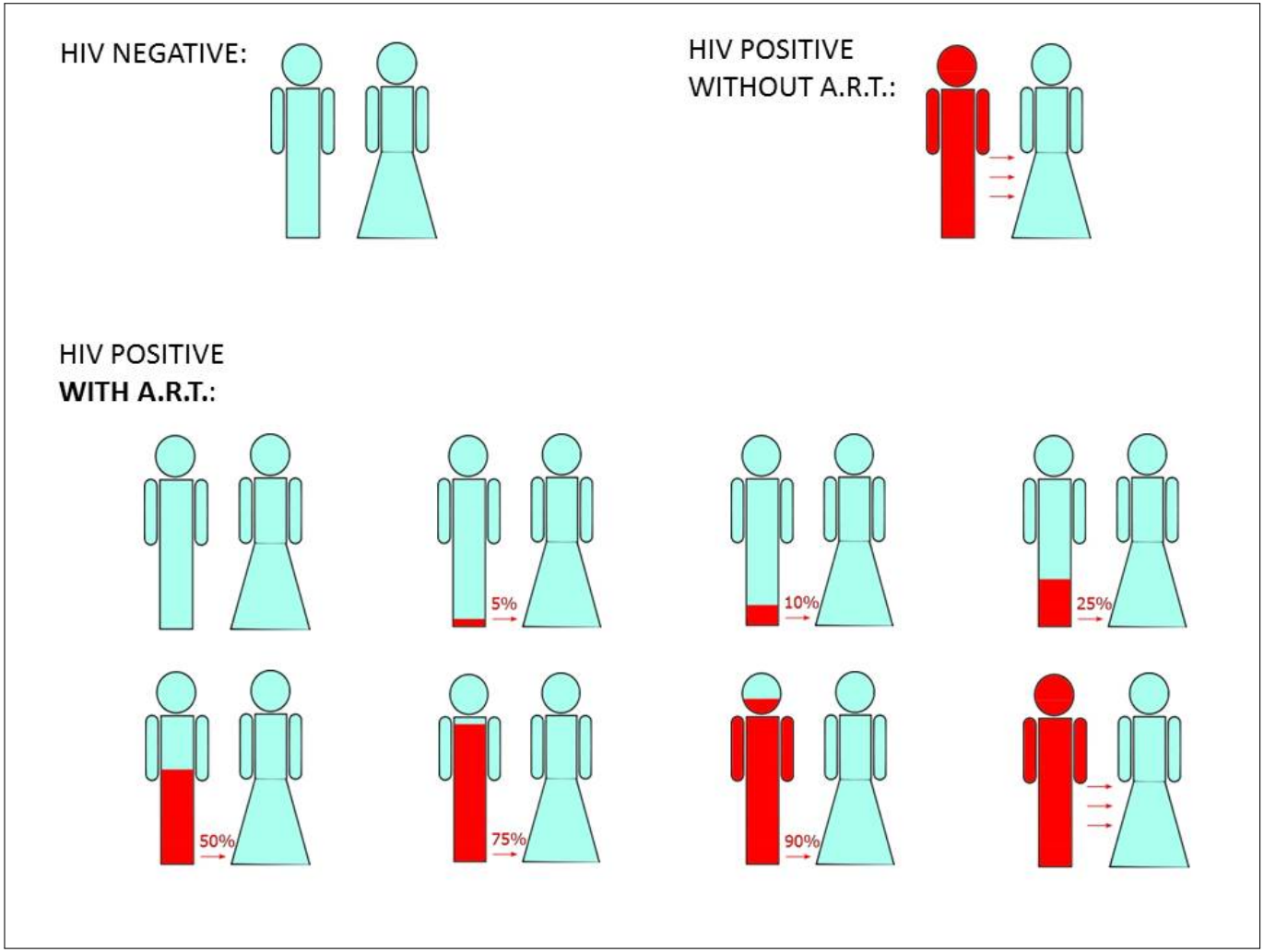


Note: The amount of red represents the viral load. The size of the arrow represents HIV transmisison risk. Equivalent infographics with an HIV-positive woman were also shown at each meeting.

Figure 5: HIV testing register

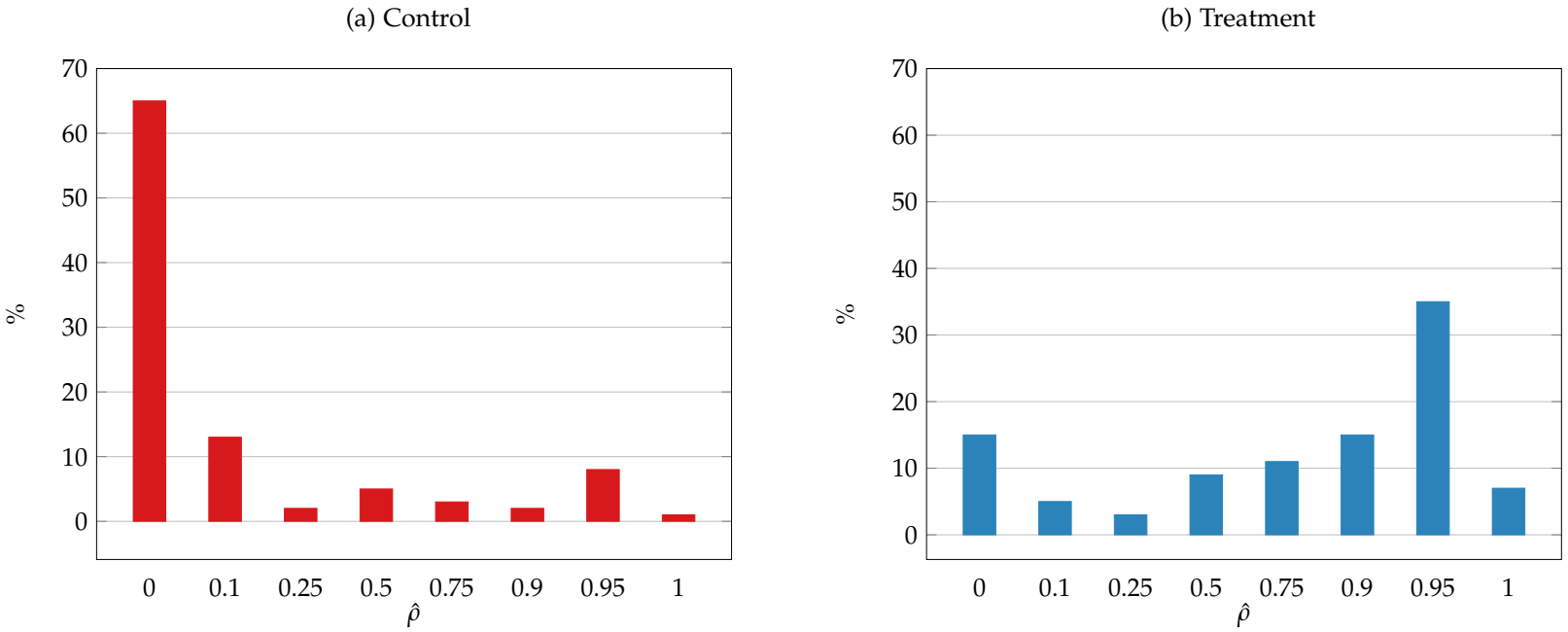
	Serial No.	Date	HTC Provider ID	Client Name	Phone / Physical Address	Sex / Pregnancy			Age	Age Group				HTC Access Type			Last HIV Test					Time Since Last Test	Partner Present at this session	
	Re-start counting on 1st July			*Fill name and contact details only if client gives consent to be contacted*		Male	Female Non-Preg.	Female Pregnant		0-11 months	1-14 years	15-24 years	25+ years	Routine HTC within Health Service	Comes with HTC Family Ref. Slip	Other (VCT, etc.)	Never Tested	Last Negative	Last Positive	Last Expos. Infant	Last Inconclusive	No. of Days Weeks Months or Years	No	Yes
1.						M	FNP	FP		A	B	C	D	PITC	FRS	Oth	LNev	L–	L+	LEx	LIn		N	Y
2.						M	FNP	FP		A	B	C	D	PITC	FRS	Oth	LNev	L–	L+	LEx	LIn		N	Y
3.						M	FNP	FP		A	B	C	D	PITC	FRS	Oth	LNev	L–	L+	LEx	LIn		N	Y

Figure 6: Infographic used to elicit beliefs



Notes: Respondents were asked to state their beliefs about the relative rate of HIV transmission for a person taking ART drugs by selecting one of eight options. The top left corresponds to the belief that an infected person taking ART drugs is not at all contagious. The bottom right corresponds to the belief that an infected person taking ART drugs and an infected person not taking ART drugs are equally contagious.

Figure 7: Beliefs $\hat{\rho}$ (ART prevention parameter)



Note: Beliefs were elicited using the infographic in Figure 6.

Table 1: Intervention

Topic	Script	Control	Treatment
Initial beliefs about private benefits of ART	*Raise your hand if you believe that a person with HIV can live a long and healthy life with ART.*	X	
Private benefits of ART	*A person who has HIV can live a long, healthy, normal life, as long as he or she takes ART properly.*	X	X
ART mechanism: reduction in viral load	*If a person with HIV takes ART he will still have HIV, but he will have a lower viral load, so the symptoms may disappear.*	X	X
Infographic (control)	Figure 3	X	
Initial beliefs about public benefit of ART	*Imagine a couple. One person is HIV positive and the other one is HIV negative. If the HIV-positive person takes ART, does that reduce the chance that the virus is passed to his or her partner? Raise your hand if you think the answer is yes.*		X
Public benefit of ART	*Actually, it is true that if a person with HIV takes ART, it can greatly reduce the chance of spreading HIV. Imagine a certain area where no one takes ART. In that area, 100 people got HIV from their partners last year. If those partners had been taking ART, only 4 people would have gotten HIV. 96 of them would have remained HIV negative.* *If a person with HIV takes ART he will become 96% less contagious. This is true for both men and women. This is because ART reduces the amount of virus in the body. When there is very little virus in the body, it is much less likely that the virus will be transmitted from one person to another.*		X
Infographic (treatment)	Figure 4		X
Other information about ART	*Only HIV-positive people should take ART. The person who is taking ART must adhere properly, taking the pills every day, exactly as instructed. If he or she forgets to take the pills, the viral load will go back up.*	X	X
Other HIV prevention methods	*For maximum protection from HIV, you should be faithful to one partner and use condoms.*	X	X
Availability of ART	*Health clinics offer free HIV testing and ART.*	X	X
Questions	*If you have other questions about HIV or ART you should ask your Health Surveillance Assistant, or at the health clinic.*	X	X

Table 2: Balance on Village-Level Covariates

	(1) Control	(2) Treatment	(3) (1) vs. (2), p-value
% of target† group tested for HIV pre-intervention	1.302	0.902	0.152
% of men in target† group tested for HIV pre-intervention	1.149	0.801	0.239
% of target† group tested jointly pre-intervention	0.252	0.126	0.145
% of target† group tested far away pre-intervention	0.548	0.403	0.327
% of target† group tested positive pre-intervention	0.205	0.137	0.223
% tested for HIV pre-intervention	1.213	1.050	0.308
% initiated ART pre-intervention	1.010	0.894	0.540
% already taking ART pre-intervention	2.582	1.884	0.166
Village in TA Chikowi region	0.400	0.424	0.839
Village distance to health centre	4.489	5.111	0.259
Village distance to Zomba Town	17.490	17.037	0.995
% houses brick‡	0.450	0.465	0.566
% houses with livestock‡	0.589	0.615	0.346
% primary school educated‡	0.289	0.305	0.790
% secondary school educated‡	0.103	0.100	0.763
% employed‡	0.207	0.246	0.264
Stratification variables			
Indicators for nearest health facility			
Village population			
Observations	60	59	119

Notes: p-values are for a regression of the covariate on village treatment status, controlling for stratification variables. The pre-intervention period is 2.5 months. The post-intervention period is 3 months for HIV testing, and 10.5 months for ART initiation. †Target population: age 15-49, non-pregnant. The target population was calculated from the Malawian National Statistics Office census at the village level. ‡This measure is based on the selected sample of surveyed meeting attendees; this selected sample should be the same in treatment and control.

Table 3: Survey Measures of Beliefs about ρ: *Does ART reduce HIV transmission?*

	(1) =1 if respondent selected ART from list of HIV prevention strategies	(2) ART reduces HIV transmission: Likert scale (rescaled 0-1)	(3) =1 if respondent thinks partner taking ART is less risky than one who was never tested	(4) Relative reduction in transmission: $\hat{\rho}$	(5) Infographic: $\hat{\rho}$
T	0.609***	0.386***	0.331***	0.467***	0.520***
	(0.034)	(0.021)	(0.040)	(0.025)	(0.030)
Mean of dep var in control	0.20	0.43	0.43	0.09	0.18
Village-level controls	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes
Obs (Individuals)	1037	1037	1037	1037	1037

Notes: Data source: survey to meeting attendees in both treatment and control villages. Dependent variables are individual responses to survey questions. ρ = the relative reduction in HIV transmission associated with antiretroviral drugs. True value: $\rho = 0.96$. (1) The outcome is an indicator for whether the respondent selected ART as one method of preventing the spread of HIV from the following list: faithfulness, abstinence, ART, circumcision, condoms, and mosquito nets. (2) Survey question: *Do you agree or disagree with the following statement? If a person who is HIV positive takes ART it will reduce the chance that he transmits HIV to his or her partner*. Likert scale: 5=strongly agree, 4=agree, 3=neither agree nor disagree, 2=disagree, 1=strongly disagree. The respondent's response was divided by 5 to obtain outcome variable. (3) The respondent used ten bottle caps to show their beliefs about the following probabilities. Absolute transmission probability: *Ten couples are serodiscordant (one HIV positive and the other negative). Suppose they do not use condoms or ART drugs. After one year, how many will have transmitted HIV to their partner?*Transmission probability with ART: *Suppose instead that they are all taking ART. How many will transmit HIV to their partners?*. These two probabilities were used to calculate the relative reduction in risk associated with ART use; the true value is 0.96. (4) The outcome is an indicator for whether the respondent believes that a person on ART drugs is less likely to transmit HIV than a person who has never been tested for HIV. (5) The respondent's selection from Table 6, converted into a measure of ρ by subtracting from 100% and rescaling. The true value is 0.96. T = respondent's village is in treatment group. All regressions are OLS. The post-intervention period is approximately 5 months. All regressions are OLS, at the individual level, with individual-level controls, village-level controls and a constant. Individual-level controls: age, gender, pregnant, married, has regular partner, employed, primary school educated, secondary school educated, has livestock, has a brick house. Village-level controls: Table 2 and community educator fixed effects. Robust standard errors are clustered at the village level and given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Survey Measures of Attitudes and Beliefs about HIV

	Attitudes Towards ART Users		Other Beliefs about HIV		
	(1) =1 if respondent prefers untested partner to partner taking ART	(2) =1 if respondent thinks a person taking ART won't find a new partner	(3) ART leads to a long and healthy life: Likert scale (rescaled 0-1)	(4) Absolute transmission probability (one year)	(5) HIV prevalence in community
T	-0.200***	-0.132***	0.010	0.001	-0.007
	(0.036)	(0.043)	(0.008)	(0.009)	(0.013)
Mean of dep var in control	0.48	0.67	0.95	0.97	0.54
Village-level controls	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes
Obs (Individuals)	1037	1037	1037	1037	1037

Notes: Data source: survey to meeting attendees in both treatment and control villages. (1) Respondent would prefer a partner who has never been tested for HIV to one who is taking ART drugs. (2) Respondent believes that a person taking ART will definitely not find a new sexual partner. (3) The respondent used ten bottle caps to show their beliefs about the one-year probability of HIV transmission for a serodiscordant couple who are not using condoms or taking ART. (4) The respondent used ten bottle caps to show their beliefs about the HIV prevalence in the village. (5) The average of four Likert-scale measures, rescaled to (0,1): current likelihood of having HIV, likelihood of getting HIV, level of worry about having HIV, level of worry about contracting HIV. T = respondent's village is in treatment group. The post-intervention period is approximately 5 months. All regressions are OLS, at the individual level, with individual-level controls, village-level controls and a constant. Individual-level controls: age, gender, pregnant, married, has regular partner, employed, primary school educated, secondary school educated, has livestock, has a brick house. Village-level controls: Table 2 and community educator fixed effects. Robust standard errors are clustered at the village level and given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: The Effect of Information and Beliefs about the Public Benefit of ART on HIV Testing

	% of population tested for HIV		
	(1) OLS	(2) OLS	(3) IV
Average beliefs $\hat{\rho}$ in village			1.224**
			(0.540)
T	0.590*	0.956**	
	(0.323)	(0.446)	
(C)*(#T villages $<$ 1km)		0.364	
		(0.461)	
(T)*(#T villages $<$ 1km)		-0.375	
		(0.607)	
#study villages $<$ 1km		-0.148	
		(0.279)	
Weak ID F-stat (KP)			171
Proportional increase in dep var	37%	60%	77%
Mean of dep var in control	1.6	1.6	1.6
Village-level controls	Yes	Yes	Yes
Obs (Villages)	119	119	119

Notes: Data sources: administrative data from 18 health facilities and survey. Dependent variable: % of village target population tested for HIV post-intervention. (1)-(2): OLS. T = village is in treatment group. C = village is in control group. (3): 2SLS with T = treatment group as instrument for beliefs. ρ = the relative reduction in HIV transmission associated with antiretroviral drugs. True value: $\rho = 0.96$. Community beliefs about ρ are approximated by the village-level average of beliefs, as obtained from the survey using the infographic in Figure 6. Target population: age 15-49, non-pregnant. The target population was calculated from the Malawian National Statistics Office census at the village level. The post-intervention period is 3 months. All regressions are at the village level, with village-level controls and include a constant. Village-level controls: Table 2 and community educator fixed effects. Robust standard errors are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: The Effect of the Information Treatment on HIV Testing Location

	% tested for HIV (IV)			% tested for HIV (OLS)		
	(1) Total	(2) Nearby	(3) Far	(4) Total	(5) Nearby	(6) Far
Average beliefs $\hat{\rho}$ in village	1.224**	0.838	0.386*			
	(0.540)	(0.519)	(0.204)			
Proportion of village believes $0 < \rho < 0.95$				0.518	-0.106	0.624**
				(0.647)	(0.626)	(0.295)
Proportion of village believes $\rho \geq 0.95$				0.815	1.055*	-0.240
				(0.698)	(0.621)	(0.296)
F-stat	171	171	171			
Proportional increase in dep var	77%	75%	80%			
Mean of dep var in control	1.6	1.11	.48	1.6	1.11	.48
Village-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs (Villages)	119	119	119	119	119	119

Notes: Data source: administrative data from 18 health facilities. Dependent variable: % of village target population tested for HIV post-intervention far/nearby. Far clinics defined as >4km further than nearest free clinic. (1)-(3): 2SLS with T = treatment group as instrument for beliefs. (4)-(6): OLS. ρ = the relative reduction in HIV transmission associated with antiretroviral drugs. True value: $\rho = 0.96$. Community beliefs about ρ are approximated by the village-level average of beliefs, as obtained from the survey using the infographic in Figure 6. Omitted reference category: % believe $\rho = 0$. Target population: age 15-49, non-pregnant. The target population was calculated from the Malawian National Statistics Office census at the village level. The post-intervention period is 3 months. All regressions are at the village level, with village-level controls and include a constant. Village-level controls: Table 2 and community educator fixed effects. Robust standard errors are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Own Beliefs vs. Perception of Community Beliefs and Self-Reported HIV Testing

	HIV Test: post-intervention			pre-intervention
	(1)	(2)	(3)	(4)
Respondent believes $\rho \geq 0.95$		-0.074	-0.004	-0.029
		(0.053)	(0.077)	(0.068)
Respondent thinks spouse believes $\rho \geq 0.95$			-0.117	-0.005
			(0.088)	(0.079)
Respondent thinks community believes $\rho \geq 0.95$	0.088*	0.138**	0.162***	-0.052
	(0.049)	(0.055)	(0.062)	(0.066)
Mean of dep var in control	0.35	0.35	0.35	0.23
Village fixed effects	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Obs (Individuals)	1037	1037	831	831

Notes: Data source: survey to meeting attendees in both treatment and control villages. Dependent variable: indicator for whether the respondent reported having an HIV test. ρ = the relative reduction in HIV transmission associated with antiretroviral drugs. True value: $\rho = 0.96$. Beliefs about ρ are obtained from the survey using the infographic in Figure 6. (5)-(8): sample restricted to married respondents. The pre-intervention period is 5 months. The post-intervention period is approximately 5 months. All regressions are OLS, at the individual level, with individual-level controls, village-level controls and a constant. Individual-level controls: age, gender, pregnant, married, has regular partner, employed, primary school educated, secondary school educated, has livestock, has a brick house. Village-level controls: Table 2 and community educator fixed effects. Robust standard errors are clustered at the village level and given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Risk Compensation

	(1) Sex acts	(2) Condoms used	(3) Unprotected sex acts	(4) Unprotected sex acts
T	0.418	-0.103	0.442	0.237
	(0.335)	(0.124)	(0.281)	(0.282)
Self-reported HIV test post-intervention				-0.010
				(0.204)
(T)*(Self-reported HIV test post-intervention)				0.557*
				(0.307)
Mean of dep var in control	1.57	0.37	1.30	1.30
Proportional increase in dep var	27%	-28%	34%	
Village-level controls	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes
Obs (Individuals)	1037	1037	1037	1037

Notes: Data source: survey to meeting attendees in both treatment and control villages. Dependent variables are individual responses to survey questions. (1) Number of sex acts, recalled over past 7 days. (2) Number of condoms used, recalled over past 7 days. (3) Number of unprotected sex acts over past 7 days calculated by subtracting (2) from (1). If this difference is negative, we set the number of unprotected sex acts equal to 0. T = respondent's village is in treatment group. ρ = the relative reduction in HIV transmission associated with antiretroviral drugs. True value: $\rho = 0.96$. Beliefs about ρ are obtained from the survey using the infographic in Figure 6. The post-intervention period is approximately 5 months. All regressions are OLS, at the individual level, with individual-level controls, village-level controls and a constant. Individual-level controls: age, gender, pregnant, married, has regular partner, employed, primary school educated, secondary school educated, has livestock, has a brick house. Village-level controls: Table 2 and community educator fixed effects. Robust standard errors are clustered at the village level and given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9: Pressure to Test for HIV

	(1) % of population joint tested for HIV	(2) =1 if respondent tested for HIV due to pressure	(3) =1 if respondent would prefer joint testing to private testing	(4) WTP for joint testing over private testing
T	0.111	0.005	0.003	-18.207
	(0.108)	(0.008)	(0.016)	(21.215)
Mean of dep var in control	.3	0.01	0.77	111.36
Village-level controls	Yes	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes
Obs (Individuals)		831	831	831
Obs (Villages)	119			

Notes: (1) Data source: administrative data from 18 health facilities in Zomba District. Dependent variable: % of village target population joint tested for HIV post-intervention. Target population: age 15-49, non-pregnant. The target population was calculated from the Malawian National Statistics Office census at the village level. The post-intervention period is 3 months. Regression is OLS at the village level, with village-level controls and a constant. (2)-(4): Data source: survey to meeting attendees in both treatment and control villages. Dependent variables are individual responses to survey questions. Sample restricted to married respondents. The post-intervention period is approximately 5 months. All regressions are OLS, at the individual level, and with individual-level controls, village-level controls and a constant. Individual-level controls: age, gender, pregnant, married, has regular partner, employed, primary school educated, secondary school educated, has livestock, has a brick house. (2) Respondent sought HIV test due to pressure. (3) Respondent would prefer a joint test over private test. Sample restricted to married respondents. (4) Respondent's willingness to pay for door-to-door joint testing campaign vs. private testing (Malawi Kwacha: 400MK = 1USD). (1)-(4): T = respondent's village is in treatment group. Village-level controls: Table 2, population, nearest health center and community educator fixed effects. Robust standard errors are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendices

A Equilibria

In this section, we characterize the pure-strategy Perfect Bayesian Equilibria of the model presented in Section 3. The *signalling equilibrium*, in which a fraction S of the population rejects potential sexual partners who have been tested, was analyzed in Section 3.2. Proposition 1 claims that there is only one other type of equilibrium: a *reverse signalling equilibrium*.

A.1 The Reverse Signalling Equilibrium

For some parameter values, the game described in Section 3 has a class of pure-strategy Perfect Bayesian Equilibria in which a fraction P of the population $\mathcal{B}$ consent only if their match has been tested, and the remaining fraction $1 - P$ consent to all matches. P must be large enough to induce universal testing, because the equilibrium relies on extreme off-equilibrium beliefs about those who do not test for HIV. Intuitively, high-risk individuals have more to gain from testing, so it is not natural to believe that a person who has not been tested is more risky than someone who has. Nonetheless, this equilibrium satisfies the definition of a Perfect Bayesian Equilibrium.

Fix P, and consider the strategy of each $a \in \mathcal{A}$. He will not test far away, as it is costly, and there is no benefit to hiding the decision since all matches consent to those who test. His benefit to testing nearby is access to ART drugs plus the guarantee that his potential sexual partner will consent next period, $\theta v(1+\delta) + \delta P y_a$, and the cost is c. He will therefore test nearby if

$$\theta v(1+\delta) + \delta P y_a > c.$$

High-risk types $\theta = \theta_H$ will always test, because we assumed $\theta_H v(1+\delta) > c$.

The proportion of low-risk types who test is equal to

$$\mathbb{P}\left(\theta_L v(1+\delta) + \delta P y_a > c\right). \tag{17}$$

If this measure is less than one, that is, testing is not universal, then this is not an equilibrium. To see why, consider the beliefs of $b \in \mathcal{B}$. If her match has not been tested, she concludes that his type is $\theta = \theta_L$. But in this case, she will consent, because we assumed that everyone consents to a person of average risk (assumption (6)), and therefore $P = 0$. This implies that for parameters such that

$$\mathbb{P}\left(\theta_L v(1+\delta) + \delta y_a > c\right) < 1$$

there is no reverse signalling equilibrium, because even if $P = 1$, that is, everyone rejects those who have not been tested, universal testing will not be achieved. Some low-risk types are not sufficiently motivated by the prospect of a sexual relationship to bother seeking an HIV test.

Conversely, a reverse signalling equilibrium exists for any $0 < P \leq 1$ such that

$$\mathbb{P}\left(\theta_L v(1+\delta) + \delta P y_a > c\right) = 1.$$

All agents $a \in \mathcal{A}$ best respond to the strategies of agents $\mathcal{B}$ by testing nearby. In this case, beliefs about a match who has not been tested ($\sigma_a = 0$) can take any value, as this action is off the equilibrium path. In order to demonstrate the existence of the equilibrium, we set these beliefs equal to $\hat{\theta}_b(0) = 1$ for all $b \in [0, P]$ and $\hat{\theta}_b(0) = 0$ for all $b \in (P, 1]$. That is, a fraction P of the population believe that a person who has not been tested is HIV positive with probability one. The remaining fraction $1 - P$ believe that a person who has not been tested is HIV negative. In this case, because it is never worth consenting to a match who is infected and untreated, $\mathbb{P}(y_b < s\tau + s_0) = 1$ (assumption (7)), all $b \in [0, P]$ will reject a partner who has not been tested. Meanwhile, because we have assumed it is always worth consenting to an average-risk match (assumption (6)),

$$\mathbb{P}(y_b > 0) \geq \mathbb{P}(y_b > \bar{h}(s\tau + s_0)) = 1,$$

all $b \in (P, 1]$ will consent to any match. In equilibrium, HIV testing is universal.

A.2 Ruling out Other Equilibria

We have described two classes of equilibria. A *signalling equilibrium* is one in which a fraction $S \in [0, 1]$ of the population rejects matches who have been tested for HIV, and otherwise all matches obtain consent [38]. A *reverse signalling equilibrium* is one in which a fraction $P \in (0, 1]$ of the population rejects those who have not been tested, and otherwise all matches obtain consent. We now describe and rule out other potential types of equilibria.

There is no equilibrium in which any agent rejects all matches

In the case of either universal testing or universal abstention from testing, consistent beliefs on the equilibrium path will equal the average HIV prevalence in the population: $\hat{\theta}_b = \bar{h}$, and by assumption (6), b will consent, because

$$y_b > \bar{h}(s\tau + s_0) > \bar{h}(s\tau(1 - \hat{\rho}_b) + s_0).$$

Consider the case in which some agents test and others do not. Because of random matching, all $a \in \mathcal{A}$ face the same expected cost of seeking a test. However, high-risk types have more to gain. This implies adverse selection among those who test, and those who do not test are therefore lower-risk than the average member of the population. So, consistent beliefs about those who do not test are $\hat{\theta}_b(0) < \bar{h}$, and by assumption (6), b will consent to those who do not seek an HIV test.

There is no equilibrium in which different agents adopt opposite strategies towards matches who have been tested

We can now restrict attention to equilibria in which each agent $b \in \mathcal{B}$ adopts a strategy of consenting to some or all matches. The *signalling* and *reverse signalling* equilibria cover the cases in which some agents always consent, and those who do not always consent all adopt the same strategies.

[38] We are including the case $S = 0$, in which all $b \in \mathcal{B}$ consent to any match, under the title *signalling equilibrium*. Within this equilbrium, $S = 0$ describes the case in which the cost of stigma is zero.

The only other potential class of equilibrium is one in which different agents $b \in \mathcal{B}$ adopt opposite strategies towards those who seek an HIV test. That is, $S > 0$ and $P > 0$.

Suppose $S > P > 0$. In this case, all low-risk types will not test, and some high-risk types may not either. Among those who do not test, the average risk is less than that the average risk in the population, so consistent beliefs are $\hat{\theta}_b(0) < \bar{h}$. By assumption (6), all $b \in \mathcal{B}$ will consent to those who do not test, so $P = 0$, which is a contradiction.

Suppose instead that $P > S > 0$. In this case, all high-risk types will test, as the net cost of stigma is negative ($S - P < 0$). We consider two subcases. First, suppose this does not induce universal testing. That is,

$$\mathbb{P}\left(\theta_L v(1+\delta) + \delta(P-S)y_a > c\right) < 1.$$

Then any person who does not test is a low-risk type, so rational beliefs are $\hat{\theta}_b(0) = \theta_L$. By assumption (6), all $b \in \mathcal{B}$ will consent to those who do not test, so $P = 0$, which again forms a contradiction. Instead, suppose that this does induce universal testing, so

$$\mathbb{P}\left(\theta_L v(1+\delta) + \delta(P-S)y_a > c\right) = 1.$$

Now, rational beliefs about those who do seek an HIV test are $\hat{\theta}_b(1) = \bar{h}$, so by assumption (6) everyone will consent. This implies $S = 0$.

B Alternative Definitions of Nearby and Far Away Testing

Throughout the paper, we have defined a *nearby* test as an HIV test that takes place at most four kilometers further than the nearest clinic to a client's home village. In this section we reproduce results on the choice of testing location using different buffer zones around the nearest clinic.

Results with no buffer zone are shown in Table A2. In these tables, we say an HIV test took place nearby only if it took place at the nearest health facility to the village, as measured by GPS coordinates. Using this definition, we see no significant link between beliefs about the public benefit of ART and the number of nearby tests. This definition of *nearby* is unsatisfactory as it does not take into account the fact that for some villages, the nearest clinic as measured in travel time may not be the same as the nearest clinic by GPS. Indeed, 61% of villages do not have a single HIV test taking place at the nearest clinic during the pre- and post-intervention periods combined. In addition, if a clinic is less than a kilometer further than the nearest clinic, we should probably not categorize that clinic visit as far away and claim that the choice is due to stigma. On this margin, other factors such as wait time or quality may play a larger role.

For the above reasons, a good definition of *nearby* should include a buffer zone. Table A3 shows results with a buffer zone of two kilometers, that is, a visit is considered *nearby* if it takes place at most two kilometers further than the nearest clinic. This choice gives results that are quantitatively similar to those presented in the main specifications with a buffer zone of four kilometers (Table 6).

C Initiation of Antiretroviral Drugs

Access to ART drugs is an enormous benefit of HIV testing for those who are infected. In the model, ART is assumed to be the only motivation for testing. It is reasonable to expect an increase in ART uptake to follow the observed increase in HIV testing.

ART initiation data[39] was digitized and provided by Dignitas International. Available data on ART use covers all 13 health facilities in the study area which offer ART drugs, for the period from January, 2013 until February, 2014, two months after the end of the information intervention.

Overall, less than 15% of those who initiate ART do so in the two months following their test result, so even if the increase in HIV testing happened immediately after the intervention, we would be unable to detect the impact on ART initiation within the time frame covered by the data. The short-run effect of the intervention on ART uptake is unsurprisingly undetectable (see Table A4). Most of the new ART patients were tested for HIV before the intervention.

ART initiation will be an important outcome to investigate during the long-run analysis of the experiment. By analyzing demand for ART, we will be able to perform an additional test of the theory, which assumes that treatment is the primary motivation for HIV testing. ART uptake is also important in terms of policy; large public and private benefits are associated with the uptake of treatment, and not with HIV testing per se.

[39] The registers are similar to the HIV testing register in Figure 5 but include additional fields. The HIV test date is indicated.

Table A1: The Effect of Information and Beliefs about the Public Benefit of ART on HIV Testing by Gender

	% of men tested for HIV			% of women tested for HIV		
	(1) OLS	(2) OLS	(3) IV	(4) OLS	(5) OLS	(6) IV
Average beliefs $\hat{\rho}$ in village			1.388**			1.051
			(0.609)			(0.643)
T	0.669*	0.975*		0.507	0.936*	
	(0.363)	(0.505)		(0.383)	(0.516)	
(C)*(#T villages $<$ 1km)		0.169			0.569	
		(0.697)			(0.488)	
(T)*(#T villages $<$ 1km)		-0.679			-0.054	
		(0.656)			(0.659)	
#study villages $<$ 1km		0.170			-0.482	
		(0.398)			(0.334)	
Weak ID F-stat (KP)			171			171
Proportional increase in dep var	50%	72%	103%	27%	50%	56%
Mean of dep var in control	1.35	1.35	1.35	1.86	1.86	1.86
Village-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs (Villages)	119	119	119	119	119	119

Notes: Data sources: administrative data from 18 health facilities and survey. Dependent variable: % of village target population tested for HIV post-intervention. (1)-(2), (4)-(5): OLS. T = village is in treatment group. C = village is in control group. (3),(6): 2SLS with T = treatment group as instrument for beliefs. ρ = the relative reduction in HIV transmission associated with antiretroviral drugs. True value: $\rho = 0.96$. Community beliefs about ρ are approximated by the village-level average of beliefs, as obtained from the survey using the infographic in Figure 6. Target population: age 15-49, non-pregnant. The target population was calculated from the Malawian National Statistics Office census at the village level. The post-intervention period is 3 months. All regressions are at the village level, with village-level controls and include a constant. Village-level controls: Table 2 and community educator fixed effects. Robust standard errors are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2: The Effect of the Information Treatment on HIV Testing Location (no buffer zone)

	% tested for HIV (IV)			% tested for HIV (OLS)		
	(1) Total	(2) Nearby	(3) Far	(4) Total	(5) Nearby	(6) Far
Average beliefs $\hat{\rho}$ in village	1.224**	-0.343	1.567***			
	(0.540)	(0.292)	(0.508)			
Proportion of village believes $0 < \rho < 0.95$				0.518	-0.450	0.968
				(0.647)	(0.419)	(0.603)
Proportion of village believes $\rho \geq 0.95$				0.815	0.086	0.729
				(0.698)	(0.359)	(0.649)
F-stat	171	171	171			
Proportional increase in dep var	77%	-44%	192%			
Mean of dep var in control	1.6	.78	.81	1.6	.78	.81
Village-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs (Villages)	119	119	119	119	119	119

Notes: Data source: administrative data from 18 health facilities. Dependent variable: % of village target population tested for HIV post-intervention far/nearby. Far clinics defined as >0km further than nearest free clinic. (1)-(3): 2SLS with T = treatment group as instrument for beliefs. (4)-(6): OLS. ρ = the relative reduction in HIV transmission associated with antiretroviral drugs. True value: $\rho = 0.96$. Community beliefs about ρ are approximated by the village-level average of beliefs, as obtained from the survey using the infographic in Figure 6. Omitted reference category: % believe $\rho = 0$. Target population: age 15-49, non-pregnant. The target population was calculated from the Malawian National Statistics Office census at the village level. The post-intervention period is 3 months. All regressions are at the village level, with village-level controls and include a constant. Village-level controls: Table 2 and community educator fixed effects. Robust standard errors are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: The Effect of the Information Treatment on HIV Testing Location (2km buffer zone)

	% tested for HIV (IV)			% tested for HIV (OLS)		
	(1) Total	(2) Nearby	(3) Far	(4) Total	(5) Nearby	(6) Far
Average beliefs $\hat{\rho}$ in village	1.224**	0.773	0.451*			
	(0.540)	(0.509)	(0.240)			
Proportion of village believes $0 < \rho < 0.95$				0.518	-0.073	0.591*
				(0.647)	(0.609)	(0.345)
Proportion of village believes $\rho \geq 0.95$				0.815	0.999	-0.185
				(0.698)	(0.604)	(0.384)
F-stat	171	171	171			
Proportional increase in dep var	77%	78%	74%			
Mean of dep var in control	1.6	.99	.61	1.6	.99	.61
Village-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs (Villages)	119	119	119	119	119	119

Notes: Data source: administrative data from 18 health facilities. Dependent variable: % of village target population tested for HIV post-intervention far/nearby. Far clinics defined as >2km further than nearest free clinic. (1)-(3): 2SLS with T = treatment group as instrument for beliefs. (4)-(6): OLS. ρ = the relative reduction in HIV transmission associated with antiretroviral drugs. True value: $\rho = 0.96$. Community beliefs about ρ are approximated by the village-level average of beliefs, as obtained from the survey using the infographic in Figure 6. Omitted reference category: % believe $\rho = 0$. Target population: age 15-49, non-pregnant. The target population was calculated from the Malawian National Statistics Office census at the village level. The post-intervention period is 3 months. All regressions are at the village level, with village-level controls and include a constant. Village-level controls: Table 2 and community educator fixed effects. Robust standard errors are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: The Effect of the Information Treatment on ART Initiation

	% initiated ART	
	(1)	(2)
T	-0.108	-0.034
	(0.070)	(0.085)
(C)*(#T villages $<$ 1km)		0.143
		(0.130)
(T)*(#T villages $<$ 1km)		-0.065
		(0.121)
#study villages $<$ 1km		0.061
		(0.090)
Village-level controls	Yes	Yes
Mean of dep var in control	.33	.33
Proportional increase in dep var	-33%	-10%
Obs (Villages)	119	119

Notes: Data source: administrative data from 13 health facilities providing ART in Zomba District. Dependent variable: % of village target population initiated ART post-intervention. T = village is in treatment group. C = village is in control group. Target population: age 15-49, non-pregnant. The target population was calculated from the Malawian National Statistics Office census at the village level. The post-intervention period is approximately 2 months. All regressions are at the village level, with village-level controls and include a constant. Village-level controls: Table 2 and community educator fixed effects. Robust standard errors are given in the parentheses with stars indicating *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.