Penn Institute for Economic Research
Department of Economics
University of Pennsylvania
3718 Locust Walk
Philadelphia, PA 19104-6297
pier@econ.upenn.edu
http://www.econ.upenn.edu/pier

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"How Beliefs about HIV Status Affect Risky Behaviors: Evidence from Malawi"
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by

Aureo de Paula, Gil Shapira and Petra E. Todd

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

Áureo de Paula Gil Shapira Petra E. Todd [2]

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[2]Áureo de Paula is an Assistant Professor and Petra Todd a Professor in the Department of Economics at the University of Pennsylvania. Both are research associates of the Population Studies Center. Gil Shapira is a graduate student in the Department of Economics at the University of Pennsylvania. For correspondence, please contact `aureo@sas.upenn.edu` or `ptodd@ssc.upenn.edu`.

Abstract

This paper examines whether and to what extent changes in beliefs about own HIV status induce changes in risky sexual behavior using data from married males living in three regions of Malawi. Risky behavior is measured as the propensity to engage in extramarital affairs. The empirical analysis is based on panel surveys for years 2006 and 2008 from the Malawi Diffusion and Ideational Change Project (MDICP), which contain detailed information on beliefs about HIV status and on sexual behaviors. Many individuals change their beliefs over time, in part because of opportunities to get tested for HIV and informational campaigns. We estimate the effect of belief revisions on the propensity to engage in extra-marital affairs using a panel data estimator developed by Arellano and Carrasco (2003). The estimator accommodates unobserved heterogeneity as well as belief endogeneity arising from the dependence of current beliefs on lagged behaviors. We find that downward revisions in the belief of being HIV positive lead to an increased propensity to engage in extra-marital affairs and upward revisions to a decreased propensity. The estimates are shown to be robust to underreporting of affairs.

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 adult prevalence rates are above 20% in several countries (UNAIDS, 2008). It is been established that heterosexual intercourse is the main mode of transmission in Africa. However, relatively little is known about whether sexual behaviors are affected by the disease, if at all. This link is important when considering the effectiveness of policy interventions designed to prevent the spread of the virus by reducing risky sexual behaviors.

This paper examines the relationship between beliefs about own HIV status and the propensity of married men in rural Malawi to engage in one type of risky behavior, extramarital relations. Their beliefs have the potential to affect behavior in different ways. People who assign a high likelihood to being HIV-positive might have less incentive to prevent contagion as they are already infected. On the other hand, the fear of infecting others (via altruism or 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.

To prevent the further spread of HIV, government and nongovernmental organizations have implemented a variety of public health interventions. The types of interventions include 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 lead to less risky behaviors, although the quantitative evidence on behavioral responses is scarce. One recent study by Thornton (2008), which is further described in section two, finds that individuals who picked up HIV test results in Malawi modestly increased condom purchases but did not alter sexual behavior. There have been some related studies of the relationship between sexual behavior and HIV prevalance rates. For example, 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 earlier reported findings in Philipson and Posner (1995) for the United States.[1]

Two ingredients are presumably 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. Second, these changes in beliefs must induce changes in behavior. With regard to the first ingredient, in the context of Malawi, the link between HIV testing interventions and belief revision is not that transparent. For example, consider Table 1, which tabulates 2004 test results given to males in our MDICP analysis sample against their reported likelihood of being HIV positive, elicited in 2006. One might expect that those who receive a positive test result would revise their belief of being positive upward (perhaps to 100%) and those who receive a negative test outcome revise their belief downward. As shown in Table 1, however, the majority of individuals who tested HIV positive in 2004 attach a zero probability of being positive two years later. There are also some individuals who test negative in 2004 but then assign a high probability to being positive in 2006. The evidence indicates that test results do not always lead to corresponding revisions in belief about own status (see also Delavande and Kohler [12]), although the reasons why some individuals seem not to be convinced by the test results 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 are a few reasons why beliefs may not accord with the test results. First, HIV positive individuals are typically asymptomatic for many years and may therefore not believe that they carry the disease, particularly in the earlier years of data collection when HIV testing was less prevalent. Second, there is anecdotal evidence that some respondents were skeptical about the quality of the tests, which was likely exacerbated by the initial delay of one or more months in providing the 2004 test results. The reported belief of being positive in 2006 despite the negative test result in 2004 could also reflect interim risky behavior. Although in theory part of this may be ascribed to "prosecutor's fallacy", the testing protocol lead to a second test whenever a positive result was

Our empirical work is based on a unique panel survey called the Malawi Diffusion and Ideational Change Project (MDICP) dataset.[3] The MDICP sample covers rural populations from three different regions in Malawi, where the HIV prevalence rate is approximately 7%. Our analysis focuses on men, who are much more likely than women to report engaging in risky behaviors, such as extramarital affairs. In our sample, concurrent sexual partnerships are fairly common. 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. In this environment, beliefs changed significantly over time, in part because of testing services that were made available in 2004, 2006 and 2008. Individuals in the MDICP sample had very limited opportunities to get tested for HIV prior to 2004. Our empirical analysis in based on data from the 2006 and 2008 panels, which collected numerical measures on beliefs (described in detail later).

Of key concern in any analysis of the relationship between behavior and beliefs is the potential for endogeneity in beliefs, arising from correlations between past behavior and current beliefs. It is well documented that in such cases both cross-section and within estimators (in linear models) are biased in large samples. We address this concern using a semiparametric panel data estimator developed by Arellano and Carrasco (2003). The estimator is well suited to our application, because it accommodates potential feedback of lagged behavior on current beliefs (a violation of strict exogeneity in a panel data setting) as well as unobservable heterogeneity. We report estimates based on the Arellano-Carrasco (2003) estimator as well as a modified version that allows for potential under-reporting of risky behaviors, along the lines suggested by Hausman, Abrevaya and Scott-Morton (1998).

The paper develops as follows. Section 2 summarizes some of the existing

obtained and then to a third test whenever the first and second tests were discordant. This probably induced a very low probability of a false positive. Finally, we only include individuals who picked up (and were hence aware of) their results.

[3]The PI of the MDICP data collection and testing project was Hans-Peter Kohler.

empirical literature on the relationship between beliefs about HIV, testing, and risky behaviors. Section 3 presents a simple two period model for exploring the determinants of risky behavior. The model illustrates that the net effect of changing beliefs on risk-taking is theoretically ambiguous, so whether beliefs affect behavior and to what extent is largely an empirical question. Section 4 presents our 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 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). Section 6 concludes and discusses directions for future research.

2 Related Literature

The notion that individuals change their behavior in response to communicable diseases is generally well accepted and there is an interesting 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 prevalence.[4] 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

[4] 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.

with a sufficiently high initial number of partners.[5]

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 recent 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.[6]

As previously noted, Thornton (2008) provides a recent empirical study examining the causal impact of receiving HIV test results on risky behavior using a subset of the 2004 round of the MDICP data that participated in the 2004 HIV testing.[7] At the time of administering the tests, the MDICP project team also carried out a social experiment that randomized incentives to pick up the test results.[8] Thornton (2008) analyzes data generated from this incentives experiment along with data from

[5]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.

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

[7]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.

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

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 increases condom purchases but does not alter sexual behavior. It is possible, though, that the two month period that elapsed between the incentives experiment and the follow-up survey may have been too short to observe substantial changes in sexual behavior.[9] Thornton also documents that individuals who tested negative generally revised 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 relationship between beliefs and behavior for the larger sample of MDICP male respondents rather than the causal effect of picking up test results for the subsample of those who got tested, (ii) the use of data gathered in the 2006 and 2008 rounds that contain more detailed measures on beliefs, and (iii) the use of a different modeling framework and estimation methodology.

Another paper that is related to our study 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 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

[9] Another relevant consideration is that if there were heterogeneity of response to the randomized incentives, then the IV estimate that Thornton (2008) reports would have the LATE interpretation. Under this interpretation, the estimate corresponds to the causal effect of picking up test results for the subset of the sample who would not have picked up the results without the incentive. See Imbens and Angrist (1994) and more recently Heckman and Urzua (2009) for discussions of the LATE interpretation of IV 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.[10] Our empirical findings are similar to those of Boozer and Philipson's, although the population we study, which consists of married males in Subsaharan African, 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 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 remark-

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

ably well calibrated to prevalence rates in the local communities.[11] Anglewicz and Kohler (2005) point out that individuals in the 2004 wave 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 much 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. In this paper, we make use of both the coarse belief categories and the finer measurements, which are further described in section four.

3 A Model of Risky Behavior Choices

The focus of this paper is on how individual's beliefs about their own HIV status affect risk-taking behaviors in an environment where own beliefs are changing over time, because of new testing opportunities and informational campaigns. As noted in the introduction, theoretical models that have been put forth 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 by 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

[11]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).

take risks.[12] 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 $g(\tilde{Y}_0) \in [0,1]$.[13] 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 an individual contracts HIV in the first period. λ can be interpreted as the mortality

[12]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 to 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.

[13]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.

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 would be expected to increase risky behavior upon learning a positive HIV test result and to decrease risky behavior upon learning a negative test result.

In a multi-period context, beliefs affect current behavior and also respond to past behavior through updating. This implies that the 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, our primary goal is to assess whether and to what extent changes in beliefs about own HIV status affect risk-taking behaviors. Such an understanding is helpful for understanding the effects of policy interventions that aim to influence beliefs, such as HIV testing or informational campaigns. 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.[14]

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. Denote by Y_{it} the *reported* measure of risk taking

[14]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.

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 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.[15] No restrictions are imposed on the shape of the conditional mean function. W_i^t is a vector

[15]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. The framework

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,

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

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:

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

also accommodates a time varying scale parameter as long as a normalization is imposed for one of the periods. The distribution can be made totally nonparametric if there are continuous covariates as noted in the article (see their footnote 7).

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)).

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.[16] 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 a change in the proportion of reported extra-marital affairs would generate variation in $F^{-1}(\widehat{h_t(W_i^t)}) - F^{-1}(\widehat{h_t(W_i^{t-1})})$ 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:

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

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

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 try to accommodate 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 incorporate ideas developed by Hausman, Abrevaya and Scott-Morton (1998) into 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 when that happens. 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.[17] In our robustness analysis, we report estimates for the coefficients of interest with varying degrees of misclassification.

5 Data and Empirical Results

5.1 Background on the MDICP Dataset

The MDICP data were gathered by the Malawi Research Group.[18] 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

[17] 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 we use $\min\left\{1, \frac{\widehat{h_t(W_i^t)}}{1-\alpha_1}\right\}$.

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

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. 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 representative sample of rural Malawi (see, for instance, Anglewicz et al. (2006)). Appendix A provides further information about the dataset.

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.[19] 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-

[19]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.[20]

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 3 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.[21] 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.

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 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, which appeared to work well.[22] Delavande and Kohler (2007) study both the categorical and more continuous measure and demonstrate that the continuous

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

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

[22] 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.

measure is well calibrated to regional HIV rates. In Table 4, 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.

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 extramarital 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 reasonm, 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 aggregation 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.

On Tables 7a-b we 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 a quadratic term in both age and beliefs. The estimates indicate that the impact of beliefs is statistically significant[23] and that people reporting higher beliefs of being HIV positive are less likely to engage in extramarital affairs.

For ease of interpretation, Tables 8a-b report the marginal effects of changes in beliefs (as indicated in the table) on the probability of engaging in extramarital affairs. The estimates imply that revising beliefs upward decreases risk-taking. For

[23] 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.

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 their risk-taking. For example, someone who decreases their belief from 2 beans to zero increases the probability of an extra-marital affair by 8.1 percentage points in 2006 (again for the linear specification and 0,1,2-10 aggregation of beans). These estimates suggest that HIV testing programs that inform individuals of their negative status and lead to a downward revision in beliefs induce an increase in risk-taking.

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.[24] 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.

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

In trying to assess the impact of underreporting on our estimation results, we re-estimated the model for different assumed levels of misreporting. We used an adapted version of Arellano and Carrasco's estimator to handle the measurement error as 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 might lead 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 nonlinear 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 $F(X,\theta)$ 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.

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 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 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 over the time period covered by the data collection, although 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. 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%).

In general, our findings suggest that HIV testing programs reduce risk-taking if they lead individuals to revise their beliefs of being HIV positive upward. The effectiveness of testing in the subsaharan setting, though, is somewhat mitigated by the fact that some individuals seem to be skeptical about the validity of the test results. On the other hand, informing people that they are negative induces a downward revision in beliefs, which has, according to our estimates, the unintended consequence of increasing risk-taking. The findings would suggest that the effectiveness of testing programs can be improved by targeting them more narrowly at individuals at higher risk of being positive who would tend to reduce their transmissive behavior. Because individuals who revise their beliefs downward tend to increase their propensity to engage in extramarital affairs, informational campaigns which mitigate this tendency may also be effective. More generally, behavior does respond to changes in beliefs and this response should be taken into account in formulating policies.

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