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"How Beliefs abut HIV Status Affect Risky Behaviors: Evidence from Malawi", Sixth Version

by

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How Beliefs about HIV Status Affect Risky Behaviors: Evidence from Malawi [1]

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Abstract

This paper examines how beliefs about own HIV status affect decisions to engage in risky sexual behavior (as measured by extramarital affairs) and analyzes the potential for interventions that influence beliefs, such as HIV testing and informational campaigns, to reduce transmission rates. The empirical analysis is based on a panel survey of married males for years 2006 and 2008 from the Malawi Diffusion and Ideational Change Project (MDICP). In the data, beliefs about HIV status vary significantly geographically and over time, in part because of newly available testing opportunities and because of cultural differences. We estimate the effect of beliefs on risky behavior using Arellano and Carrasco's (2003) semiparametric panel data estimator, which accommodates unobserved heterogeneity and belief endogeneity. Results show that changes in the belief of being HIV positive induce changes in risky behavior. Downward revisions in beliefs increase risky behavior and upward revisions decrease it. We modify Arellano and Carrasco's (2003) estimator to allow for underreporting of extramarital affairs and find the estimates to be robust. Using the estimates and a prototypical epidemiological model of disease transmission, we show that better informing people about their HIV status on net reduces the population HIV transmission rate.

1 Introduction

The AIDS epidemic imposes a large toll on populations in Sub-Saharan Africa through high rates of mortality and morbidity. About two thirds of people infected with HIV worldwide reside in the region, and several countries have adult prevalence rates above 20% (UNAIDS, 2008). Heterosexual intercourse is known to be the main mode of transmission in Africa, but relatively little is known about how the prevalence of the disease has influenced sexual behaviors. Understanding the behavioral link is important to developing effective policy interventions, such as well targeted HIV testing programs and informational campaigns, that aim to modify sexual behavior and ultimately lower transmission rates.

This paper studies how beliefs about own HIV status affect decisions to engage in risky sexual behavior, as measured by extramarital affairs, using data on married men in rural Malawi. From a theoretical perspective, the effect of beliefs on HIV status is ambiguous. People who assign a high likelihood to being HIV-positive may take more risks as they are already infected. On the other hand, the fear of infecting others (via altruism, social norms or sanctions) might deter transmissive behaviors. Similarly, people who assign a low likelihood to own infection may have a greater incentive to take precautions to avoid infection, but may also take more risks because of less concern about infecting others. Reducing risky behavior of HIV-positive persons generally reduces transmission rates. However, for HIV negative persons, the relationship between risky behavior and transmission rates is less clear. As noted by Kremer (1994) and Kremer and Morcom (1998), it is at least theoretically possible that increasing risky behavior of HIV-negative persons improves the pool of potential sex partners and lowers transmission rates.

To prevent the further spread of HIV, government and nongovernmental organizations have implemented a variety of public health interventions, including increasing access to testing and treatment services, informational campaigns, and condom distribution programs. It is hoped that informing individuals about their own HIV status and about methods of avoiding transmission will reduce transmission rates, although the quantitative evidence on behavioral response is scarce. A study by Thornton (2008), described in more detail in section two, finds that individuals who picked up HIV test results in Malawi modestly increased condom purchases but did not alter sexual behavior over a two month timeframe. Another study by Oster (2007) finds little evidence that sexual behavior responds to local prevalence rates using Demographic and Health Surveys data for a subset of African countries. Her findings accord with reported findings in Philipson and Posner (1995) for the United States.[1]

Two ingredients are necessary for a program intervention to effectively reduce HIV transmission. First, the intervention must alter individuals' beliefs, about own HIV status, the HIV prevalence in their environment and/or about the technology for transmission, and, second, these belief changes must induce changes in behavior. In the context of rural Malawi, the link between HIV testing and beliefs has been tenuous. Tables 1a and 1b tabulate 2004 and 2006 test results given to males in our MDICP analysis sample against their reported likelihood of being HIV positive, elicited in 2006 and 2008, respectively.One would expect those receiving a positive test result to revise their belief of being positive upward (perhaps to 100%) and those receiving a negative test outcome to revise their belief downward. However, as seen in Tables 1a and 1b, the majority of individuals who tested HIV positive in 2004 and 2006 report a zero probability of being positive two years later. There are also some individuals who test negative in 2004 and 2006 but assign a high probability to being positive two years later. The evidence reported in this paper and in Delavande and Kohler (2009b) indicate that belief revisions are not closely aligned with test results, although the reasons why are not fully understood. [2]

[1]However, Oster finds some evidence that behavior responds to disease prevalence among the subgroups of richer individuals and those with higher life expectancies.

[2]There is anecdotal evidence that some MDICP respondents were skeptical about the quality of the tests administered in 2004, which was likely exacerbated by the initial delay of one or more months in providing the results. There are a few other reasons why beliefs may not accord with the test results. First, HIV positive individuals are typically asymptomatic for many years and may

This paper analyzes how program interventions affect beliefs about own HIV status and how changes in beliefs affect behavior, providing evidence on two key mechanisms determining effectiveness of program interventions. The effect of HIV testing programs on beliefs has been previously examined, but the belief-behavior relationship has so far not been studied. Our analysis is based on panel data from the Malawi Diffusion and Ideational Change Project (MDICP), which contains unique measures of beliefs about own HIV status (described below) that vary substantially, geographically and over time, in part because of testing opportunities and cultural differences. This paper also examines to what extent better informing people about their HIV status, whether positive or negative, can decrease the population HIV transmission rate. As previously noted, the theoretical effect of HIV testing programs on transmission rates is ambiguous and it is at least theoretically possible that HIV testing could increase risk taking among some segments of the population.

The MDICP sample covers rural populations from three different regions in Malawi, where the overall HIV prevalence rate is approximately 7%. Our analysis focuses on on men, who are much more likely than women to report having extramarital affairs. The MDICP survey is unusual in that it includes measures of individuals' reported beliefs about their own and their spouse's HIV status as well as information on whether they engaged in risky behaviors. Concurrent sexual partnerships are fairly common in the data and there is substantial variation in beliefs over time. Our empirical analysis in based on data from the 2006 and 2008 survey waves, which collected the detailed measures on beliefs (described below).

Of key concern in any analysis of the relationship between sexual behavior and beliefs is the potential for endogeneity, arising from a possible dependence of

therefore not believe that they carry the disease, particularly in the earlier years of data collection when HIV testing was less prevalent. The reported belief of being positive in 2006 despite a negative test result in 2004 could also reflect interim risky behavior. Although in theory part of this may be ascribed to "prosecutor's fallacy", in actuality the testing protocol required a second test whenever a positive result was obtained and a third test whenever the first and second tests were discordant. This induced a very low probability of a false positive.

current beliefs on past behavior. In this case, both cross-section and within estimators (in linear models) are biased. For this reason, we use a semiparametric panel data estimator developed by Arellano and Carrasco (2003), which accommodates potential feedback of lagged behavior on current beliefs (a violation of strict exogeneity in a panel data setting) and also allows for unobservable heterogeneity. We also develop and implement a modified version of Arellano-Carrasco's (2003) estimator that allows for potential under-reporting of risky behaviors.

We use the estimated dynamic panel data model to perform counterfactual experiments that simulate behavior in an environment where individuals are better informed about their HIV status, either because HIV testing results are more credible, because more people get tested, or because of educational campaigns that better inform people about prevalence rates and risks of transmitting the disease. Using a prototypical Susceptible-Infective (SI) epidemiological model, of the kind exposited in Hyman et al. (2001), we simulate the effects of changing beliefs on the population transmission rate. The simulation results show that making the population better informed about HIV status on net leads to a reduction in the transmission rate. Interestingly, our empirical findings provide support for the theoretical mechanism described in Kremer (1994) and Kremer and Morcom (1998). Although HIV-negative individuals increase their number of sexual partners, their increased risk exposure is offset by an overall reduction in the probability of a random partner being HIV-positive. That is, the sexual partner pool improves by a reduction in transmissive behavior by HIV-positive individuals and by increased engagement of HIV-negative individuals.

The paper develops as follows. Section 2 summarizes related empirical literature on the relationship between beliefs about HIV, testing, and risky behaviors. Section 3 presents a two period model for exploring the determinants of risky behavior, which illustrates that the net effect of changing beliefs on risk-taking is theoretically ambiguous and provides a justification for the variables included in our empirical analysis. Section 4 presents the empirical strategy for estimating the causal effect of beliefs about own HIV status on risk-taking behaviors in a way that takes into account the predeterminedness of beliefs and unobserved heterogeneity. Section 5 describes the empirical results, which indicate that beliefs about own HIV status affect the propensity to engage in extra-marital affairs. Notably, individuals who revise their beliefs upward curtail risky behavior whereas individuals who revise beliefs downward increase risky behavior. Section 5 also considers the potential problem of measurement error in reported extra-marital affairs, where the measurement error is potentially nonclassical and non-mean-zero (in our case, underreporting of affairs). We develop a modified version of the Arellano and Carrasco (2003) estimator and examine robustness of the estimates to allowing for measurement error. Lastly, Section 6 presents simulations of how changing beliefs affects the population HIV transmission rate and section 7 concludes.

2 Related Literature

The notion that individuals change their behavior in response to communicable diseases is generally well accepted and there is a theoretical literature that explores the general equilibrium implications of this type of behavioral response. An early example is Kremer (1996), who presents a model where behavior is allowed to vary with disease prevalence.[3] In his model, the probability of infection is a function of the number of partners, the transmission rate and the disease prevalence. Kremer shows that those with relatively few partners respond to higher prevalence levels by reducing their sexual activity, because higher prevalence makes the marginal partner more "expensive." Interestingly, Kremer's model leads to a fatalistic behavior for those with a sufficiently high initial number of partners.[4]

[3]Earlier models of disease transmission typically do not allow prevalence to affect behavior, which is often encoded by a contact parameter that is assumed to be exogenous.

[4]For those individuals, an increase in prevalence may reduce the probability of infection from the marginal partner (even though the risk of contagion from the first few partners increases), leading to an increase in the optimal number of partners.

Philipson (2000) surveys alternative theoretical frameworks of how behavior responds to disease prevalence. These include models of assortative matching (HIV-positives matching with HIV-positives and HIV-negatives with HIV negatives), which are shown to have a dampening effect on the spread of the disease (Dow and Philipson, 1996); models that relate prevalence rates and the demand for vaccination; models for the optimal timing of public health interventions in the presence of elastic behavior; and, of particular relevance to our study, models for studying the implications of information acquisition (testing) for asymptomatic diseases such as HIV. In another theoretical study, Mechoulan (2004) examines how testing could lead to increased sexual behavior of selfish individuals that turn out to be HIV-positive. He shows that without a sufficient fraction of altruistic individuals, testing can increase disease incidence.[5]

A recent empirical study examining the causal impact of receiving HIV test results on risky behavior is Thornton (2008), who uses a subset of the 2004 round of the MDICP data that participated in the 2004 HIV testing.[6] At the time of administering the tests, the MDICP project team carried out a social experiment that randomized incentives to pick up the test results.[7] Thornton (2008) analyzes data generated from the experiment along with data from a two month follow-up survey that she administered to study how picking up the test results affects condom purchases and risky sexual behavior. Using the randomized incentive as an instrument for picking up the results, she finds that learning the result modestly increased condom purchases but did not alter sexual behavior. It is possible that the two month period that elapsed

[5]This phenomenon is sometimes referred in this literature as the Philipson-Posner conjecture (see Philipson and Posner (1993)).

[6]In 2006 and 2008, the MDICP team again offered individuals the opportunity to get tested, this time with an improved testing procedure (rapid response blood tests rather than the oral swabs used in 2004) that eliminated the time delay between testing and test results. Another difference is that all individuals tested received their results. In 2006, almost everyone (93.6%) elected to get tested and receive the results, as further discussed in section 5 below.

[7]The incentive amounts ranged from no incentives to incentives of 300 Kwachas, which is approximately a few days wage of a laborer.

between the incentives experiment and the follow-up survey may have been too short to observe substantial changes in sexual behavior. Another consideration is that if there were heterogeneity in response to randomized incentives, then the IV estimate that Thornton (2008) reports has a local average treatment effect (LATE) interpretation. The estimate would then correspond to the causal effect of picking up test results for the subset of the sample who would have gotten tested but would not have picked up the results otherwise without the incentive.[8] Thornton also documents that individuals who tested negative tended to revise their subjective beliefs about being HIV positive downward and that those who tested positive did not significantly revise their beliefs.

Our study differs from Thornton's in a number of dimensions, including (i) a focus on identifying the causal belief-behavior relationship for the larger sample of MDICP male respondents that is not conditional on having gotten tested in 2004, picking up test results, or having responded to incentives, (ii) the inclusion of data gathered in the 2006 and 2008 rounds that contain more detailed measures on beliefs than the 2004 round, (iii) the use of a different modeling framework and estimation methodology, and the (iv) the simulation of effects of changing beliefs on the population HIV transmission rate.

Another related paper is Boozer and Philipson (2000), which analyzes the relationship between HIV status, testing and risky behavior using data from the San Francisco Home Health Study. Our identification strategy for estimating the effects of changes in beliefs on behavior is similar to theirs in that we also make use of belief information gathered in two different time periods, where individuals had the opportunity to get tested in the intervening period. In the SFHHS survey all individuals who were unaware of their status (around 70%) were tested immediately after the first wave of interviews and learned their status. Boozer and Philipson use those who already knew their status, the remaining 30%, as a control group and

[8] See Imbens and Angrist (1994) and Heckman and Urzua (2009) for discussions of the LATE interpretation of IV treatment effect estimates.

find that belief revisions towards a lower probability of a positive status increase sexual activity. That is, individuals who considered themselves highly likely to be infected and discover they are not increase the number of partners and those who believe themselves to be relatively unlikely to be infected and discover otherwise reduce their number of partners.[9] Our empirical findings are similar to those of Boozer and Philipson's, although the population we study, which consists of married males in Subsaharan Africa, could potentially have different behavioral responses from those of the predominantly homosexual San Francisco population that Boozer and Philipson analyze. Our estimation approach also differs from the difference-in-difference strategy used by Boozer and Philipson.

Other related papers in the epidemiology literature find little or mixed evidence of behavioral response to HIV testing (see, for example, Higgins et al. (1991), Ickovics et al. (1994), Wenger et al. (1991) and Wenger et al. (1992)). An exception is Weinhardt et al. (1999), who note that "the heterogeneity of effect sizes ... suggest[*s*] that participants' responses to HIV-CT [(HIV counseling and testing)] are multiply determined and complex. However, with only a few exceptions, HIV-CT studies have not been informed by theories of behavior change,"p.1402). In a recent paper, Wilson (2008) estimates the effects of antiretroviral therapy (ART) provision on the decision to get tested using data from Zambia. He finds that most of the effect of ART is concentrated on individuals attaching low prior probabilities of HIV infection. Wilson interprets these findings as evidence of a non-random selection mechanism for the allocation of ART in Zambia.

Delavande and Kohler (2007) use the MDICP dataset to study the accuracy of individuals' reported expectations of being HIV positive. They provide detailed documentation of the method used in the MDICP surveys to elicit the probabilistic expectations that we use in our empirical analysis. They find that the probability assessments on HIV infection gathered in the 2006 round of the survey are remarkably

[9] The authors caution that the latter result nevertheless relies on the behavior of only five individuals in their sample.

well calibrated to local community prevalence rates.[10] Using verbal assessments of likelihood (no, low, medium or high likelihood), Anglewicz and Kohler (2009) point out that individuals in the 2004 wave, however, seem to over-estimate the risk of being infected. 10% of husbands and 18% of wives estimate a medium or high likelihood of current infection while actual prevalence in 2004 was lower: 6% for men and 9% for women. In reconciling the evidence from the 2004 survey with the well-calibrated probabilistic assessments in the later wave, Delavande and Kohler note problems of interpersonal comparability of the coarse belief categories and that, even if anchoring techniques are used (such as vignettes), complications would still remain in translating the coarse categories into more precise assessments. For recent surveys on the use of expectations data in development, see Attanasio (2009) and Delavande, Giné and McKenzie (2011). In this paper, we make use of both the coarse belief categories and the finer measurements, as further described in section four.

3 A Model of Risky Behavior Choices

As noted in the introduction, theoretical models in the literature are usually ambiguous as to the sign of the effect of changes in beliefs about one's own HIV status on risk-taking behaviors. On the one hand, downward revisions in beliefs, as may arise from learning a negative test result, should increase the expected length of life and thereby increase the benefits from risk avoidance. On the other hand, learning a test result might also be informative about the technology for HIV transmission. In our sample, individuals tend to overestimate the probability of becoming infected with HIV from one sexual encounter with an infected person and learning that they are negative despite a past life of risky behavior could increase their willingness to take

[10] For the 2004 wave of the MDICP data, the likelihood of own infection is reported only in broader categories (whether an individual thinks it highly likely, likely, unlikely or not at all possible that he or she is HIV positive).

risks.[11] Altruism also plays an important role in HIV transmission, as people who are altruistic towards others would be expected to curtail risky behaviors after an upward revision in beliefs. Other factors that may reduce transmissive behavior are social or legal sanctions imposed on HIV positive individuals.

To explore the relationship between beliefs on own HIV status and sexual behavior, we next present a simple two period model. It assumes that individuals choose their level of risky behavior in the first period and update their beliefs on own HIV status in a Bayesian way. Let $\tilde{Y}_0 \in \mathbb{R}$ denote an individual's chosen level of risky sexual behavior (risky behavior represents activities such as having unprotected sex or engaging in extramarital affairs). The probability of infection is an increasing function of risky behavior and we denote it by $g(\tilde{Y}_0) \in [0, 1]$.[12] To be sure, other factors such as the prevalence rate in the community modulate the link between sexual behavior and the likelihood of infection and could be incorporated into the function $g(\cdot)$. We abstract from such influences here for ease of presentation, but the empirical analysis includes conditioning variables intended to hold constant local prevalence rates. Let B_0 denote the individual's prior belief about his own HIV status. Individuals potentially obtain satisfaction from risky sexual behaviors in the first period. We also allow one's perception on HIV status to directly affect utility: $U(\tilde{Y}_0, B_0)$. How beliefs affect the marginal utility of risky behavior can be regarded as a measure of altruism or the degree to which social sanctions on transmissive behavior by HIV-positive individuals affect the utility of sexual intensity. In the second period, individuals receive a "lump-sum "utility flow equal to $\overline{U}$, but this is reduced by $\lambda\overline{U}$ if

[11] The probability is thought to be about 0.1% (see Gray *et al* (2001)).This channel is not in the model we present here. Individuals in the survey do not seem to revise their beliefs about the probability of infection from one sexual encounter substantially from 2004 to 2006. This channel is nevertheless allowed to operate in our empirical analysis.

[12] The probability of infection may be the perceived probability of infection. In a multiperiod context, this belief may also be updated through time but we take it as predetermined when the risky behavior decision is taken. In the data, the average reported belief about infection from a single sexual encounter is not statistically different across the two waves.

an individual contracts HIV in the first period. λ can be interpreted as the mortality rate for an HIV-positive individual. The discount factor is β. Beliefs are updated in a Bayesian way. The belief of being HIV positive in the second period (B_1) depend on previous period beliefs (B_0) plus the probability of having contracted the disease last period:

$$B_1 = B_0 + (1 - B_0)g(\tilde{Y}_0) \tag{1}$$

The individual's problem is then

$$\max_{\tilde{Y}_0} \quad \{U(\tilde{Y}_0, B_0) + \beta(1 - \lambda B_1)\overline{U}\}$$

or, equivalently,

$$\max_{\tilde{Y}_0} \quad \{U(\tilde{Y}_0, B_0) + \beta(1 - \lambda B_0 - \lambda(1 - B_0)g(\tilde{Y}_0))\overline{U}\}.$$

The first order condition yields:

$$U_1(\tilde{Y}_0, B_0) - \beta\lambda(1 - B_0)g'(\tilde{Y}_0)\overline{U} = 0 \tag{2}$$

where $U_1(\cdot,\cdot)$ denotes the derivative of $U(\cdot,\cdot)$ with respect to its first argument. This condition implicitly defines $\tilde{Y}_0$ as a function of the belief variable B_0. Furthermore,

$$\frac{d\tilde{Y}_0}{dB_0} = -\frac{U_{12}(\tilde{Y}_0, B_0) + \beta\lambda g'(\tilde{Y}_0)\overline{U}}{U_{11}(\tilde{Y}_0, B_0) - \beta\lambda(1 - B_0)g''(\tilde{Y}_0)\overline{U}}$$

which, given a concave (in $\tilde{Y}_0$) utility function, is positive if $U_{12}(\tilde{Y}_0, B_0) + \beta\lambda g'(\tilde{Y}_0)\overline{U} > 0$ and $g''(\tilde{Y}_0) > 0$. The latter is reasonable if the probability of infection $g(\tilde{Y}_0)$ is low (take for instance $g(\cdot)$ to be a logistic or normal cdf and consider the low rates of transmission per sexual act). If an individual's marginal utility from (risky) sexual behavior is insensitive to his or her perception on HIV status (that is, not altruistic or amenable to social sanctions if HIV-positive), $U_{12}(\tilde{Y}_0, B_0) + \beta\lambda g'(\tilde{Y}_0)\overline{U} = \beta\lambda g'(\tilde{Y}_0)\overline{U}$ which is positive. As long as one's marginal utility does not decrease much (relative to $\beta\lambda\overline{U}$), higher prior beliefs are associated with riskier behaviors. A person who is not altruistic (i.e. $U_{12}(\cdot) = 0$) would be expected to increase risky behavior upon learning a positive test result and to decrease risky behavior upon learning a negative test result. Intuitively, if one is already infected, sexual behavior poses no further risks while still providing utility.

In a multi-period context, beliefs affect current behavior and respond to past behavior through updating. Prior belief B_0 is based at least in part on previous choices regarding $\tilde{Y}_0$. As described in the next section, dependence of beliefs on previous behavior poses challenges in estimation, because it leads to a potential lack of strict exogeneity in a panel data model. Another potential source of endogeneity arises from any unobservable traits that affect both beliefs B_0 and behavior $\tilde{Y}_0$.

4 Empirical Framework

As noted in the introduction, we aim to assess whether and to what extent changes in beliefs about own HIV status affect risk-taking behaviors. The behavioral model developed in the previous section implies a decision rule for risky behavior that depends on beliefs about own HIV status (see equation (2)). Our empirical specification of the decision rule introduces additional covariates to allow for time-varying determinants of behavior, such as age. It also controls for time invariant determinants by incorporating correlated random effects. Time invariant determinants may include religiosity, education, local prevalence rates (which were roughly constant over the 2006-2008 time period we study), and individual or region specific costs of risky sexual behavior.[13]

We next describe the nonlinear panel data estimation strategy used to control for endogeneity of beliefs and for (correlated) unobservable heterogeneity. Let $\tilde{Y}_{it}$ denote the *actual* measure of risk taking behavior of individual i in period t, which in our data is an indicator for whether the individual engaged in extra marital affairs over the previous 12 months.[14] A possible alternative measure of risky behavior is

[13]As described below in section 5.2, our sample covers three geographic regions that have cultural and economic differences, including differences in religiosity, polygamous practices and wealth.

[14]We implicitly assumed that this variable captures the sexual behavior at the time of the survey. As discussed below, misreporting would tend to bias estimates download. We address this potential

condom use, but it is not available in the 2008 survey. Previous work nevertheless finds that condom use (though not condom purchase) is relatively inelastic in Malawi. Only 7% of those individuals tested in 2004, for example, reported using condoms.[15] Denote by Y_{it} the *reported* measure of risk taking behavior of individual i in period t. Below, we allow for misreporting in the variable $\tilde{Y}_{it}$ so $\tilde{Y}_{it}$ and Y_{it} may differ with positive probability. B_{it} denotes an individuals' beliefs at time t about their own HIV status, measured on a 0 to 1 scale, with 0 being no likelihood of being positive and 1 being HIV positive with certainty.

The empirical specification can be written as:

$$\tilde{Y}_{it} = \mathbf{1}[\alpha + \beta B_{it} + \gamma X_{it} + u_{it} \geq 0]. \tag{3}$$

Following Arellano and Carrasco (2003), we impose the following fixed effect error decomposition:

$$u_{it} = f_i + v_{it}$$

where v_{it} is an idiosyncratic shock and f_i is a time invariant effect that is potentially correlated with the included covariates.

In the previously described behavioral model, current beliefs about HIV status depend on prior beliefs and last period behaviors through updating (equation (1)):

$$B_{it} - B_{it-1} = (1 - B_{it-1})g(\tilde{Y}_{it-1})$$

where $\tilde{Y}_{it-1}$ is a function of f_i and v_{it-1} (equation (3)). This updating implies a potential correlation between B_{it} and $\tilde{Y}_{it-1}$, and therefore between B_{it} , v_{it-1} and f_i, which amounts to a violation of the strict exogeneity assumption that is often invoked in panel data settings. An advantage of the Arellano and Carrasco (2003) estimator is

problem of misreporting in our robustness analysis.

[15]Other measures of risky behavior could in principle be used, but would require different methodologies. For example, considering the number of extra-marital affairs instead of an indicator function for any affair would require a fixed effects model for *censored count data*. To our knowledge, existing methodologies for such frameworks require strict exogeneity, an inappropriate assumption for beliefs in this context.

that it only requires weak exogeneity and not strict exogeneity. Following Arellano and Carrasco (2003), we make a distributional assumption on the composite error term:

$$u_{it}|W_i^t \sim \Lambda\left(\mathbb{E}(f_i|W_i^t)\right)$$

where $\Lambda(\cdot)$ is the standard logistic distribution and $\mathbb{E}(f_i|W_i^t)$ is its mean.[16] No restrictions are imposed on the shape of the conditional mean function. W_i^t is a vector that assembles *previous and current* values of B_{it} and X_{it} and *past* values of Y_{it}. In our case, W_i^t will have a discrete support as our covariates all have discrete supports. Then,

$$\underbrace{\mathbb{P}(Y_{it}=1|W_i^t)}_{\equiv h_t(W_i^t)} = \Lambda\left(\alpha + \beta B_{it} + \gamma X_{it} + \mathbb{E}(f_i|W_i^t)\right).$$

where $h_t(W_i^t)$ can be easily estimated in the data as our covariates have discrete support. Applying an inverse transformation function, the above expression is equivalent to

$$\Lambda^{-1}\left(h_t(W_i^t)\right) - \alpha - \beta B_{it} - \gamma X_{it} = \mathbb{E}(f_i|W_i^t)$$

which, first-differenced, yields:

$$\Lambda^{-1}\left(h_t(W_i^t)\right) - \Lambda^{-1}\left(h_{t-1}(W_i^{t-1})\right) - \beta\Delta B_{it-1} - \gamma\Delta X_{it-1} = \epsilon_{it}$$

where

$$\epsilon_{it} = \mathbb{E}(f_i|W_i^t) - \mathbb{E}(f_i|W_i^{t-1}).$$

By the Law of Iterated Expectations,

$$\mathbb{E}(\epsilon_{it}|W_i^{t-1}) = 0.$$

[16]The logistic distribution is not essential and can be replaced by any other known distribution (we adopt a logistic distribution as in Arellano and Carrasco's simulations and empirical application). A normal distribution delivers essentially the same results as those presented here. With enough time periods, the framework also accommodates a time varying scale parameter as long as a normalization is imposed for one of the periods. Because we only use two time periods the model is homoskedastic. The distribution can be made totally nonparametric if there are continuous covariates as noted in the article (see their footnote 7).

This conditional moment restriction can be used to construct a moment-based estimator for the parameters of interest. In the case of covariates with finite support, the conditional moments above are equivalent to the following unconditional moments (see Chamberlain, (1987)):

$$\mathbb{E}[Z_{it}\epsilon_{it}] = 0$$

where Z_{it} is a vector of dummy variables, each corresponding to a cell for W_i^{t-1}. Arellano and Carrasco suggested constructing a GMM estimator based on the empirical moments:

$$\frac{1}{N} \sum_{i=1}^{N} Z_{it}\Big[\Lambda^{-1}\left(\widehat{h_t(W_i^t)}\right) - \Lambda^{-1}\left(\widehat{h_{t-1}(W_i^{t-1})}\right) - \beta\Delta B_{it} - \gamma\Delta X_{it}\Big]$$

for $t = 2, \ldots, T$. The estimator is asymptotically normal and its asymptotic variance, taking into account the estimation of h, can be obtained by conventional methods for multistage estimation problems (see for example Newey and McFadden (1994)). As in linear panel data models, because the conditional moments identify the parameters of interest, there is no initial conditions problem. (see Hsiao (2003) (pp.85-86)). [17]

For our weighting matrix we use $1/N \sum_{i=1}^{N} Z_{it}Z_{it}'$, which is a diagonal matrix giving more weight to the cells that have more individuals.[18] To handle the cases in which $\hat{h}$ is 0 or 1, we adopt a slight modification of Cox's (1970) small sample adjustment to the logit transformation:

$$F^{-1}(p) = \log\left(\frac{p + (100n)^{-1}}{1 - p + (100n)^{-1}}\right).$$

The conventional small-sample adjustment uses $(2n)^{-1}$ instead of $(100n)^{-1}$ above and is employed by Arellano and Carrasco in their paper. The former is chosen so that the asymptotic bias is $o(n^{-1})$ (see Cox (1970), pp.33-4), but is inadequate when some cells are relatively small. In our case, a change in cell size from 2006 to 2008 without

[17]See the discussion in Arellano and Carrasco (2003) (p.128) though.

[18]Arellano and Carrasco suggest using the inverse of this matrix, which would put more weight on the smaller cells. We conjecture that the inverse weighting matrix was a type-setting error and that the intended weighting is the usual GMM weighting that gives more weight to cells with lower variance.

a change in the proportion of reported extra-marital affairs would generate variation in $F^{-1}(\widehat{h_t(W_i^t)}) - F^{-1}(h_t\widehat{(W_i^{t-1}}))$ for smaller cells. To mitigate the influence of these variations on our estimator, we replace $(2n)^{-1}$ by $(100n)^{-1}$. With this modification, the asymptotic bias is $O(n^{-1})$ (though not $o(n^{-1})$).

As mentioned previously and further described below, we have access to both detailed quantitative (in categories 0-10 reflecting a probability of 0-1) and cruder categorical data (measured in categories no likelihood, low, medium or high likelihood)on individuals beliefs about their own HIV infection. We used both of these belief measures to form moments for the GMM estimation. We avoid splitting the cells further and add the following empirical moments to our estimator:

$$\frac{1}{N}\sum_{i=1}^{N} l_{it-1}\left[\Lambda^{-1}\left(\widehat{h_t(W_i^t)}\right) - \Lambda^{-1}\left(h_{t-1}\widehat{(W_i^{t-1}})\right) - \beta\Delta B_{it} - \gamma\Delta X_{it}\right].$$

The vector l_{it-1} contains dummies for the categorical belief variables in 2006 (no likelihood, low, medium or high likelihood). Finally, as in Arellano and Carrasco (2003), we assume that $E(f_i) = 0$ and obtain two additional moments (one for each year), which allow us to estimate the constant term α.

To facilitate the interpretation of the estimated parameters, we also present the effects of belief changes from B' to B'' on behavior:

$$\begin{aligned}\Delta_t(B', B'') &\equiv \mathbb{P}(\alpha + \beta B'' + \gamma X_{it} + u_{it} \geq 0) - \mathbb{P}(\alpha + \beta B' + \gamma X_{it} + u_{it} \geq 0)\\ &= \mathbb{E}\left[\Lambda(\alpha + \beta B'' + \gamma X_{it} + \mathbb{E}(f_i|W_i^t))\right] - \mathbb{E}\left[\Lambda(\alpha + \beta B' + \gamma X_{it} + \mathbb{E}(f_i|W_i^t))\right].\end{aligned}$$

These are computed as in Arellano and Carrasco (2003), replacing population expectations and parameters by sample averages and estimates. In particular,

$$\mathbb{E}\widehat{(f_i|W_i^t)} = \Lambda^{-1}(\widehat{h_t(W_i^t)}) - \hat{\alpha} - \hat{\beta}B'' - \hat{\gamma}X_{it}.$$

As in that paper, we note that this marginal effect measures the *direct* effect of beliefs on behavior, abstracting from any additional *indirect* effects that arise via its influence on $\mathbb{E}(f_i|W_i^t)$ (similar considerations are also discussed in Chamberlain (1984) (pp.1272-4)). In our case, the individual effect absorbs elements such as tribal affiliation, cultural and other time-invariant socio-demographic categories that (although correlated) are unlikely to respond to a change in beliefs.

Finally, we also consider the possibility of misreporting in the data in our robustness analysis. In particular, we allow for the possibility that some fraction of individuals who engage in risky behavior report that they do not and explore how varying degrees of misreporting affect our estimates. To this end, we adapt ideas developed by Hausman, Abrevaya and Scott-Morton (1998) to the Arellano-Carrasco (2003) framework to allow for misreporting of $\tilde{Y}_{it}$. We assume that individuals always report truthfully when they do not engage in extra-marital affairs and with a probability α_1 lie about having an extra-marital affair. Thus,

$$\mathbb{P}(Y_{it} = 1|\tilde{Y}_{it} = 0) = 0 \qquad \mathbb{P}(Y_{it} = 0|\tilde{Y}_{it} = 1) = \alpha_1.$$

With misreporting, the conditional probability of reporting risky behavior takes the form:

$$\mathbb{P}(Y_{it} = 1|W_i^t) = (1-\alpha_1)\Lambda\left(\alpha + \beta B_{it} + \gamma X_{it} + \mathbb{E}(f_i|W_i^t)\right)$$

which, by the same steps as in the previous derivation leads to the following first-difference expression:

$$\Lambda^{-1}\left(\frac{h_t(W_i^t)}{1-\alpha_1}\right) - \Lambda^{-1}\left(\frac{h_{t-1}(W_i^{t-1})}{1-\alpha_1}\right) - \beta\Delta B_{it} - \gamma\Delta X_{it} = \epsilon_{it}$$

where

$$\epsilon_{it} = \mathbb{E}(f_i|W_i^t) - \mathbb{E}(f_i|W_i^{t-1}).$$

Using the Law of Iterated Expectations, we again obtain estimation moments for the parameters of interest.[19] In our robustness analysis, we report estimates for the coefficients of interest with varying degrees of misclassification.

[19]One important problem in implementation is that $\frac{\widehat{h_t(W_i^t)}}{1-\alpha_1}$ may be above one in small samples. To guard against this small-sample problem we use $\min\left\{1, \frac{\widehat{h_t(W_i^t)}}{1-\alpha_1}\right\}$.

5 Data and Empirical Results

5.1 Background on the MDICP Dataset

The MDICP data were gathered by the Malawi Research Group.[20] The Malawian population is composed of more than 20 different ethnic groups with different customs, languages and religious practices. Malawi's three different administrative regions (North, Center and South) are significantly different in several aspects that are potentially relevant to our analysis. The MDICP gathers information from five rounds of a longitudinal survey (1998, 2001, 2004, 2006, 2008) that together contain extensive information on sexual behavior and socio-economic background on more than 2,500 men and women. We use the later two rounds of the survey that include detailed information on beliefs about own HIV status. We were not able to include previous years as they do not contain numerical beliefs. Also, we only analyze data on married men, who are much more likely to report extramarital affairs than women. The MDICP survey contains information on sexual relations, risk assessments, marriage and partnership histories, household rosters and transfers as well as income and other measures of wealth. The data also include information on village-level variables as well as regional market prices and weather related variables. Recent studies on the quality of this dataset have validated it as a reasonably representative sample of rural Malawi (see, for instance, Anglewicz et al. (2006)). Appendix A provides further information about the dataset.

The MDICP dataset measured beliefs about own HIV status using two different measurement instruments. In the 2004, 2006 and 2008 surveys, individuals were asked to choose one of four categories: no likelihood, low likelihood, medium

[20]The data collection was funded by the National Institute of Child Health and Human Development (NICHD), grants R01-HD044228-01, R01-HD050142, R01-HD37276 and R01-HD/MH-41713-0. The MDICP has also been funded by the Rockefeller Foundation, grant RF-99009#199. Susan Watkins was the PI for the last three grants. Hans-Peter Kohler was the PI for the first two. Detailed information on this survey can be obtained at `http://www.malawi.pop.upenn.edu/`.

likelihood and high likelihood. In the 2006 and 2008 surveys, the categorical measure was supplemented with a probability measure. One might be concerned that low education populations would have difficulty in reporting a probability measure. For this reason, the MDICP survey used a novel bean counting approach to elicit probabilities where these were measured on a 0-10 bean scale where more beans for a particular event correspond to a higher probability assessment for that event (see Appendix for details).[21] Delavande and Kohler (2009a) study both the categorical and more continuous measure and demonstrate that the continuous measure is well calibrated to regional HIV rates.

5.2 Descriptive Analysis

Table 2 shows the mean and standard deviations for the variables used in our analysis. The total sample size is 485 married men for whom data were collected in both the 2006 and 2008 rounds of the survey.[22] The average age of the sample is 46 in the 2008 round. The sample resides in three regions of Malawi: Balaka (South), Rumphi (North) and Mchinji (Center). Although the original sample was designed to include about equal numbers of respondents from each of the three districts, the share of men from Balaka drops in later waves both in the full MDICP data and our analysis subsample. In our subsample, 36% of the men are from Rumphi, about 33% from Mchinji, and about 31% from Balaka. The explanation for the higher attrition in Balaka is higher rates of migration typical to the area.

The different characteristics of the three administrative regions of Malawi are evident in our sample. Across the three regions, the predominant religion is Chris-

[21] Individuals were first given examples of how to represent the likelihood of common events using 0-10 beans, such as the chance of having rain the next day, and then asked to report the likelihood of being HIV positive using the bean measure.

[22] Because our analysis relates to extramarital affairs, we restrict the sample to men who were married in both rounds. We include men who may have been married to different women in the two years. In the sample there were 72 single men in 2006 and 57 in 2008. Of those, 4 were single in both waves.

tianity (73.6%) with the remainder Muslim (23.0%) and a small percentage reporting other religions or no religion. Most of the overall sample has only some primary schooling (71.5%), with 10.5% never attending school and 16.5% having some secondary schooling. About 15.9% of the sample are polygamous; the polygamy rate for 2006 in Rumphi is higher than that in Balaka and Mchinji, with about 24% in Rumphi, 19% in Balaka and 11% in Mchinji. Muslims represent about two thirds of the Balaka sub-sample but are less than 2% in the other two sites. Balaka has the highest percentage of respondents who never attended school and the lowest percentage of respondent with some secondary schooling. Rumphi has the lowest rate for respondents without any schooling, and the highest rate of respondents with some secondary schooling. Owning a metal roof (as opposed to thatch, which is most commonly used), is an indicator of wealth in rural Malawi. Rumphi has the highest percentage of respondents residing in a dwelling with a metal roof, at 27%, while Balaka and Mchinji both have 17%. In addition, individuals nationwide are mainly affiliated with three tribes and speak a variety of local languages. Finally, individuals in our sample have on average between five and six children and 35% report that they desire more children.

Table 2 also reports the average own beliefs about being HIV positive in 2006 and 2008 and the average reported beliefs about the spouse. In 2006, 82.0% report that they have close to zero chance of being HIV positive. In 2008, the percentage in this category decreases to 54.0%. In 2006, 4.6% of individuals believed that they had a medium or high chance of being HIV positive, but this percentage increases to 10.1% in 2006. Figure 1 depicts the change in the belief distribution over time, which is measured on a scale of 0 to 10, with 0 being no likelihood and 10 being perfect certainty. As seen in the figure, the belief distribution is shifting towards higher beliefs between 2006 and 2008.

As seen in Table 2, in 2006 the average number of beans representing the belief that one's spouse is HIV positive is 0.62, in comparison to 1.38 in 2008 (on a scale of 0 to 10 beans). Even though individuals were not informed about their spouse's test result for confidentiality reasons (if their spouse got tested), about 96% of the wives report voluntarily sharing their test results with their husbands in our sample.[23]

In Table 3, we examine how the continuous belief measure (the bean measure) varies within the coarser subjective belief categories. For 2006, people who report their infection probability as being in the low category choose a number of beans corresponding to a 17.2% average probability. The bean average for the medium category corresponds to a 44.8% probability and the bean average for the high category to a 76.7% probability.

With regard to risky behaviors, 4.3% reported having an extramarital affair in the last 12 months in 2006 in comparison with 10.5% in 2008. Table 4 examines the temporal pattern in extramarital affairs. 86.2% of the sample does not report having an affair in either 2006 or 2008, 3.3% reports having an affair in 2006 but not in 2008, and 9.5% report having an affair in 2008 but not in 2006. About 1.0% report engaging in extramarital relations in both 2006 and 2008. As previously noted, HIV testing was offered in 2004, 2006 and 2008. 93.6% of the sample was tested in 2006, in comparison with 83% tested in 2004 and 82.9% in 2008. The majority (68.9%) got tested in all three years.[24] Eight individuals (1.6%) got tested only in 2004 (of which only five picked up the results in 2004), 4.7% took the test only in 2006 and less than 1% took it only in 2008. Among those tested in 2006, 3.8% tested positive, and in 2008, 5.0% tested positive. It is interesting to note that 8 individuals tested positive in 2004 and picked up their results at that time, but nonetheless decided to get tested again in 2006 and 2008.

Table 5 explores the potential determinants of decisions about extramarital affairs using cross-sectional analysis applied to 2006 data. A probit regression of an indicator for extra-marital affairs on beliefs and other covariates shows that beliefs are a statistically significant predictor of affairs. People who assign a higher probability of themselves being HIV positive are more likely to report engaging in extramari-

[23]Categorical belief variables about spouse's HIV status were not collected in 2008.

[24]The individuals who got repeatedly tested had all picked up their test results in 2004.

tal affairs. In the cross-section, the reported probability of being HIV positive also decreases with age. These correlations do not have a causal interpretation though, because they do not account for unobserved heterogeneity or for the potential endogeneity of beliefs. Because the individual effect f_i positively affects the likelihood that $y_{i,t-1}$ is positive and this in turn positively affects beliefs by increasing the probability of infection since the last period, beliefs and the residual are positively associated, introducing an expected upward bias in the estimation. Indeed, our estimates reported below show that when the endogeneity is taken into account the relation between behavior and beliefs is reversed. It should be noted that a simple within estimator would also have biases even in a linear model (see, for instance, Bond (2002)). The methodology we use, that was suggested by Arellano and Carrasco (2003), allows us to handle the endogeneity properly.

5.3 Estimated Causal Effects

We next report estimates based on model (3) using the Arellano and Carrasco (2003) methodology and generalized method of moments, as described in section 4. The estimation requires that we construct cells based on W_i^{t-1}, which includes lagged belief measures and age. In principle, cells could be constructed separately for all possible values of the discrete covariates, but in practice this procedure would lead to many small cells that are imprecisely estimated. For this reason, we aggregate some of the cell categories and, following the recommendation in Arellano and Carrasco, exclude in estimation very small cells (consisting of one or two individuals). Specifically, we define the cells by first dividing individuals into age quintiles bins and also according to aggregated belief categories. We consider the following two belief aggregations: 0,1,2-10 beans and 0,1,2-4,5-10 beans. Although the cells are defined based on aggregate categories, we use the disaggregated age and belief variables in forming the difference $\Lambda^{-1}\left(h_t(W_i^t)\right) - \Lambda^{-1}\left(h_{t-1}(W_i^{t-1})\right) - \beta\Delta B_{it-1} - \gamma\Delta X_{it-1}$.

Tables 6a and 6b show the cell sizes for the two alternative bean aggregation schemes. In the first scheme, we discard five cells and 6 individuals and use in estimation 23 cells and 479 individuals. For the second scheme, we discard seven cells and nine individuals and use in estimation 27 cells and 476 observations. Once we append the four moments from the categorical belief variables and the two moments for the levels (see section 4), we obtain a total of 29 and 33 moments, respectively. The weighting matrix is a diagonal matrix with $\frac{1}{N}\sum_{i=1}^{N} Z_i Z_i'$ in the upper diagonal block and an identity in the lower diagonal block.

Tables 7a-b report the estimated coefficients obtained for two different specifications (each table reports estimates for a different specification). All the specifications include linear terms in beliefs and age. The second specification also includes quadratic terms in age and beliefs. The estimates indicate that the impact of beliefs is statistically significant and that people reporting higher beliefs of being HIV positive are less likely to engage in extramarital affairs.[25]

For ease of interpretation, Tables 8a-b report the marginal effects of changes in beliefs (indicated in the table) on the probability of engaging in extramarital affairs. The estimates imply that revising beliefs upward decreases risk-taking. For example, an individual who changes beliefs from 4 beans to 10 beans would decrease the probability of having an extramarital affair by 2.4 percentage points in 2006 according to the linear specification and the 0,1,2-10 bean aggregation (see Table 8a). The estimates also indicate that individuals who revise their beliefs downward increase risk-taking. For example, someone who decreases their belief from 2 beans to zero increases the probability of an extra-marital affair by 8.5 percentage points in 2006 (again for the linear specification and 0,1,2-10 aggregation of beans).[26]

[25] A joint test of the statistical significance of the belief variables shows that they are statistically significant at a 5% level for the second specification.

[26] If we estimated a linear probability specification without instrumenting, we get similar results. However, using TSLS and using lagged beliefs as instruments, the coefficient estimates on beliefs are generally insignificantly different from zero. With a binary outcome variable, however, the linear probability model would not properly difference away the individual effect except in the special case of a uniform error distribution on u_{it},

Many HIV testing programs seek to reduce risk-taking behaviors by providing individuals with better information about their own HIV status, but our results show that the behavioral response with regard to risk-taking will depend on whether their status is positive or negative. The strategy of disseminating HIV tests can be successful only insofar as the test results affect individual beliefs about their own status and these changes in beliefs in turn bring about appropriate changes in behavior. As noted in Thornton (2008), "[t]esting is only beneficial to the extent that it provides new information that can be used for updating behavior. (...) Previous studies examining the effects of HIV testing on sexual behavior have not only been inconclusive, but also suffer from selection bias in terms of which individuals chose to learn their results." (p.1845) One implicit assumption of many studies of the impact of HIV testing is that those who test positive or negative revise their beliefs accordingly. In the larger MDICP sample and also in the subsample that participated in Thornton's (2008) experiment, some individuals seem not to believe the test results. Given the link between beliefs and behavior indicated by our analysis, a likely explanation for Thornton's (2008) results regarding lack of changes in sexual activity is that the tested individuals did not sufficiently update their beliefs. Using the more recently collected data on numerical beliefs, we are able to determine that changes in beliefs do affect behavior. However, HIV testing does not necessarily affect beliefs, particularly when there are significant lags between taking the test and receiving the results, as occurred in the 2004 testing administration. Because we use data on beliefs for all respondents, regardless of whether tested, we bypass the self-selection issue of who chooses to participate in testing.

5.4 Robustness

5.4.1 Misreporting

Because many of the surveyed topics concern sensitive issues, an obvious concern is the potential for misreporting. In this subsection, we explore the robustness of the previously estimated specification to allowing for measurement error in extra-marital affairs. To investigate the potential problem of misreporting, the MDICP team carried a small set of qualitative interviews with men that had reported not having extramarital affairs during the 1998 round of the survey, when slightly over 9% of the interviews admitted to having had extra-marital affairs. These follow-up interviews were very casual (no questionnaire or clipboard, typically no tape recorder) and were later transcribed by the principal investigators in the field.[27] Many of those who had originally denied infidelity, admitted otherwise in these informal interviews. Even though the reference period in the 1998 survey was longer and the men may tend to exaggerate in these casual conversations, this provides some evidence of some underreporting by the respondents during the more formal interviews.

To assess the impact of underreporting on our estimation results, we re-estimated the model for different assumed levels of misreporting, using the adapted version of Arellano and Carrasco's estimator that was described in section 4. The results are shown in Tables 9a and 9b for the alternative specifications and bean aggregation levels and for varying levels of misreporting. The first row displays the estimates presented in our main analysis (i.e. without misreporting) and subsequent rows display the estimates for higher levels of misreporting (α_1). We find that higher levels of misreporting lead to higher coefficient magnitudes.

To gain intuition for why misreporting leads to an attenuation bias in the estimated coefficients, consider for simplicity a linear model. Under linearity, $\mathbb{E}(Y|X) = ((1-\alpha_1)\beta)'X$ and the estimated parameters are attenuated by $\alpha_1 > 0$. In our non-linear case, $\mathbb{E}(\tilde{Y}|X) = F(X,\theta)$ and misreporting leads to $\mathbb{E}(Y|X) = (1-\alpha_1)F(X,\beta)$ (also see Hausman et al. (1998)).

In a nonlinear model, the misreporting parameter α_1 could in principle be identified, which it cannot be in a linear model. In practice, though, our estimation procedure could not recover an estimate of α_1, possibly because the shape of $F(X,\theta)$

[27] The transcripts are available online at `http://www.malawi.pop.upenn.edu/Level%203/Malawi/level3_malawi_qualmobilemen.htm`)

is close to linear over the relevant range. Nevertheless, from our estimation with alternative values of α_1, we learn that the magnitude of the bias in the estimated coefficients is not large for wide range of potential misreporting values, indicating that our estimated impact of beliefs on risky behavior is fairly robust to misreporting (see Tables 9a and 9b).[28]

5.4.2 Additional Regressors

In Table 10, we further investigate how our results are affected by the inclusion of additional covariates, namely reports on past behavior and perceived local HIV prevalence.

In the theoretical model of section 3, past behavior only influenced current behavior through the updating of beliefs. However, it could conceivably have an independent effect on current behavior, for example, by affecting search costs for finding extramarital partners. In Tables 10a-b we display coefficient estimates obtained when lagged behavior is included as an additional covariate. The inclusion of this variable has little effect on our estimated coefficients on beliefs.

Our previous estimations also assumed that perceived risk of HIV infection are held constant by inclusion of individual random effects. Actual local prevalence rates were fairly stable from 2006 to 2008, but it is possible that individuals' beliefs about prevalence varied over time. For these reasons, we estimated an additional specification that includes past behavior and perceived local prevalence as additional covariates. The variable used to measure perceived local prevalence rate is the respondents' answer to the following question: "If we took a group of 10 people from this area-just normal people who you found working in the fields or in homes-how many of them do you think would now have HIV/AIDS?" We notice that the average perceived prevalence is substantially above the prevalence in our sample, raising some concerns about this variable. In addition, the perceived infection risk is also affected

[28]In principle, the misreporting could also depend on covariates, although this would complicate the estimation procedure.

by the perceived likelihood of contamination from a sexual encounter. The inclusion of this variable complicates our estimation procedure some, because the cells used in the estimation now need to be constructed using these additional covariates. We base the new cells on quartiles of perceived prevalence, but the average number of individuals per cell still drops from 21 to less than 10 once prevalence is included. The estimated effect of beliefs on risky behavior is nevertheless still negative once prevalence is added and the coefficient is highly significant in the linear specification.

6 Counterfactual Simulations of Changing Beliefs on HIV Transmission Rate

In this section, we use our estimates to evaluate the effects of a hypothetical policy intervention that makes individuals better informed about their own HIV status, either because their beliefs are more responsive to testing results and/or because more individuals get tested. Traditional epidemiological models characterize the spread of diseases by differential equation systems representing the flow of individuals between susceptibility and infectivity. For a review of SI (Susceptible-Infective) or SIR (Susceptible-Infective-Recovered) models, see Anderson and May (1991) or Hethcote (2000). We present a simplified version of these kinds of models in Appendix B that we use to simulate the effect of increasing the responsiveness of beliefs about own HIV status to HIV test results on the population HIV transmission rate.

In these models, a crucial ingredient is the rate at which individuals are infected by the disease. For HIV, Hyman et al. (2001) assume that the (annual) transmission rate λ depends on the number of partners (r), the proportion of infected partners (I) and the probability of infection by an infected partner ($\beta(r)$). The probability of infection depends on the average number of contacts with a given partner ($c(r)$), which can vary with the number of partners. We follow Hyman et al. (2001) and assume that the relationship between the number of contacts per partner and the number of partners is:

$$c(r) = 104r^{-0.5} + 1.$$

With one partner per year, the above equation implies 105 encounters in a year, roughly two per week. As the number of partners increases, the number of encounters per partner asymptotes to one. Using information on frequency of sexual contacts reported in 2006, we confirmed that the number of contacts per partner does in fact decay in the data as the number of partners increases.

We also follow Hyman et al.(2001) in assuming that the probability of infection from an infected partner is

$$\beta(r) = 1 - (1 - \xi)^{c(r)}$$

where ξ is the probability of infection from a single contact with an HIV-positive individual which we assume to be 0.1% (see footnote 12).

Lastly, we adapt the model by assuming that infected and uninfected individuals may have a different numbers of sexual partners (r_I and r_U, respectively). In this SI model, the probability that an uninfected individual becomes infected (the transmission rate) during a given year is

$$\lambda = r_U \beta(r_U) \frac{r_I I}{r_I I + r_U(1 - I)}$$

This probability is equal to the product of the number partners an uninfected person has (r_U), the probability of infection per partner (given the number of partners) ($\beta(r_U)$) and the probability that a random partner is infected (given by the ratio above). We use as baseline the probabilities of extra-marital affairs and the average number of sexual partners derived from the 2006 wave of the survey.[29] For that year, the probability of having an extramarital affair was 7.23% for HIV-negative individuals and 7.69% for HIV-positive individuals. Conditional on having an extra marital

[29] The sample used for estimating the number of partners and the probability of extramarital affairs is all married men who are interviewed and tested for HIV in 2006, which is 841 men, a somewhat larger sample than that used in estimating the panel data model. 39 men are HIV positive and the remainder negative. A limitation of the analysis is that it is based on married males, so we are implicitly assuming that the average behavior of married males extends to their sexual partners.

affair, the (average) reported number of partners was 3.22 for HIV-negative people and 3.33 for HIV-positive people. Conditional on not having an extra marital affair, the (average) number of partners (wives) was 1.3 for HIV-negative individuals and 1.26 for HIV-positive individuals (recall that some men in our sample have multiple wives). The number of partners for an uninfected person (r_U) is then taken to be

$$r_U = \mathbb{E}(\#\text{partners}|\text{affair}, U) \times \mathbb{P}(\text{affair}|U) + \mathbb{E}(\#\text{partners}|\text{no affair}, U) \times (1 - \mathbb{P}(\text{affair}|U))$$

and r_I is defined analogously. Under these assumptions, an uninfected individual has 87.7 contacts per partner on average in a given year. We take the proportion of infected individuals to be 8%, roughly the prevalence rate in our sample and in line with other reported numbers for rural Malawi. The probability of infection for an infected individual can be calculated as $\lambda = 0.955\%$.

We perform two counterfactual experiments. First we assume that all individuals get tested and fully adjust their beliefs upon receiving the results. As previously noted, many individuals currently do not revise their beliefs in a way that reflects their test results.[30] We explore how increasing the responsiveness of beliefs to test results would alter the population HIV transmission rate. Under our simulation, those that receive positive results (8% of the sample) revise their beliefs to "10 beans" whereas those that receive a negative result revise their beliefs to "zero beans". We assume a baseline belief corresponding to "two beans". According to Table 8, the marginal effect of these changes is to decrease the probability of an extra-marital affair for the positive individuals in 2006 by 5.1 percentage points and to increase the probability of an extra-marital affair for the negative individuals in 2006 by 8.5 percentage points. The new transmission rate is then $\lambda = 0.853\%$, which is lower than the initial rate of 0.953%.[31]

With full belief revision, the pool of sexual partners improves, diminishing the likelihood of contact with an infected individual. This happens for two reasons.

[30] See, for example, the evidence provide by Delavande and Kohler (2009b).

[31] If α is not zero and there is misreporting in extra-marital affairs, our estimates are lower bounds and the reduction would be even higher.

First, HIV-positives decrease their number of partners, which reduces the probability of having an encounter with a positive person. Second, HIV-negatives increase their number of partners, which improves the pool of potential contacts but also increases the population at risk for becoming infected. Our results provide some support for these mechanisms, discussed in Kremer (1994) and Kremer and Morcom (1998) in the context of a traditional SIR model with heterogeneity in the number of partners as we have here.

As an alternative, consider a policy that concentrates resources on increasing the responsiveness of HIV-positive individuals only, for example, an HIV testing program that is targeted narrowly at persons who are likely to be positive. Our simulations find that such a policy also obtains a reduction in the transmission rate, but not by as much. That is, if we assume that upon testing HIV-positive individuals increase their belief from "two beans" to "ten beans" but HIV-negative individuals maintain their beliefs, the probability of infection is 0.89%. The pool of sexual partners improves as infected individuals reduce their sexual activity, but not as much as when uninfected also increase their sexual activity. The results are summarized on Table 11.

These results are mainly illustrative of how the estimates from the dynamic panel data model can be used to study the effects of policy interventions. A full assessment of the effectiveness of alternative policies would require consideration of costs as well as the benefits in terms of life-years saved and possibly also of the distributional effects.

7 Conclusions

This paper examines the relationship between beliefs about HIV status and risky sexual behavior in the form of extra-marital affairs using a unique panel dataset from Malawi that includes detailed longitudinal measures of subjective beliefs and behaviors. The individuals in our sample were given the opportunity to get tested for

HIV in 2004, 2006 and 2008 and most availed themselves of the testing opportunities, often multiple times. Our analysis sample exhibits substantial revisions in beliefs both geographically and over the time period covered by the data collection. The changes in reported beliefs do not always accord with test results.

Simple cross-sectional correlations suggest that individuals who believe they have a higher likelihood of being HIV positive engage in riskier behaviors. These correlations do not have a causal interpretation, though, because of unobserved heterogeneity and because behavior is likely to be correlated over time, with beliefs being updated to reflect additional risk posed by lagged behaviors. In a panel data setting, this correlation between current beliefs and lagged behaviors leads to a violation of strict exogeneity. To control for endogeneity of the belief variable as well as for individual unobserved heterogeneity, we use an approach developed by Arellano and Carrasco (2003). Our estimates indicate that downward revisions in beliefs lead to a higher propensity to engage in extramarital affairs and that upward revisions in beliefs lead to a lower propensity. Because beliefs affect behavior, the lack of impact of testing on frequency of sexual activity found by Thornton (2008), for example, may be ascribed to incomplete revision of beliefs by tested individuals. Our results point to the need for further research into why individuals who get tested may not revise their beliefs and into whether the availability of new, rapid response tests has made beliefs more responsive to test results. We also modified the Arellano and Carrasco (2003) estimator to incorporate reporting error, along the lines of Hausman, Abbrevaya and Scott-Morton (1998). Our empirical estimates are fairly robust to measurement error in a wide range (0-60%).

Our simulation of the effects of better informing individuals about their own HIV status, using a prototypical epidemiological model of disease transmission calibrated to the Malawi data, showed that an intervention along these lines would reduce the population HIV transmission rate, despite some increase in risk-taking behavior in the HIV-negative population. This suggests that policy interventions that make testing more credible and improve the availability and take-up of testing are likely to reduce the HIV transmission rate. Such policies might include informational campaigns, more frequent or more easily available testing, improved testing methods and providing cash incentives to get tested or to pick up test results.

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Appendix A

Malawi. Malawi is a landlocked country in Southern Africa with a population of about 13.5 million. In the UNDP's 2007 Human Development Index, combining data collected in 2005 on health, education and standards of living, Malawi was ranked 164 out of 177 countries, with a rank of 1 being the most developed. Malawi's GDP per capita was ranked 174, at US$667, making Malawi a poor country even by Sub-Saharan standards. Malawi is one of the countries worst hit by the HIV/AIDS epidemic with an estimated prevalence rate of 12% in the overall population and 10.8% in the rural areas (Demographic Health Survey, 2004).

The Northern region, where Rumphi is located, is primarily patrilineal with patrilocal residence. Almost all of its population is Christian, predominantly protestant. This region, which has the smallest population, is also the least densely populated and least developed in terms of roads and other infrastructure. However, it has the highest rates of literacy and educational attainment. The most commonly spoken language in the region is chiTumbuka, the language of the Tumbuka tribe, which is the biggest tribe in the area. The northern region has the highest rates of polygamy, but the lowest HIV prevalence for men age 15-19, estimated to be around 5.4%. The HIV prevalence for similar age women is higher than that of the central region (Department of Health Services). The Central region, where Mchinji is, is predominantly Christian as well, with a mix of Catholics and protestants. The largest group in the region is the Chewa tribe, which is the largest ethnic group in all of Malawi. Its language, chiChewa, is the most spoken in the region as well as in the whole country. (English is nevertheless the official language.) The Chewa tribe historically used a matrilineal lineage system with matrilocal residence. Today, the lineage system is less rigid, with mixed matrilocal and patrilocal residence (Reniers, 2003). The Central Region is home to Lilongwe, the capital city which in recent years has become the biggest city in the country. Finally, the Southern region, where Balaka is, predominantly uses matrilineal lineage systems with matrilocal residence. It has a large Muslim population, concentrated mainly in the north-east part of the region around the southern rim of Lake Malawi. The Southern Region has the largest population and is the most densely populated. It has the lowest rates of literacy and percentage of people ever attending school.

MDICP Sampling. The MDICP collected data from three out of Malawi's 28 districts, one in each of the three administrative regions. The districts are Rumphi in the north, Mchinji in the center, and Balaka in the south. The original sample, drawn in 1998, consisted of 1,541 ever married women aged 15-49 and 1,065 of their husbands. The consequent waves targeted the same respondents and added any new spouses. In 2004, 769 adolescents and young adults, aged 14-28 were added to the sample, out of which 411 were never married. The original sample wasn't designed to be representative of rural Malawi, but is similar in many socioeconomic characteristics to the rural samples in the Malawi Demographic and Health Surveys, which are representative (Watkins et al. 2003, Anglewicz et al. 2006).

Belief Data. The MDICP elicited the beliefs of the respondents about own infection status using a novel bean counting approach. Each respondent was given a cup, a plate, and 10 beans. The interviewer then read the following text:

> I will ask you several questions about the chance or likelihood that certain events are going to happen. There are 10 beans in the cup. I would like you to choose some beans out of these 10 beans and put them in the plate to express what you think the likelihood or chance is of a specific event happening. One bean represents one chance out of 10. If you do not put any beans in the plate, it means you are sure that the event will NOT happen. As you add beans, it means that you think the likelihood that the event happens increases. For example, if you put one or two beans, it means you think the event is not likely to happen but it is still possible.

> If you pick 5 beans, it means that it is just as likely it happens as it does not happen (fifty-fifty). If you pick 6 beans, it means the event is slightly more likely to happen than not to happen. If you put 10 beans in the plate, it means you are sure the event will happen. There is not right or wrong answer, I just want to know what you think.
>
> Let me give you an example. Imagine that we are playing Bawo. Say, when asked about the chance that you will win, you put 7 beans in the plate. This means that you believe you would win 7 out of 10 games on average if we play for a long time.

After this introduction, each respondent was asked to choose the number of beans that reflect the likelihood of common events such as going to the market in the following two weeks or a death of a newborn in the community. For these questions, if the respondents chose 0 or 10 beans they were prompted: "Are you sure this event will almost surely (not) happen?" The respondents were not prompted for the following questions.

The variable used in this analysis to represent beliefs about own infection is the respondents' chosen number of beans when they are asked to: "Pick the number of beans that reflect how likely you think it is that you are infected with HIV/AIDS now."

Definition of risky behavior variables. Our measurements for risky behavior were taken from the "Sexual Behaviors" section of the survey. In the section, the respondents were asked their number of sexual partners and to name up to three of their partners in the prior 12 months, including spouses, and a series of questions about the partnerships were asked. We consider a man to have had an extramarital affair if he reported any relationship with a woman who is not his wife. For the rare cases in which a man has three or more wives, the extramarital affairs variable equals one if the number of reported sexual partners in the prior 12 months exceeds the number of wives.

Appendix B

This appendix presents a simplified version of the SI model in Hyman et al. (2001). As in that article, we describe here a version where the number of partners for infected and uninfected persons is the same, $r_U = r_I$ though the model can be easily extended to accommodate heterogeneity and we allow for heterogeneity in our simulations reported in section 6. Kremer(1994) and Kremer and Morcom (1998) considers a similar model with heterogeneity in the number of partners but no variation in sexual contacts as the number of sexual partners increases.

The system starts with a proportion U_0 of uninfected (or susceptible) individuals. At a rate λ (which depends on the proportion of infected individuals) individuals move from uninfected to infected. Uninfected individuals are also born and die (of causes other than HIV) at a rate μ. Infection increases the death rate by ν. The dynamic system is

$$\begin{aligned}\frac{dU}{dt} &= \mu(U_0 - U) - \lambda U \\ \frac{dI}{dt} &= \lambda U - (\mu + \nu)I\end{aligned}$$

It is possible to add a third group of people who leave the set of individuals at risk (i.e. are no longer sexually active) but are still alive. In this model, it can be shown that

$$\lambda = r\beta I$$

where β is defined as in section 6. If $r_U = r_I$, this formula corresponds to the one given in section 6. Hyman et al. (2001) study versions of this model with heterogeneous infectivity. Like Kremer (1994) and Kremer and Morcom (1998) we focus on heterogeneity in the number of partners. For further examples of SI and SIR models, see Anderson and May (1991) or Hethcote (2000).

Table 1a
HIV test results in 2004 and reported beliefs
of own probability of infection in 2006[(a)]

	HIV test outcome in 2004	
Reported belief category in 2006	Negative	Positive
zero probability	401	8
low probability	77	6
medium probability	12	2
high probability	15	4

(a) Sample of males who got tested in 2004 and picked up the test result.

Table 1b
HIV test results in 2006 and reported beliefs
of own probability of infection in 2008[(a)]

	HIV test outcome in 2006	
Reported belief category in 2008	Negative	Positive
zero probability	232	6
low probability	144	5
medium probability	31	2
high probability	8	2

(a) Sample of males who got tested in 2006 and picked up the test result.

Table 2
Descriptive Statistics for males
Interviewed in 2006 and 2008 MDICP samples

Variable	Mean	Std. Deviation
Age (in 2008)	46.126	11.511
Muslim	0.230	0.421
Christian	0.736	0.442
No school	0.105	0.307
Primary education only	0.715	0.452
Secondary education	0.165	0.372
Higher education	0.124	0.111
Reside in Balaka	0.311	0.463
Reside in Rumphi	0.356	0.479
Reside in Mchinji	0.332	0.471
Percent polygamous (2006)	0.159	0.366
Percent polygamous (2008)	0.180	0.385
Number of children (2006)	5.325	2.712
Number of children (in 2008)	5.571	2.656
Number of children not reported (in 2006)	0.041	0.199
Number of children not reported (in 2008)	0.000	0.000
Metal roof 2006	0.159	0.366
Metal roof 2008	0.206	0.405
Believe that own prob of HIV is zero in 2006	0.822	0.383
Believe that own prob of HIV is low in 2006	0.133	0.340
Believe that own prob of HIV is medium in 2006	0.019	0.136
Believe that own prob of HIV is high in 2006	0.027	0.162
Believe that own prob of HIV is zero in 2008	0.548	0.498
Believe that own prob of HIV is low in 2008	0.351	0.478
Believe that own prob of HIV is medium in 2008	0.076	0.266
Believe that own prob of HIV is high in 2008	0.025	0.155
Subjective probability assigned to being HIV positive (number of beans) (in 2006)	0.664	1.657
Subjective probability assigned to being HIV positive (number of beans) (in 2008)	1.276	1.693
Subjective probability assigned to spouse being HIV positive (2006)	0.620	1.495
Subjective probability assigned to spouse being HIV positive (2008)	1.383	1.890
Report extramarital affair in last 12 months in 2006	0.043	0.204
Report extramarital affair in last 12 months in 2008	0.105	0.307
Took HIV test in 2006	0.936	0.245
Took HIV test in 2008	0.829	0.377
Number of observations	485	--

Table 3
Average subjective belief of being HIV positive, reported by Bean measure, within coarse belief categories

	Average belief measure (number of beans)
Believe that HIV probability is zero in 2006	0.18
Believe that HIV probability is low in 2006	1.72
Believe that probability is medium in 2006	4.48
Believe that probability is high in 2006	7.67

Table 4
Probabilities of engaging in extramarital affairs in 2006 and 2008 [a)]
(number of observations in parentheses)

	No extramarital affair in last 12 months in 2008	Extramarital affair in last 12 months in 2008
No extramarital affair in last 12 months in 2006	86.2% (418)	9.5% (46)
Extramarital affair in last 12 months in 2006	3.3% (16)	1.0% (5)

(a) Sample of males interviewed in the 2006 and 2008 surveys.

Table 5
Probit estimation exploring the determinants of extramarital affairs in 2006 and 2008
(Std error in parentheses)

Variable	Specification (1)	(2)	(3)	(4)	(5)	(6)
Bean count measure of subjective belief	0.076**	…	0.075**	…	0.074**	…
	(0.030)		(0.033)		(0.033)	
Believe HIV prob is low†	…	0.222	…	0.178	…	0.174
		(0.142)		(0.146)		(0.146)
Believe HIV prob is medium or high†	…	0.076	…	0.041	…	0.023
		(0.232)		(0.241)		(0.240)
Age in 2006	…	…	-0.058	-0.059	-0.050	-0.050
			(0.039)	(0.038)	(0.038)	(0.037)
Age squared in 2006	…	…	0.000	0.000	0.000	0.000
			(0.000)	(0.001)	(0.000)	(0.001)
Moslem	…	…	-0.279	-0.266	-0.274	-0.261
			(0.223)	(0.226)	(0.225)	(0.227)
No school†	…	…	0.538	0.501	0.555*	0.525
			(0.318)	(0.314)	(0.318)	(0.315)
Primary school†	…	…	0.544**	0.505**	0.556**	0.520
			(0.252)	(0.250)	(0.251)	(0.250)
Resides in Balaka †	…	…	0.033	-0.005	0.020	-0.017
			(0.215)	(0.215)	(0.214)	(0.215)
Resides in Rumphi†	…	…	-0.392**	-0.454**	-0.387**	-0.447**
			(0.174)	(0.177)	(0.174)	(0.176)
Polygamous	…	…	-0.086	-0.061	-0.038	-0.011
			(0.196)	(0.196)	(0.179)	(0.179)
Number of children	…	…	0.029	0.030	…	…
			(0.029)	(0.029)		
Number of children not reported	…	…	0.242	0.263	…	…
			(0.516)	(0.512)		
Metal Roof	…	…	0.083	0.014	0.107	0.040
			(0.174)	(0.174)	(0.171)	(0.172)
Year Dummy	YES	YES	YES	YES	YES	YES
Pseudo R-Squared	0.038	0.034	0.087	0.087	0.0855	0.0846
Number of observations	970	967	958	955	958	955

* p < 10%, ** p < 5%, *** p < 1%

† The omitted categories are: Secondary school or some years of higher education, resides in Mchinji, believe HIV prob is zero

Table 6a
Cell sizes for indicated bean ranges and age grouped in quintiles

Cell	Age 2008†	Bean 2006	Extra-Marital Affair 2004	cell_size	Total
1	5	0	No	72	
2	4	0	No	68	
3	3	0	No	67	
4	2	0	No	64	
5	1	0	No	56	
6	1	2-10	No	18	
7	1	0	Yes	17	
8	2	2-10	No	12	
9	3	2-10	No	12	
10	3	1	No	11	
11	4	2-10	No	11	
12	2	0	Yes	9	
13	3	0	Yes	9	
14	1	1	No	7	
15	2	1	No	7	
16	2	2-10	Yes	6	
17	4	1	No	6	
18	4	0	Yes	5	
19	5	1	No	5	
20	5	2-10	No	5	
21	1	1	Yes	4	
22	1	2-10	Yes	4	
23	5	0	Yes	4	479
24	5	2-10	Yes	2	
25	2	1	Yes	1	
26	3	2-10	Yes	1	
27	4	2-10	Yes	1	
28	5	1	Yes	1	485

†For Age 2008, a value of 1 represents the first quintile, 2 represents the second quintile, and so on.

Table 6b
Cell sizes for indicated bean ranges and age grouped in quintiles

Cell	Age 2008†	Bean 2006	Cheat 2004	cell_size	Total
1	5	0	no	72	
2	4	0	no	68	
3	3	0	no	67	
4	2	0	no	64	
5	1	0	no	56	
6	1	0	yes	17	
7	3	1	no	11	
8	2	2-4	no	10	
9	1	2-4	no	9	
10	1	5-10	no	9	
11	2	0	yes	9	
12	3	0	yes	9	
13	3	2-4	no	8	
14	4	2-4	no	8	
15	1	1	no	7	
16	2	1	no	7	
17	4	1	no	6	
18	4	0	yes	5	
19	5	1	no	5	
20	1	1	yes	4	
21	1	2-4	yes	4	
22	3	5-10	no	4	
23	5	0	yes	4	
24	5	2-4	no	4	
25	2	2-4	yes	3	
26	2	5-10	yes	3	
27	4	5-10	no	3	476
28	2	5-10	no	2	
29	5	2-4	yes	2	
30	2	1	yes	1	
31	3	2-4	yes	1	
32	4	5-10	yes	1	
33	5	1	yes	1	
34	5	5-10	no	1	485

†For Age 2008, a value of 1 represents the first quintile, 2 represents the second quintile, and so on.

Table 7a[(a)]
Estimated coefficients for effects of beliefs on the propensity to engage in extramarital affairs
Linear specification

Bean Aggregation	# observations	# cells used in GMM	Coefficients: Constant	Age	Belief
			-63.948***	1.373***	-1.552***
0,1,2-10	479	23	(10.239)	(0.231)	(0.359)
			-101.534***	2.240***	-3.168***
0,1,2-4,5-10	476	27	(19.174)	(0.439)	(0.760)

* p < 10%, ** p < 5%, *** p < 1%

(a) The estimates are reported for the two different bean aggregation schemes used in implementing the GMM procedure. The age categories are aggregated into quintiles.

Table 7b[(a)]
Estimated coefficients for effects of beliefs on the propensity to engage in extramarital affairs
Specification including quadratic terms in age and beliefs

Sample			Coefficients				
Bean Aggregation	# observations	# cells used in GMM	Constant	Age	Belief	Age Squared	Belief Squared
			-113.337*	2.179	0.303	0.008	-1.361*
0,1,2-10	479	23	(62.345)	(1.924)	(4.124)	(0.015)	(0.811)
0,1,2-4,			-123.43**	2.395	0.145	0.008	-1.461**
5-10	476	27	(48.045)	(1.658)	(2.904)	(0.016)	(0.673)

* p < 10%, ** p < 5%, *** p < 1%

(a) The estimates are reported for the two different bean aggregation schemes used in implementing the GMM procedure. The age categories are aggregated into quintiles.

Table 8a.
Average marginal effects implied by estimated coefficients in Table 7a
Linear Specification

Bean Change		Bean Aggregation[(a)]			
		{0,1,2-10}		{0,1,2-4,5-10}	
From	To	2006[(b)]	2008[(b)]	2006[(b)]	2008[(b)]
0	10	-0.137	-0.305	-0.174	-0.364
1	10	-0.081	-0.204	-0.077	-0.227
2	10	-0.051	-0.132	-0.049	-0.137
3	10	-0.035	-0.082	-0.038	-0.071
4	10	-0.024	-0.046	-0.030	-0.032
5	10	-0.017	-0.023	-0.023	-0.011
6	10	-0.012	-0.011	-0.017	-0.006
7	10	-0.008	-0.006	-0.013	-0.003
8	10	-0.004	-0.003	-0.009	-0.001
9	10	-0.001	-0.001	-0.004	0.000
1	0	0.056	0.101	0.096	0.137
2	0	0.085	0.173	0.124	0.227
3	0	0.101	0.223	0.135	0.292
4	0	0.113	0.259	0.143	0.332
5	0	0.120	0.283	0.150	0.353
6	0	0.125	0.294	0.156	0.358
7	0	0.129	0.299	0.160	0.361
8	0	0.133	0.302	0.164	0.363
9	0	0.135	0.304	0.169	0.364

(a) The estimates are reported for the two different bean aggregation schemes used in implementing the GMM procedure. The age categories are always aggregated into quintiles.

(b) The marginal effects are obtained for each individual in the 2006 and 2008 samples and are averaged across individuals to obtain the marginal effect estimates reported in the table.

Table 8b. Marginal Effects
Specification including quadratic terms in age and beliefs

Bean Change		Bean Aggregation[a]			
		{0,1,2-10}		{0,1,2-4,5-10}	
From	To	2006[b]	2008[b]	2006[b]	2008[b]
0	10	-0.154	-0.344	-0.137	-0.330
1	10	-0.121	-0.293	-0.098	-0.272
2	10	-0.071	-0.176	-0.061	-0.160
3	10	-0.053	-0.107	-0.046	-0.091
4	10	-0.046	-0.076	-0.039	-0.064
5	10	-0.026	-0.027	-0.024	-0.016
6	10	-0.021	-0.013	-0.020	-0.006
7	10	-0.018	-0.009	-0.018	-0.003
8	10	-0.012	-0.003	-0.012	-0.003
9	10	-0.008	-0.002	-0.008	-0.003
1	0	0.033	0.051	0.040	0.058
2	0	0.083	0.169	0.076	0.170
3	0	0.101	0.237	0.091	0.238
4	0	0.108	0.268	0.098	0.266
5	0	0.128	0.318	0.113	0.313
6	0	0.133	0.331	0.117	0.324
7	0	0.135	0.335	0.119	0.326
8	0	0.142	0.341	0.126	0.327
9	0	0.146	0.342	0.130	0.327

(a) The estimates are reported for the two different bean aggregation schemes used in implementing the GMM procedure. The age categories are always aggregated into quintiles.

(b) The marginal effects are obtained for each individual in the 2006 and 2008 samples and are averaged across individuals to obtain the marginal effect estimates reported in the table.

Table 9a
Estimated coefficients for effects of beliefs on the propensity to engage in extramarital affairs for varying levels of misreporting
Linear specification

	Bean Aggregation[(a)]			
	{0,1,2-10}		{0,1,2-4,5-10}	
	Coefficients		Coefficients	
α_1	Age	Belief	Age	Belief
0.00	1.373	-1.552	2.240	-3.168
0.05	1.381	-1.568	2.256	-3.199
0.10	1.390	-1.584	2.273	-3.232
0.15	1.400	-1.602	2.292	-3.267
0.20	1.411	-1.621	2.313	-3.304
0.25	1.423	-1.641	2.335	-3.344
0.30	1.437	-1.663	2.359	-3.387
0.35	1.452	-1.687	2.387	-3.434
0.40	1.470	-1.713	2.418	-3.486
0.45	1.492	-1.743	2.457	-3.546
0.50	1.530	-1.778	2.531	-3.645
0.55	1.557	-1.816	2.570	-3.706
0.60	1.591	-1.863	2.617	-3.773

(b) The estimates are reported for the two different bean aggregation schemes used in implementing the GMM procedure. The age categories are aggregated into quintiles.

Table 9b
Estimated coefficients for effects of beliefs on the propensity to engage in extramarital affairs for varying levels of misreporting
Specification including quadratic terms in age and beliefs

	Beans 0,1,2-10				Beans 0,1,2-4,5-10			
	Coefficients				**Coefficients**			
α_1	**Age**	**Belief**	**Age Squared**	**Belief Squared**	**Age**	**Belief**	**Age Squared**	**Belief Squared**
0.00	2.179	0.303	0.008	-1.361	2.395	0.144	0.008	-1.461
0.05	2.204	0.305	0.008	-1.372	2.422	0.145	0.008	-1.474
0.10	2.231	0.308	0.008	-1.385	2.450	0.144	0.008	-1.487
0.15	2.259	0.310	0.008	-1.398	2.479	0.144	0.008	-1.501
0.20	2.289	0.312	0.007	-1.412	2.511	0.143	0.008	-1.515
0.25	2.321	0.315	0.007	-1.426	2.545	0.141	0.008	-1.531
0.30	2.356	0.317	0.007	-1.442	2.582	0.138	0.008	-1.547
0.35	2.394	0.318	0.007	-1.459	2.623	0.133	0.008	-1.564
0.40	2.436	0.318	0.007	-1.477	2.668	0.124	0.008	-1.581
0.45	2.483	0.317	0.007	-1.495	2.721	0.104	0.008	-1.597
0.50	2.555	0.297	0.007	-1.501	2.818	-0.007	0.007	-1.588
0.55	2.607	0.298	0.007	-1.528	2.870	-0.004	0.007	-1.615
0.60	2.667	0.294	0.007	-1.559	2.930	-0.006	0.007	-1.642

Robustness: Beliefs and Extramarital Affairs Regressions

Table 10a. (No quadratic terms) [(a)]

Sample			Coefficients				
Bean Group	# resp	# cells	Constant	Age	Belief	Lagged Behavior	Perceived Prevalence
0,1,2-10	479	23	-62.676***	1.353***	-1.484***	-5.305***	
			(9.525)	(0.215)	(0.324)	(1.525)	
	407	42	-30.557***	0.592***	-0.567***		-0.090
			(5.917)	(0.135)	(0.191)		(0.202)
0,1,2-4,5-10	476	27	-98.425***	2.176***	-3.026***	-4.758***	
			(18.088)	(0.415)	(0.705)	(1.866)	
	396	42	-34.826***	0.684***	-0.750***		-0.064
			(7.831)	(0.178)	(0.280)		(0.204)

* p < 10%, ** p < 5%, *** p < 1%

(a) The estimates are reported for the two different bean aggregation schemes used in implementing the GMM procedure. The age categories are aggregated into quintiles and the perceived prevalence, into quartiles.

Table 10b. (Quadratic terms)[(a)]

Sample			Coefficients							
Bean Group	# resp	# cells	Constant	Age	Belief	Age Squared	Belief Squared	Lagged Behavior	Perc Prev	Perc Prev Squared
0,1,2-10	479	23	-110.645*	2.109	0.321	0.008	-1.338	-4.435		
			(65.732)	(1.995)	(4.342)	(0.015)	(0.837)	(5.063)		
	407	42	-9.509	-0.393	-0.007	0.009	-0.093		2.328***	-0.373***
			(20.354)	(0.782)	(1.205)	(0.008)	(0.199)		(0.775)	(0.125)
0,1,2-4, 5-10	476	27	-119.71**	2.300	0.249	0.008	-1.453**	-4.515		
			(50.700)	(1.712)	(3.059)	(0.016)	(0.689)	(5.227)		
	396	42	-17.424	-0.161	-0.433	0.008	-0.039		2.329	-0.371
			(22.853)	(0.838)	(1.336)	(0.008)	(0.216)		(0.821)	(0.132)

* p < 10%, ** p < 5%, *** p < 1%

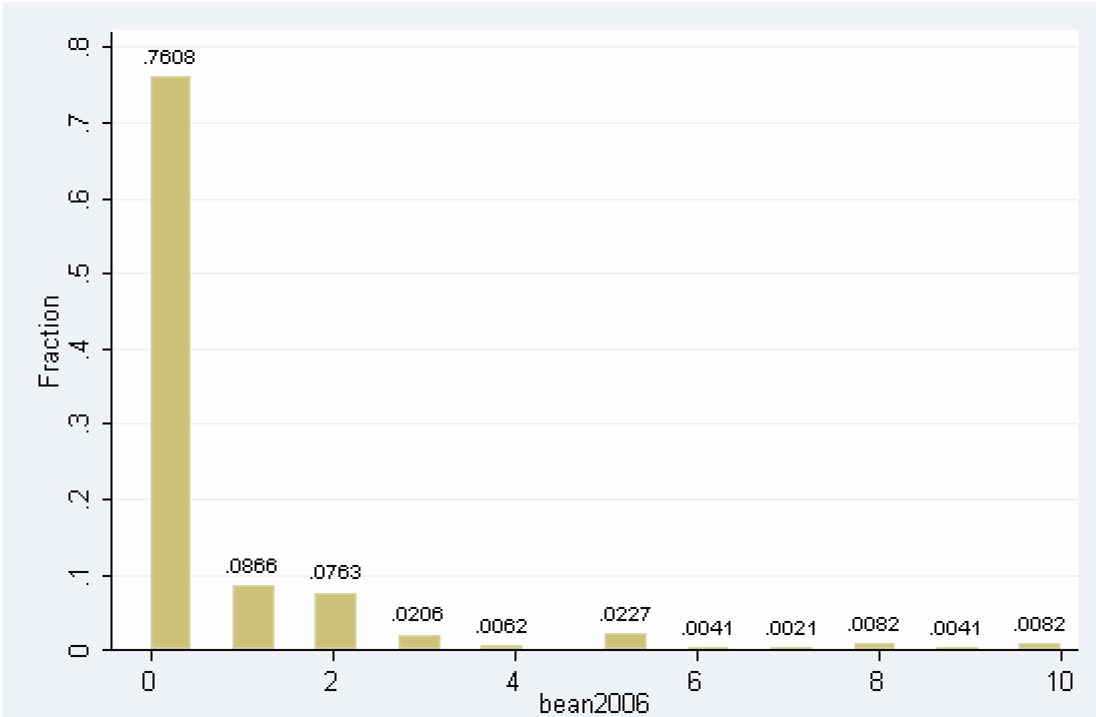
(a) The estimates are reported for the two different bean aggregation schemes used in implementing the GMM procedure. The age categories are aggregated into quintiles and the perceived prevalence, into quartiles.

Table 11a
Counterfactual Experiments on Increased Responsiveness of Beliefs to Testing

Baseline Parameters	Value
Pr(Affair | Uninfected)	7.23%
Pr(Affair | Infected)	7.69%
E(# Partners | Affair, Uninfected)	3.22
E(# Partners | Affair, Infected)	3.33
E(# Partners | No Affair, Uninfected)	1.3
E(# Partners | No Affair, Infected)	1.26
I (Prevalence Rate)	8%
ξ (Infection prob from single contact)	0.1%

Table 11b
Counterfactual Experiments on Increased Responsiveness of Beliefs to Testing

	λ (Probability of Infection)
Baseline	0.955%
Full Belief Revision (U and I)	0.853%
Full Belief Revision (I only)	0.890%



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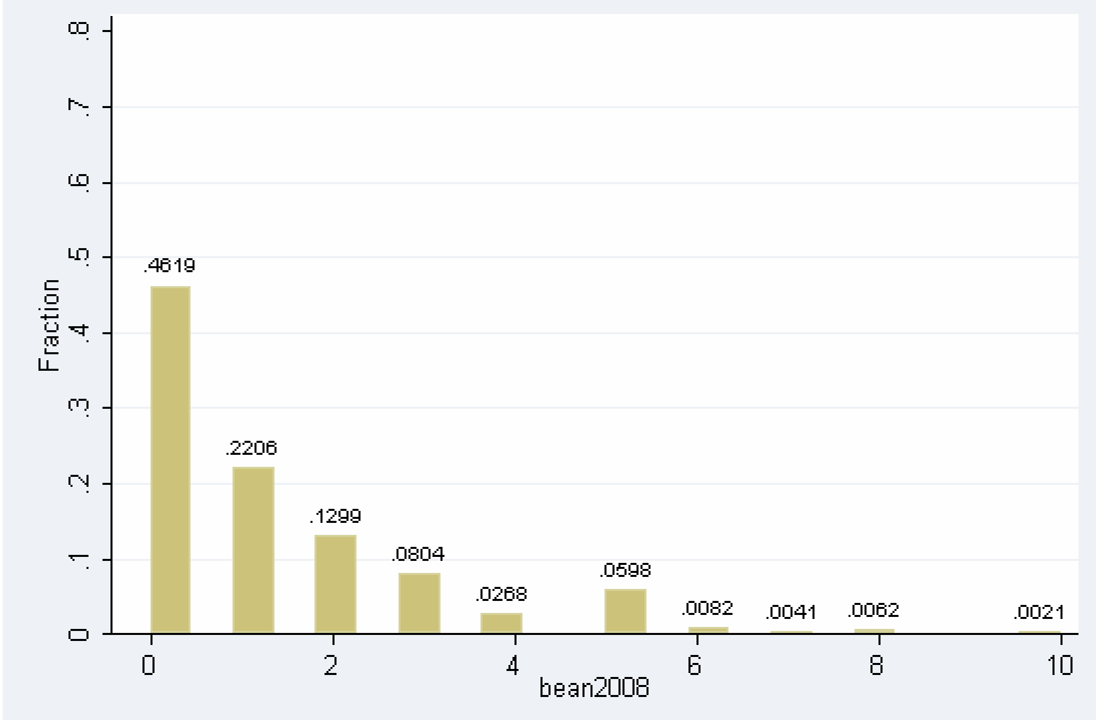

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Figure 1: Belief Distribution (2006 and 2008)

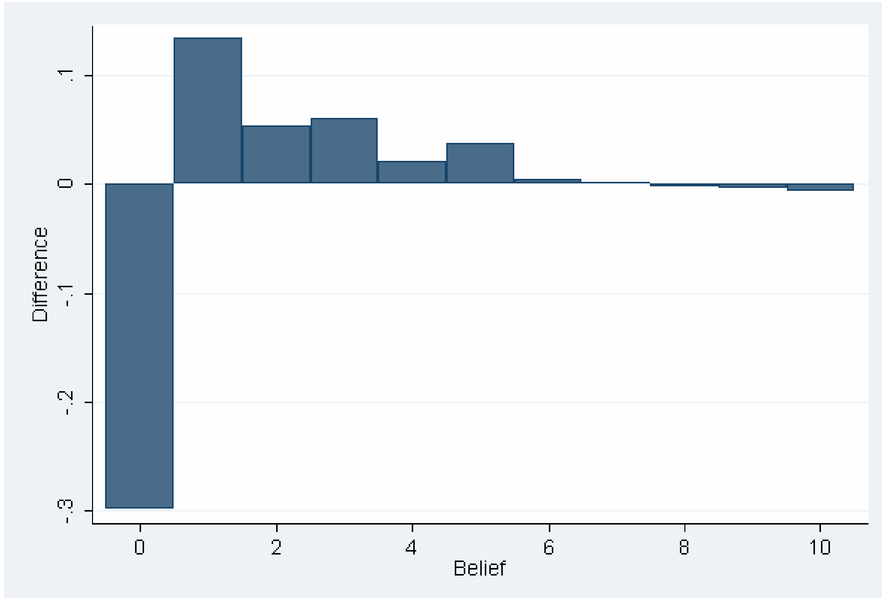

Figure 2: Bean Frequency Changes (= Relative Freq in 2008
– Relative Freq in 2006)