Mortality Risk Information, Survival Expectations and Sexual Behaviors*

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Abstract

Individuals in low-income settings are often overly pessimistic about survival risk. This paper provides evidence from a randomized experiment that provided mature adults aged 45+ in Malawi with information about population mortality risks. We find a positive treatment effect on expectations about population survival and about HIV transmission risk associated with having multiple sex partners. The latter is driven by the expectations of HIV+ people living longer, making the pool of potential partners riskier. Consistent with the change in perceived HIV transmission risk, treated individuals are less likely to engage in risky sexual practices one year after the intervention.

Keywords: subjective mortality expectations, HIV/AIDS, sexual behavior, lifecycle decision-making

JEL Codes: I12, J10, C8

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1 Introduction

Subjective expectations are an important determinant of health-related behaviors in low income countries (LICs) as individuals face substantial uncertainty about their own and other family members' health, the relationship between health inputs and outcomes, and the risk environment affecting the severity of the disease burden. Despite the centrality of health-related expectations, there is evidence that many individuals have inaccurate perceptions about the returns of health-seeking behaviors such as better nutrition, immunization, safe sex practices, and relevant health risks such as HIV prevalence, water contamination and survival (Delavande and Kohler 2012; Fitzsimons et al. forthcoming; Kerwin 2018; Madajewicz et al. 2007). These misperceptions may be a significant driver of the under-investment in health observed in LICs (Dupas and Miguel 2017; Kremer, Rao and Schilbach 2019).

Pessimism about survival risk is particularly notable and widespread. For example, mature adults aged 45+ years in the Malawi Longitudinal Study of Families and Health (MLSFH) report average subjective 5-year survival probabilities of 46–58% in the years from 2006 to 2018, compared to 83–87% suggested by current life-tables. Similar patterns have been documented as part of an emerging literature in India and the Philippines, among migrants in Nepal, and in some higher-income contexts (Bago d'Uva, O'Donnell and van Doorslaer 2017; Capuno et al. 2019; Delavande and Kohler 2009; Delavande and Rohwedder 2011; Delavande, Lee and Menon 2017; Shrestha 2019). This overly-pessimistic assessments of mortality risk suggest a provocative question for health policy: Could policies achieve longer, healthier and "better" lives by correcting overly-pessimistic expectations about mortality? In other words, is there a *benefit of knowledge* in terms of health for accurately knowing population mortality risks?

We investigate this question by analyzing the impact of a randomized information intervention about population-level mortality on individuals' subjective expectations and health investment, with a particular focus on risky sex in sub-Saharan Africa (SSA). Accurate knowledge about population mortality risk might promote safe sex practices because population risks are likely important inputs in the formation of individual-specific health risks relevant for behaviors. On the one hand, less pessimistic population survival expectations may lead to less pessimistic expectations about *own* survival. Theory predicts that overall improvements in life expectancies encourage human capital investments, such as safe sex practices, as individuals can reap the returns for a longer period (e.g., Becker 1993; Ben-Porath 1967). Indeed, several studies have documented that actual gains in life expectancy translate in more investments in schooling and health (Jayachandran and Lleras-Muney 2009; Oster, Shoulson and Dorsey 2013).[1] On the other hand, more accurate knowl-

[1]We expect a priori our intervention to lead to an improvement in own survival from all causes of death as we communicated to the respondents a variety of factors for the gains in life expectancy. However, it is also possible for the perceived gains to be larger for non-HIV mortality risks than for HIV mortality risk. This

edge about population mortality may lead individuals to realize that HIV+ individuals live longer, making the pool of available partners riskier. This in turn increases the HIV transmission risk associated with having multiple partners, augmenting the cost of risky sex, and hence encouraging safe sex practices (e.g., Dupas 2011*a*, Delavande and Kohler 2016).

Prior to this study, no population-based randomized controlled trials (RCTs) have directly evaluated hypotheses about the health benefits of more accurate mortality expectations. To fill this niche, we designed a *Benefits-of-Knowledge health-information intervention* ("BenKnow Intervention") that consisted of two components: First, respondents watched three videos delivering the narrative that people nowadays live longer in Malawi with an explanation for these gains (e.g., better access to health care, availability of antiretroviral treatment (ART), fewer food shortages). Second, they received visual statistical information about the survival chances of individuals of the same age and gender.

Our BenKnow intervention targets mature adults aged 45 and older in rural Malawi. The intervention and baseline data collection was implemented in 2017, and follow-up data were collected in 2018. At least three aspects make mature adults a relevant study population for the BenKnow health-information intervention: First, mature adults in HIV-affected SSA countries such as Malawi have survived through periods with significant mortality fluctuations during adult ages, making it particularly difficult for individuals to make inference about mortality risks. Second, mature adults contribute importantly the spread of HIV because they continue to be sexually active and often have younger (extramarital) partners and/or risky sexual behaviors (Dupas 2011*a*). Third, the number of mature adults in Africa is projected to more than triple between 2015 and 2050 (UN Population Division 2017), and it is critical to develop health and social policies targeted at enhancing the health and well-being of this growing subpopulation.

A rare feature of our study is that we collected very detailed information on individuals' subjective expectations about their own and population survival, as well as other important health outcomes. This allows us to analyze which subjective expectations respond to the information intervention, and in turn lead to behavioral change. Understanding the mechanisms through which the intervention influences decision-making is critical for assessing the scope of potential scale-up of interventions or application to other contexts.

Our analyses document a positive treatment effect of the intervention on expectations about population survival one year after the intervention: there is a 6.1% increase in the subjective probability that a healthy individual will survive in five years, given a baseline survival expectations of 70%. The magnitude of the effect is slightly larger when looking at the survival expectations for hypothetical individuals who are HIV+ (6.6%), and individuals who are sick with AIDS but on ART (7.1%). We do not find treatment effects

would still encourage safe sex practices. In a competing mortality risks model, there is more to gain from HIV avoidance behavior if non-HIV mortality is lower (Dow, Philipson and Sala-i Martin 1999; Philipson and Posner 1995, 1993). Indeed, Oster (2012) finds that the reduction in risky sex as a response to higher HIV prevalence is larger in places with lower malaria prevalence or maternal mortality.

on the survival expectations for hypothetical individuals who are sick with AIDS and do not receive ART, which is consistent with the BenKnow intervention materials (specifically the videos) highlighting the importance of ART in improving life expectancy in Malawi. These findings are important because they indicate that individuals were able to understand, process and memorize the information we provided during the health-information intervention.

The positive treatment effects on population survival expectations had ramifications for other health expectations. In particular, we find a positive effect of the BenKnow intervention on the subjective probability of contracting HIV conditional on having multiple sex partners. Importantly, there is no corresponding treatment effect on the subjective beliefs about the "technology" of HIV transmission, that is, infection risk conditional on behaviors and partner HIV status. Hence, the increase in the subjective transmission risk associated with multiple partners appears driven by an increase in the perceived HIV prevalence of potential partners. The latter increase is consistent with the positive treatment effect on the survival risk of HIV+ individuals, who remain for longer in the partners' pool.

Importantly, and contrary to our priors, the BenKnow intervention did *not* change *own* survival expectations, neither in the short-run (2 weeks after the intervention) in which no compensating behaviors driven by the new information could have occurred, nor in the long-run (one year after the intervention). This null result holds even if we exclude respondents with accurate baseline expectations, or those for whom own survival expectations are different from their population survival expectations (and for whom the information may therefore be irrelevant to own survival). While we cannot rule out all alternative mechanisms, our analyses suggest that the updating of population-level survival expectations without updating of own survival expectations is explained by individuals having more private information about their own survival than about the survival of others, making expectations about own survival much less responsive to new information.

The positive treatment effect on the perceived HIV transmission risk with multiple partners should motivate safer sex practices. Indeed, our key policy-relevant finding is that the BenKnow health-information intervention resulted in statistically significant reduction in sexual risk taking. The magnitude of the treatment effect is substantively important. For example, one year after the intervention, the predicted probability of having multiple partners without condom is 7.6% in the control group and 6.4% in the treatment group, corresponding to a 19% reduction in the riskiest behavior in terms of HIV transmission. Similarly, the predicted probability of abstinence in the last 12 months is 33.3% in the control group and 36.1% in the treatment group, i.e., a 8% increase in the safest behavior. The results are robust to alternative specifications allowing for misreporting of sexual behavior. We also document a reduction in pregnancies and births, two outcomes not affected by misreporting of sexual behaviors, in the treatment villages subsequent to the BenKnow intervention.

Individuals in the treatment villages are also more likely to be married at follow-up, which is due to a 6 percentage point (or 8%) increase in the probability of getting married for respondents who are not married at baseline. Marriage may be seen as a risk-reduction strategy for singles who want to commit to a low-risk partner. The increased expectations of population-level survival—and thus potential marriage partners—provides an additional explanation of the rise in marriage in response to the BenKnow intervention.

Our paper contributes to a growing literature on the role of information provision on health behavior and human-capital decisions in low income countries (for reviews, see Dupas and Miguel 2017; Dupas 2011*b*). This literature is motivated by the fact that beliefs and misconceptions are important determinants of health behavior (Banerjee and Duflo 2011; Kim and Kim 2020; Kremer, Rao and Schilbach 2019). For example, related to our context, recent studies have shown that: information on the relative risk of HIV infection by partner's age leads to decreases in unprotected sex and pregnancies among teenagers (Dupas 2011*a*), information about HIV status influences subsequent sexual behavior and marriage transitions (Delavande and Kohler 2012; De Paula, Shapira and Todd 2014; Fedor, Kohler and Behrman 2015; Thornton 2008, 2012), information about the HIV transmission risk leads to reduction in sexual risk-taking for individuals with the highest priors who had become fatalistic (Kerwin 2018), and information about the reductions in HIV risk resulting from male circumcision influences circumcision uptake and sexual behavior (Chinkhumba, Godlonton and Thornton 2014; Godlonton, Munthali and Thornton 2016).

Our analyses add to this literature in several novel dimensions. First, we provide evidence on *how* our information intervention affects subjective expectations, and in turn, health behaviors. Beliefs are rarely measured in studies investigating the role of information on health behaviors (Kremer, Rao and Schilbach 2019). In our context, the BenKnow treatment effects on sexual behaviors appear driven by the upward revisions of the HIV transmission risk associated with risky sex, which is an aspect that the BenKnow intervention did not target to modify. Our results thus underscore the usefulness of collecting comprehensive expectations data to better understand why programs fail or succeed, and that the mechanisms underlying treatment effects might be quite complex. Second, our findings indicate that the elasticities of beliefs to information may heavily depend on the extent of private information. These insights are important as they allow to adjust and modify interventions in subsequent scale-ups and follow-up studies to enhance their effectiveness. Finally, our analyses suggest that expectations of mortality risks, and specifically too pessimistic assessments of survival, are a possibly important and modifiable determinant of health and related life-cycle behaviors. Such pessimistic assessments are likely to occur in populations with rapid improvements in mortality. While possibly not as dramatic as in countries affected by HIV/AIDS, social, political and economic crises have also resulted in substantial increases in adult mortality rates, and subsequent rapid recoveries of life expectancy (Brainerd and Cutler 2005; Ruhm 2016). In contemporary high HIV-prevalence contexts such as Malawi, a BenKnow health-information intervention that reduces misperceptions about mortality risks is a potentially useful policy tool to curtail HIV infection.

This paper also belongs to a recent literature studying how subjective expectations are updated in response to new information. This research is often conducted with surveys that elicit priors and posteriors about outcomes such as fertility, future earnings, inflation or housing (Armantier et al. 2016; Armona, Fuster and Zafar 2018; Delavande 2008; Wiswall and Zafar 2014). The advantage of our design is that we are able to observe the revised expectations one year after the provision of information—a time lag substantially larger than other studies—and to link the change in expectations to real-life behavior, as opposed to stated behavior or behavior in incentivized lab-style experiments. Our results call for encouragement and caution: individuals in low income settings use the information we provided to make important lifecycle decisions, but not all expectations are equally malleable.

2 Background

2.1 Context and Motivation

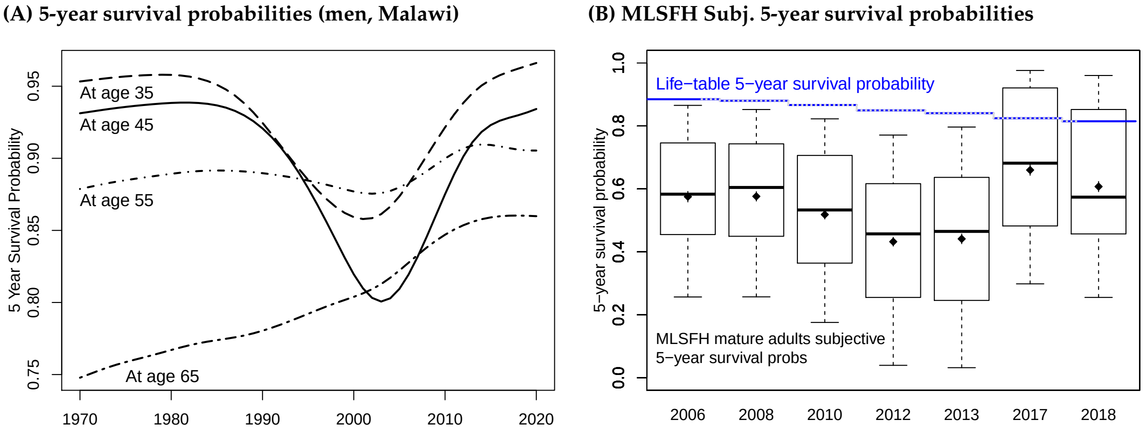
Malawi's Human Development Index rank 172 out of 189 countries and territories in 2018, and its per-capita GDP is equal to about 2% of the global average. In rural areas, where our study is based and most Malawians (85%) live, the majority of individuals engage in home production of crops, complemented by some market activities. Life expectancy at birth was 59.6 for men and 66.9 for women in 2017 (GBD Collaborators 2018). HIV prevalence among 14–49 year olds is estimated at 10.4% (women: 12.2%; men: 8.3%) in 2018, with an incidence of 4.4 per 1,000 (Malawi DHS 2017).[2] Despite successes in reducing HIV incidence, the HIV epidemic had, and continues to have, major effects on virtually all aspects of life, many of which were documented by the MLSFH (Kohler et al. 2015). Importantly, access to antiretroviral treatment (ART) in Malawi expanded during the past decade, attaining a 79% coverage among adults in 2018, resulting in significant reductions in adult mortality.[3]

While reductions in multiple diseases have contributed to declining infant mortality and increasing adult life expectancy (GBD Collaborators 2018), it is the widespread roll-out of ART that is widely credited with reversing the decline of adult survival rates during the last decade (Bor et al. 2013). During the HIV/AIDS epidemic, objective survival probabilities for adults changed immensely (Figure 1A): 35-year old males attained a 5-year survival probability of 95% around 1985, which dropped below 86% in 2002, having re-

[2]HIV prevalence is lower in rural areas (7.4%), where the MLSFH study population is based, as compared to urban areas (14.6%) (Malawi DHS 2017).

[3]UNAIDS AIDS info Database, https://aidsinfo.unaids.org, accessed January 2020.

Figure 1: 5-year survival probabilities 1970–2020 (Malawi), and 5-years subjective survival probabilities for MLSFH mature adults



Panel A: Based on 2017 UN Word Population Prospects (UN Population Division 2017). *Panel B:* For MLSFH mature adults (aged 45+) who participated in the 2012/13 and 2017/18 MLSFH mature adults data collection. The boxplot-like graph displays the mean (dot) and median (center line) of the corresponding 5-year survival expectations, as well as the 10th (lower whisker), 25th (bottom of box), 75th (top of box), and 90th (upper whisker) percentiles of the distribution. Life-table survival probabilities are merged by age and gender from the UN Malawi 2005–15 life tables (UN Population Division 2017).

covered to 96% by 2017.

In contrast to the recent trends that have given rise to a cautiously-optimistic outlook about curtailing the consequences of the HIV/AIDS epidemic (UNAIDS 2015), there is consistent evidence that mature adults in Malawi have distorted and overly-pessimistic survival expectations: they substantially *underestimate* their own survival probabilities (Figure 1B). Until about 2013, while adult survival was improving significantly, MLSFH mature adults became increasingly pessimistic about own survival (Figure 1B), much more than is justified due to the respondents' aging. This trend was partially reversed in 2017, possibly as a result of favorable rains and an exceptionally good harvest, reverting again to more pessimistic assessments by 2018. Despite these year-to-year fluctuations and the significant variation across individuals (Figure 1B), the basic implication has remained unchanged: the vast majority of our mature adult study participants underestimate population survival, with pessimism being least pronounced but still substantial (70%) in 2017 when our baseline was implemented.

The frequent experience of poverty-related and HIV/AIDS-related mortality and socioeconomic shocks during the last two decades and the overestimates of salient health risks such as HIV prevalence and HIV transmission probabilities are likely driving factor behind the elevated mortality expectations in our study population, and the resulting pessimism about own and population-level survival rates (Figure 1 and Table C.2).[4] Con-

[4]For instance, in 2008–10, when the MLSFH last asked the respective questions, the 2017 MLSFH mature adult reported a 63% HIV infection risk during a single intercourse without condom with a HIV+ person, as compared to an accurate average risk of less than .5% (Boily et al. 2009); MLSFH mature adults also reported a

tributing to mortality misperceptions potentially are also common cognitive biases such as denominator neglect or salience biases, often documented among health-care professionals, where individuals fail to accurately relate events (such as deaths) to exposures (denominator counts or person years lived) (Tversky and Kahneman 1973).

2.2 Mature Adults, Sexual Risk-taking and the HIV-AIDS Epidemic

Our study focuses on mature adults aged 45 and older for several reasons. *First*, mature adults are an essential subpopulation in SSA LICs because of their growing demographic relevance, their almost universal labor force participation with virtually no retirement, and their important contributions to intergenerational transfers and their pivotal caretaking roles in families affected by HIV/AIDS (UN Population Division 2017). *Second*, the (actual) mortality risks in contexts such as Malawi continue to be relatively high at mature adult ages (Figure 1). As a result, survival expectations are arguably important for life-course decision-making and well-being.

Third, and most important for this study, mature adults continue to be sexually active (Figure C.1), engage in risky sexual behaviors (Freeman and Anglewicz 2012), and contribute importantly to the spread of HIV across all age groups (Vollmer et al. 2017). Only 36% of the MLSFH mature adults did *not* have sex in the last 12 months (49% for women and 15% for men), and only 57% of sexually-active respondents had sex exclusively their spouse during the last 12 months (50% for women and 67% for men). Marriage and divorce/widowhood among mature adults are common, and remarriage is often swift (Reniers 2003). In 2017, 8% of MLSFH mature adults tested HIV-positive, corresponding to an increase of 40% since 2012 that is driven by respondents aged 45-49 years.[5] Despite this increasing HIV prevalence, mature adults are also less likely to adopt safe sexual behaviors, discuss HIV prevention with partners, or disclose a HIV-positive status within relationships compared to younger persons (Freeman and Anglewicz 2012). Moreover, a substantial fraction of older men ("sugar daddies") engages in sex with younger women (Dupas 2011*a*).

Fourth, the HIV risk associated with risky sexual behaviors of mature adults is further exacerbated by the fact that HIV+ mature adults are disadvantaged in terms of access-

77% annual probability of becoming infected when married to a HIV+ spouse, as compared to an accurate risk of about 12% (de Walque 2007). MLSFH mature adults in 2010 also estimated an average local HIV prevalence in their communities of 37%, as compared to a prevalence among all MLSFH respondents of about 6% (Kohler et al. 2015); mature adults also expected in 2010 a continued substantial increase in HIV prevalence within the next five years, which did not materialize as rural HIV prevalence remained approximately constant during 2010–16 (Malawi DHS 2017). *Note:* In all MLSFH analyses for 2008–10, observations are taken from 2010, and if not available, from 2008; analyses included MLSFH mature adults who participated in the 2017 baseline survey for this study.

[5]Similar patterns occur more broadly across SSA. For example, using data from 27 SSA countries, Vollmer et al. (2017) find an average annual growth rate of HIV prevalence of 4.2 percent for older adults, while HIV prevalence is decreasing at a rate of 3.5 percent for adults aged below 45 years. These dynamics are changing the 'hump-shaped' age pattern of HIV prevalence with peak HIV prevalence for "young" mature adults around age 45–50.

ing ART. Most HIV testing campaigns, which provide a primary gateway to treatment for HIV+ individuals, focus on primary reproductive ages, and in rural Malawi, routine HIV testing of women and their partners is primarily conducted as part of pre-natal care. As a result, only 60% of the 2012 and 82% of the 2017 HIV+ MLSFH mature adults are on antiretroviral treatment. 43% of the 2017 HIV+ mature adults have been on treatment for 4 years or less. Importantly for our subsequent interpretation of our results, the imperfect ART uptake and adherence implies that HIV+ mature adults are often not virally suppressed. They remain sources of HIV infection to their partners, and as the HIV prevalence among mature adults increases due to increased survival of HIV+ adults, the sexual partners of mature adults face increased HIV risk.

Fifth, because ART was not available throughout much of their adult lives, MLSFH mature adults have a heightened awareness about the importance of sexual and marital behaviors as a critical aspect of investing in health across the life-course. While the relationships between behaviors and health evolved as individuals got older, epidemiological contexts changed (e.g., increased relevance of non-communicable diseases), and new technologies became available (e.g., ART), for MLSFH mature adults, the triad between sexual/marital behaviors, health and survival continues to be closely intertwined. In perceptions as well as in reality, changes in sexual risk taking continue to be a primary mechanisms of reducing HIV infection risks and ensuring long-term health amount mature adults.

3 Data and BenKnow Health-Information Intervention

3.1 Mature Adults Cohort of the Malawi Longitudinal Study of Families and Health (MLSFH-MAC)

The Malawi Longitudinal Study of Families and Health (MLSFH) is an ongoing longitudinal panel study established in 1998 that examines how families and individuals cope with the social, economic, demographic and health consequences of the HIV/AIDS epidemic (Kohler et al. 2015). Our "*Benefits of Knowledge*" (BenKnow) study is based on the MLSFH Mature Adult Cohort (MLSFH-MAC), which was established by selecting in 2012 MLSFH respondents aged 45+ years, and enrolling them as part of an extensive aging and health baseline survey with follow-up waves in 2013, 2017, and 2018 (Kohler et al. forthcoming).[6] In 2017 and 2018, the two waves that are primarily relevant for the BenKnow

[6]The key inclusion criteria in 2012 for enrollment in the MLSFH-MAC were twofold: (*i*) being a MLSFH respondent aged 45 years or older in 2012; and (*ii*) having been interviewed in both the 2008 and 2010 MLSFH data collection rounds. The second criteria ensured that at least three waves of mental health and subjective well-being data were available for each baseline participant in 2012. Baseline enrollment in the MLSFH-MAC included 1,266 individuals clustered in 130+ villages, representing more than 90% of the 1,402 eligible MLSFH respondents who met the enrollment criteria (= target sample). Migration out of the study areas and mortality were the primary reasons for not enrolling eligible respondents. At each follow-up, the study population was augmented with additional MLSFH respondents who newly reached eligibility. To ensure an adequate repre-

Table 1: Descriptive statistics by treatment status

	All Respondents				HIV– Respondents Only		
	mean	control	treated	p-val	control	treated	p-val
Age	59.1	58.8	59.4	.300	59.3	59.9	.384
Male %	40.0	40.0	40.0	1	40.5	39.3	.653
Married %	73.4	74.1	72.7	.557	75.4	73.3	.391
Divorced %	8.8	7.9	9.7	0.222	7.0	9.2	.148
Widow %	17.8	18.0	17.6	0.821	17.6	17.5	.958
Years of schooling	3.5	3.5	3.6	.547	3.5	3.6	.694
HIV+ %	7.5	6.3	8.7	.088			
Expectations %							
Own survival (5 yrs)	67.0	66.9	67.0	.964	67.3	67.7	.763
Own survival (10 yrs)	44.1	43.6	44.6	.577	44.1	45.1	.586
Pop. survival (healthy)	70.0	70.7	69.4	.321	71.0	69.9	.399
Pop. survival (HIV+)	62.0	63.1	60.9	.093	63.7	61.6	.123
Pop. survival (AIDS)	49.2	50.2	48.1	.212	50.9	48.7	.195
Pop. survival (ART)	56.9	57.7	56.1	.266	58.4	56.6	.275
Pop survival (uncond)	69.0	68.8	69.2	.746	69.0	69.2	.859
HIV probability	18.6	17.1	20.1	.022	14.6	15.9	.253
HIV probability spouse	18.2	16.9	19.5	.064	15.3	16.4	.387
Sexual behavior %							
no sex	35.5	34.2	36.8	.294	34.0	37.4	.195
single partner	56.9	57.6	56.2	.583	57.9	56.4	.586
multiple partners, condom	1.2	1.5	1.0	.366	1.0	0.6	.405
multiple partners, no condom	6.3	6.7	6.0	.591	7.0	5.5	.255
Max observations	1481	748	733		682	652	

Notes: The table presents summary statistics for the main variables used in the empirical analysis for the whole sample and separately by treatment group and for individuals tested negative for HIV. The variables refer to the 2017 baseline survey. Control and treatment show the mean for the BenKnow control and the treatment groups. p-val shows the p-value of a t-test where the null hypothesis is that the difference in means between treatment and control group is zero. The first four columns refer to the whole sample while the last 3 refer to those tested negative for HIV during HIV Testing and Counseling (HTC).

study, the MLSFH-MAC collected a broad range of information including detailed data on probabilistic expectations and sexual behaviors.

Columns 1 in Table 1 report summary statistics for the MLSFH-MAC cohort in 2017, the *baseline* for our BenKnow study. Respondents are 59 years old on average, 60% are female,[7] they only have on average 3.5 years of schooling and 7.5% tested positive for HIV. Virtually all respondents have been married at least once in their lives but separations and remarriages are frequent. At baseline, 73% are married, 18% are widowed and 9% are

sentation of HIV+ individuals in the cohort, age-eligible HIV+ respondents were enrolled if they participated in either the 2008 *or* 2010 MLSFH data collection. Though the ongoing enrollment and migration follow-ups, the MLSFH-MAC cohort expanded to 1,257 respondents in 2013, 1,606 in 2017, and 1,532 in 2018. A detailed description of the data, including analyses of data quality and attrition, is provided in the MLSFH-MAC Cohort Profile (Kohler et al. forthcoming).

[7]The higher presence of females in the sample is related to the original MLSFH survey design that, in 1998, sampled ever-married women and their spouses. While subsequent waves have expanded the MLSFH sample, the original sampling frame continues to result in an overrepresentation of women in the sample.

divorced or separated.

The BenKnow health-information intervention was implemented by a separate team within two weeks subsequent to the 2017 MLSFH-MAC Main Survey. Shortly after the BenKnow intervention, a HIV Testing and Counseling (HTC) team visited the respondents in both the treatment and control group to administer a HIV testing and counseling sessions followed by a short survey.[8] Take-up of the HIV test was essentially universal (97.4%), and virtually all respondents opted to receive the result of the HIV test.[9] The 2018 MLSFH-MAC study population, fielded about one year after the 2017 wave, constitutes our *follow-up* survey. Our final analyses sample includes 1,481 respondents who completed all the required surveys (the 2017 and 2018 surveys and the intervention if in treatment group). Attrition from 2017 to 2018 was less than 5%, and attrition rates are similar by treatment status.[10] Figure 2 presents the timeline of data collection.

3.2 Benefits-of-knowledge (BenKnow) Health Information Intervention

The BenKnow intervention randomly assigned 2017 MLSFH-MAC respondents to a treatment and a control group, with randomization occurring at the village-level to avoid spillover effects between groups. Within each of the three study regions, villages were paired by size starting from the two biggest villages, followed by the two second biggest, etc. Then we randomly assigned treatment status to one village in each pair. The procedure guaranteed a similar sample size in the treatment group ($N = 779$) and control group ($N = 774$). The response rate for the BenKnow intervention was more than 98% (among 2017 survey respondents), resulting in 770 respondents enrolled in the treatment group. The BenKnow intervention consisted of the following two core components, with the complete interviewer scripts and additional information provided in the Appendix:

a) Narratives about changing mortality provided by video clips: Respondents were initially shown 3 video clips with a duration of about four minutes each. In these short video clips, individuals (trained local actors following a prepared script) explained how they noticed that people nowadays live longer in rural Malawi. The first video depicts a carpenter in his workshop, the second a female tailor in her shop sitting at a sewing machine and the third an old man sitting in front of his house. The videos emphasize overall that people live

[8] In 2013 and 2017, the HTC team also screened for blood pressure before the HIV test and for blood sugar a day after. Those who were measured with high blood pressure or high blood sugar were given a referral card for seeking care. Around 17% of the respondents received this card. The share of respondents who got the referral card for the first time in 2017 is not statistically different between treatment and control (a t-test for equality of the means gives a p-value equal to 0.19).

[9] Among the HIV+ individuals, very few tested positive for the first time. Out of 104 HIV+ respondents, only 8 respondents tested positive for the first time in 2017 as part of our survey procedure and were not currently under ART (in 2017, in rural Malawi, ART as prevention was not implemented). Among the HIV– individuals, 55% report a strictly positive probability of being infected with HIV in 2017 prior to the HTC visit. So overall, more than half of the sample receive new information about their HIV status

[10] The attrition rate is 3.4% for control and 4.8% for treatment (p-value of a t-test for equality is 0.185 when clustering at the village level).

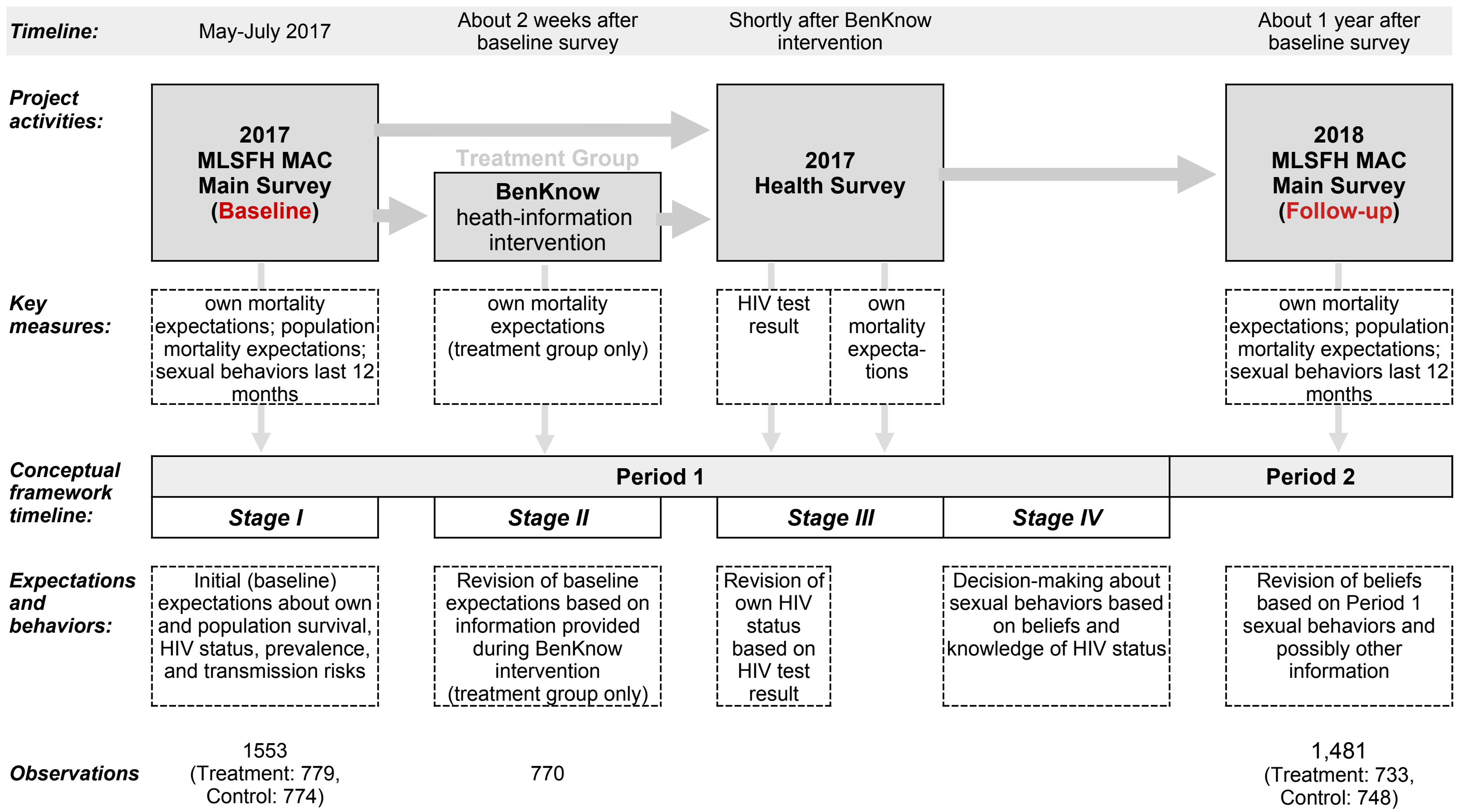


Figure 2: Research design and sequence of study activities

longer due to better access to food, health care, and availability of ART. Studies support that video narratives are a useful way to convey scientific information to non-experts by increasing comprehension, interest, and engagement (Bruner 2009). Evidence presented via such narratives are also more likely to be memorized (Schank and Berman 2002).

b) Life-table survival probabilities conveyed via visual aids: Subsequent to the videos, respondents were shown a health-information sheet with visual information on 5-year and 10-year life-table survival probabilities for individuals of the same gender and within the same 5 year age group, with different figures conveying how many persons, out of 10 alive at the time of the intervention, could be expected to be alive five or ten years in the future.[11] A BenKnow health-information sheet is illustrated in Figure B.1, and Table B.1 reports the complete set of BenKnow age- and gender-specific 5 and 10 year survival and death probabilities. The statistics purposely emphasized both the survival and mortality risk to avoid anchoring. While the videos conveyed a general narrative of improved survival, the life-table probabilities provided precise statistical information about mortality risk.

3.3 MLSFH Data on subjective expectations

Detailed subjective expectations data has been a hallmark of the MLSFH since 2006 (Delavande and Kohler 2009, 2012, 2016), including expectations about mortality (own and population), HIV infection and transmission, and the experience of socioeconomic shocks. These expectations were elicited by asking respondents to allocate up to ten peanuts (prior to 2017, beans) on a plate to express the likelihood that an event will occur, allowing respondents to split a peanut in half when stating their expectations.[12] The following MLSFH expectations are of particular relevance for the present study, with Appendix A providing the full text of the 2018 MLSFH expectations module and Figure 2 showing when these various expectations were collected.

a) Own mortality expectations, reflecting respondents' subjective expectations that they would die within a 5-year and 10-year time horizon from the day of the interview ("*Pick the number of peanuts to express the likelihood that you will die with a 5-year [10-year] period beginning today.*"). Own mortality expectations were elicited up to four times: during the 2017

[11] Life table survival probabilities were obtained from the Global Burden of Disease Collaborative Network. Global Burden of Disease Study 2016 (GBD 2016) Results. Seattle, United States: Institute for Health Metrics and Evaluation (IHME), 2017. Available from http://ghdx.healthdata.org/gbd-results-tool.

[12] This interactive approach for eliciting expectations has been applied to several other contexts (Delavande, Lee and Menon 2017; Delavande, Gine and McKenzie 2011). Prior to 2017, respondents allocated up to 10 beans, thus being able to state probabilities in 10 percentage point increments. Peanuts, which can be split in half, were introduced since 2017 to allow respondents to express subjective probabilities in 5 percentage point increments. This relatively coarse measurement of probabilities could be a problem for very low probability events. However, mortality risks of our respondents are not that small. As shown in Figure 1A, 55 year-old (resp. 60 year-old) respondents have a 90% (resp. 85%) of surviving in the next 5 years. Moreover, the gap between objective risk and population survival expectations in the next 5 years is strictly larger than 5 percentage points for 76% of the respondents, and strictly larger than 10 percentage point for 65% of the respondents, suggesting that the overestimation is not an artefact of the elicitation format.

MLSFH-MAC Survey, during the BenKnow intervention (treatment group only), during the HTC survey shortly after the intervention (treatment and control groups) and about one year after the BenKnow intervention during the 2018 MLSFH-MAC survey.

b) Population mortality expectations, measuring respondents' perceived likelihood that the following hypothetical individuals would die within 5-year period: (*i*) a woman/man who is healthy and does not have HIV; (*ii*) a woman/man who is infected with HIV; (*iii*) a woman/man who is sick with AIDS; (*iv*) a woman/man who is sick with AIDS and is treated with ART; (*v*) a woman/man will die in the 5 years (not conditional on a specific health outcome/status). All hypothetical individuals were described as being of the same age and gender as the respondent ("*Pick the number of peanuts that reflects how likely you think it is that one of the following persons will die within a five-year period beginning today: A man [woman] your age who is healthy and does not have HIV?*," and variations thereof for *ii*–*iv*). Population mortality expectations were elicited during the 2017 MLSFH-MAC Survey and during the 2018 MLSFH-MAC survey.

c) HIV-related expectations, measuring (*i*) the subjective probability of the respondent being currently infected with HIV; (*ii*) the perceived likelihood that his/her spouse is currently infected with HIV; and in 2010 and 2018 also (*iii*) the subjective expectation of becoming infected with HIV within the next 12 months conditional on various sexual behavior, including if married to someone who is infected with HIV/AIDS and if one has several sexual partners in addition to the spouse ("*Pick the number of peanuts that reflects how likely you think it is that you are infected with HIV/AIDS now*," and variations thereof for *ii*–*iv*).

The above mortality expectations are converted to survival probabilities (= 1 minus #peanuts divided by 10) and respectively referred to as *own survival* probabilities and *population survival* probabilities. Survival probabilities are generally consistent with each other in terms of time horizon and health status (Column 1 in Table 1). Respondents reported in 2017 on average a 67% chance of surviving for the next 5 years, and a 44% chance of surviving in the next 10 years. They expect a hypothetical healthy individual to have a 70% chance to survive in the next 5 years, compared to 62% for someone who is HIV+, 49% for someone who is sick with AIDS and 57% for someone who is treated with ART. The chance of surviving not conditional on health status is 69% which is just below the average reported survival for healthy individuals. There is substantial variation in survival probabilities (Figure 1), with answers taking all values between 0 and 1, some heaping at 0.5 and 1 for the 5-year and 0 and 0.5 for the 10-year horizon, and few respondents taking advantage of the possibility to split the peanut (less than 3%) to indicate probabilities at five percentage points intervals (Figure C.2). Importantly, there is substantive information conveyed in these probabilistic expectations: respondents who reported a lower probability of surviving to the next 5 or 10 years in 2010 are less likely to be alive in 2017 (Figure C.3), and respondents in 2018 who reported lower survival probabilities also report a lower expected age at death and fewer remaining life years (Table C.1).

3.4 MLSFH Data on sexual behavior

Sexual behavior in the MLSFH MAC is captured via questions about whether the respondent had sex in the last 12 months, the number of sexual partners in the last 12 months, and whether condom was used in the last sexual intercourse. Based on these questions, we construct three indicators of risky sexual behavior to look at both the extensive (being sexually active) and the intensive margin (multiple partners and condom use). Summary statistics for the variables entering the sexual risk indices are reported in Table 1.

Sexual Risk Index 1 (SRI1): 0 = not sexually active in the last 12 months, 1 = sexually active in the last 12 months.

Sexual Risk Index 2 (SRI2): 0 = not sexually active in the last 12 months, 1 = sex with one partner, 2 = sex with multiple partners.

Sexual risk index 3 (SRI3): 0 = not sexually active in the last 12 months, 1 = sex with one partner, 2 = sex with multiple partners and condom at last intercourse, 3 = sex with multiple partners and no condom at last intercourse.

Self-reported sexual behavior questions have been consistently shown to correlate with biomarker-based or pregnancy-based indicators of sexual behavior (McClelland et al. 2011).[13] Yet, we recognize the fact that self-reported sexual behavior is often difficult to measure through self reports, and the above variables may be subject to measurement error. We discuss the robustness of our results to potential misreporting in Section 5.2, using analytic approaches that allow for measurement error in the reporting of sexual behaviors as well as newly-collected 2019 MLSFH data on pregnancy outcomes in the BenKnow treatment and control villages.

3.5 Balance at baseline

Columns 3 and 4 in Table 1 confirm that the treatment and control groups are comparable on baseline observable characteristics. Importantly, own and population survival probabilities are very similar, and the sample is well balanced according to age, gender, sexual behavior, marital status and years of schooling. HIV prevalence is slightly higher in the treatment group (8.7% versus 6.3%, statistically significant at the 10% level), and as a result, we observe a slight imbalance in the subjective probability of being infected with HIV and also in the survival probability conditional on being HIV+. This imbalance is likely due to chance. When we restrict our analysis to individuals tested negative to HIV in

[13]Prior validity studies suggest that, while the level of these risky behaviors is potentially to be misreported, the self-reported indicators of risky behavior very likely discriminate between respondents with different levels of risky behaviors. Moreover, while a quasi-experimental design in which respondents were randomly allocated to one of three interviewing modes—face-to-face interviews, paper and pencil self-administered interviews, and audio computer-assisted self-interviewing (audio-CASI)—documented significant differences in reported rates of premarital sex across interview modes (Mensch et al. 2008), the analyses could not conclude a ranking of different methods in terms of measurement error. In particular, respondents reported twice as much sexual activity in the interviewer mode as in the audio-CASI mode, contradicting the hypotheses that interviewer-administrated survey question result in a underreporting of sexual behaviors.

2017, all variables are balanced at conventional statistical levels, including beliefs about HIV status and survival probabilities conditional on being HIV+ (columns 6 and 7 of Table 1). Our main analyses focus on the entire sample, but the appendix presents results with interaction of HIV status and treatment, as well as for HIV– individuals only.

4 Conceptual framework

We present a simple conceptual framework that highlights the interrelations between subjective expectations and sexual behaviors within a lifecycle framework similar to the one from Delavande and Kohler (2016). The periods and stages closely mirror the various the data collection steps and are presented in Figure 2.

4.1 Sexual behaviors, subjective expectations and mortality information

Consider an individual living for two periods. Before period 1, the individual is randomly allocated into a treatment or a control group. In period 1, divided in four stages, the individual is endowed with prior beliefs that may be updated upon receipt of new information (Stages I to III), and engages in sexual behavior a based on updated beliefs (Stage IV). For tractability we consider two levels of sexual behavior: safe sex (such as sex with spouse only) denoted by $a = 0$, and risky sex (such as sex with extra-marital partners in addition to spouse) denoted by $a = 1$. The individual enjoys utility $V(a)$ in period 1. In period 2, she makes no further decision and, if alive, enjoys a health-dependent utility equal to $U^- > 0$ if HIV- and $U^+ = U^- - c$, with $0 < c < U^-$, if HIV+.

At Baseline (*Stage* I *in period 1*), she is endowed with a set of individual-specific subjective expectations P_{I} about the following three aspects: **(1)** *Survival to the next period,* including (i) own survival S_{I}, and own survival S_{I}^{+} and S_{I}^{-} conditional on being HIV+ and HIV– respectively; and (ii) population survival S_{I}^{pop+} for HIV$^+$ individuals and S_{I}^{pop-} for HIV$^-$ individuals; **(2)** *HIV status*, the probability f_{I} of being currently infected with HIV; **(3)** *HIV transmission risks*, including (i) the probability $p_{\mathrm{I}}^{0}(\Pi_{\mathrm{I}})$ of contracting HIV associated with action $a = 0$. This probability depends on the probability Π_{I} of contracting HIV if having regular sex with an HIV+ partner (i.e., the technology of HIV transmission when holding the partner's HIV+ status constant), and the probability f_{I}^{s} that the spouse is infected with HIV. In particular, $p_{\mathrm{I}}^{0} = \Pi_{\mathrm{I}} \times f_{\mathrm{I}}^{s}$; (ii) the probability $p_{\mathrm{I}}^{1}(\Pi_{\mathrm{I}}, L_{\mathrm{I}}^{HIV})$ of contracting HIV associated with action $a = 1$, which is an increasing function of both the HIV transmission technology Π_{I} and the perceived local HIV prevalence L_{I}^{HIV}.

At the BenKnow Intervention Stage (*Stage* II *in period 1*), individuals in the treatment group T receive information about population mortality risk. This information may lead them to revise any of their baseline beliefs P_{I} to P_{II}^{T}. Taking HTC (*Stage* III *in period 1*) results into account, individuals' Stage III subjective expectations differ by both HIV test result and BenKnow treatment assignment.

Subsequent to HTC, the individual chooses her sexual behavior (*Stage* IV *in period 1*). Subjective expected lifetime utility at the end of Stage III depends on Stage III subjective expectations and the sexual behavior a, and is given by

$$V(a) + f_{\text{III}} S_{\text{III}}^{+} U^{+} + (1 - f_{\text{III}}) \left[(1 - p_{\text{III}}^{a}) \left(S_{\text{III}}^{-} U^{-} \right) + p_{\text{III}}^{a} \left(S^{+} U^{+} \right) \right]. \tag{1}$$

Within the above framework, risky sex may increase the direct pleasure from sex in period 1 but, by potentially increasing the subjective risk of becoming HIV+, it may also decrease the subjective probability of surviving into the future, and therefore of enjoying future period utility at all, while also decreasing the probability of enjoying U^{-} rather than U^{+}. The individual will choose risky sex $a = 1$ if and only if the subjective expected lifetime utility associated with risky sex is greater than that associated with safe sex, i.e.:

$$V(1) - V(0) > (1 - f_{\text{III}}) \left(p_{\text{III}}^{1}(\Pi_{\text{III}}, L_{\text{III}}^{HIV}) - p_{\text{III}}^{0}(\Pi_{\text{III}}) \right) \left((S_{\text{III}}^{-} - S_{\text{III}}^{+}) U^{-} + S_{\text{III}}^{+} c \right). \tag{2}$$

We maintain the assumptions that (a) the perceived HIV transmission risk associated with safe sex is smaller than that associated with risky sex (i.e. $p_{\text{III}}^{1}(\Pi_{\text{III}}, L_{\text{III}}^{HIV}) - p^{0}_{\text{III}}(\Pi_{\text{III}}) \geq 0$), and ($b$) the subjective survival conditional on being HIV- is larger than that conditional on being HIV+ ($S_{\text{III}}^{-} - S_{\text{III}}^{+} \geq 0$), to ensure that the right-hand-side of Eq. (2) is positive.

In *Period 2*, the individual makes no further decisions, but enjoys period 2 utility and revises her beliefs to P_2^T if in the treatment group and P_2^C if in the control group.

4.2 Predicted BenKnow treatment effects and hypotheses

We now discuss the potential impact of the BenKnow information treatment on subjective expectations and sexual behavior. The BenKnow treatment targeted population survival expectations, knowledge of which is likely to be an important input in the formation of both own survival risk and perceived local HIV prevalence. As seen in Section 4.1, these two expectations are relevant for the decision to engage in risk sex.

4.2.1 Subjective Expectations

We measure the expectations P_{I} in stage I of period 1 (baseline), and P_2 in period 2 (follow-up) (see Figure 2). With the exceptions of own survival expectations S_{III} measured by the HTC team, the other expectations P_{III} are not observed. Given this timing and potential feedbacks from behavior on beliefs, it is useful to consider two classes of expectations to conceptualize the effect of the information treatment.

(1) Expectations about outcomes for which an individual has *no* control (population survival, local HIV prevalence, HIV transmission risk condional on behavior). For this class, the difference between P_{III}^{T} and P_{III}^{C} will be the same as the difference between P_2^T and P_2^C and driven by the BenKnow information only.

(2) Expectations about outcomes for which individuals have *some* control through their behaviors (own survival expectations, the probability of being HIV$^+$, which may be shaped by sexual behavior). For this class, the difference between P_2^T and P_2^C is driven by both the BenKnow information and choices that took place after the BenKnow intervention (e.g., risky sex) that may differ by treatment status. Importantly, the extra measurement S_{III} enables us to identify the treatment effects on own survival expectation driven by the BenKnow information only.[14]

Our analyses focus on several specific hypotheses that we can test with our data:

a) Revision of expectations targeted by the BenKnow information only: The BenKnow treatment provided information on population survival emphasizing gains for both HIV+ and HIV- individuals. Because population survival expectations are underestimated on average at baseline, we expect a positive treatment effect on population survival expectations for HIV$^-$ individuals S_{III}^{pop-} and for HIV+ individuals S_{III}^{pop+}, and thus a positive treatment effect on S_2^{pop-} and S_2^{pop+} (**Hypothesis 1**).

b) Revision of other expectations from the BenKnow information only: We anticipate population survival expectations to be an important input for other individual-specific health risks. As such, the treatment effect on population survival expectations is likely to have trickle down effect for other expectations.

First, we anticipate a positive treatment effect on own survival expectations S_{III} (**Hypothesis-2a**). Such an increase would take place if individuals perceive a positive correlation between population survival S_{III}^{pop-} and S_{III}^{pop+} and own survival S_{III}^{-} and S_{III}^{+}, and use own survival expectations conditional on HIV status to form overall survival expectations (e.g., in a Bayesian setting, $S_{\text{III}} = (1 - f_{\text{III}})\, S_{\text{III}}^{-} + f_{\text{III}} S_{\text{III}}^{+}$).

Second, we anticipate a positive treatment effect on the subjective local HIV prevalence L_{III}^{HIV}, leading to a positive treatment effect on the subjective pobability of contracting HIV if one has extra-marital partners $p_{\text{III}}^{1}\left(\Pi_{\text{III}}, L_{\text{III}}^{HIV}\right)$ and thus $p_2^1(\Pi_2, L_2^{HIV})$ (**Hypothesis 3**). The increase in the local HIV prevalence would be driven by the increase in S_{III}^{pop+}, which implies that HIV+ persons are not dying so fast upon infection and remain in the pool of sexual partners for longer. Theoretically, as long as the percentage increase in S_{III}^{pop+} is larger than the percentage increase in S_{III}^{pop-}, or if they both increase by the same value in percentage point (since $S_{\text{III}}^{pop+} < S_{\text{III}}^{pop-}$), the local HIV prevalence L_{III}^{HIV} increases.[15]

c) Revision of expectations from the BenKnow information and feedback from behavior: If the intervention reduced risky sexual behavior (see discussion below), we expect a positive

[14] Because the HTC and baseline were separated by less than two weeks, it is reasonable to assume that there are not (yet) feedbacks from individual behavior on own survival expectations.

[15] Suppose that we start in period 0 with a population of n HIV+ individuals and a population of healthy individuals standardized to 1. In the following period, assuming for simplicity no births and no new HIV infections, the proportion of HIV+ individuals in the population will be $L^{HIV} = \frac{nS^+}{nS^+ + S^-} = \frac{1}{1+\frac{S^-}{nS^+}}$. Assuming a percentage increase of $S^-$by α^-, and a percentage increase of $S^+$by α^+, the new proportion of HIV+ individuals will be $L^{HIV}(\alpha^-, \alpha^+) = \frac{1}{1+\frac{S^-(1+\alpha^-)}{nS^+(1+\alpha^+)}}$. We have that $L^{HIV}(\alpha^-, \alpha^+) > L^{HIV}$ if $\alpha^- < \alpha^+$.

treatment effect on own survival expectations S_2 in the long-run (**Hypothesis 2b**), and a negative treatment effect on the probability f_2 of being HIV+ (**Hypothesis 4**).

4.2.2 Sexual behavior

We anticipate overall a negative BenKnow treatment effect on the propensity to engage in risky sex (**Hypothesis 5**). The above BenKnow treatment effects on subjective expectations will be crucial for our ability to identify the mechanism(s) underlying changes in sexual behaviors, and we focus in particular on two potential pathways:

a) Improvement in own survival expectations: A positive treatment effect in own survival expectations S_{III} (**Hypothesis 2a**) driven by a joint increase in S^-_{III} and S^+_{III} that leaves the relative mortality risk $(S^-_{\text{III}} - S^+_{\text{III}})$ unchanged increases the right-hand-side of Eq. (2), reducing the propensity for risky sex. Intuitively, a general improvement in own non-HIV and HIV survival risk increases the weight of future utility, and hence the benefits from safe sex (e.g. Becker, 1993). Although less likely because the intervention emphasized a variety of factors driving the gains in survival, it is still possible to have a joint increase in S^-_{III} and S^+_{III} leading to a rise in the relative survival risk $(S^-_{\text{III}} - S^+_{\text{III}})$. This would also increase the right-hand-side of Eq. (2) and promote safe sex practice. Intuitively, an increase in the relative survival risk by HIV status makes contracting HIV more costly in terms of mortality (Philipson and Posner 1995, 1993).[16]

b) Increase in the HIV risk with multiple partners: A positive treatment effect on the transmission risk associated with having multiple partners $p^1_{\text{III}}(\Pi_{\text{III}}, L^{HIV}_{\text{III}})$ (**Hypothesis 3**) would increase the right-hand-side of Eq. (2), reducing the propensity to engage in risky sex. Intuitively, an increase in the subjective risk of becoming HIV+ associated with the risky sex action makes it less appealing.

Note that, for illustration purposes, our model in Section 4.1 abstracts from partnership formation. We discuss some examples showing that the effect of the BenKnow treatment on partnership formation is ambiguous. For single individuals, marriage may be perceived as a HIV risk-reduction strategy (Greenwood et al. 2017), and the BenKnow intervention may thus encourage it. For an individual married to an unfaithful spouse, having sex with spouse only might be risky. As a result of BenKnow, she may seek to adopt a safer behavior such as abstinence, which can occur within marriage or by divorcing the current spouse, or selecting a safer partner, by divorcing the current spouse and re-marrying a low risk spouse. The BenKnow intervention may however conversely lead her to believe that her spouse will no longer be unfaithful due to the increased risk of extra-marital sex, making sex with spouse only actually safer. Other considerations may also be relevant. For example, higher survival rates of potential or current spouses increase the benefits of marriage.

[16] More generally, assuming an α^- percentage increase for S^-, and an α^+ percentage increase of S^+, the right-hand-side of (2) will increase if $\alpha^- S^- U^- > \alpha^+ S^+ U^+$.

5 Results

We initially analyze the effects of the BenKnow intervention on subjective expectations (Section 5.1), and subsequently show that these revisions of subjective expectations had significant negative effects on risky sexual behavior (Section 5.2).

5.1 BenKnow treatment effect on subjective expectations

Our analyses for the BenKnow treatment effect on subjective expectations are specified as follows: Let $\Delta y_{ij} = y_{ij(2018)} - y_{ij(2017)}$ be the revisions of expectation y between follow-up and baseline for individual i in village j. We estimate

$$\Delta y_{ij} = \beta_0 + \beta T_j + \sum_{s=1}^{S} \tau_s I_{j\in s} + X_{ij}\gamma + \varepsilon_{ij} \tag{3}$$

where T_j is a dummy that equals 1 if village j is in the BenKnow treatment group and 0 otherwise, and β is the BenKnow treatment effect. The model also includes a vector of observed predetermined individual characteristics X_{ij} (age group, gender and years of schooling),[17] and fixed effects for the randomization strata s (within-region village pairs) (Bruhn and McKenzie 2009), where τ_s denotes strata fixed effects, $I_{j\epsilon s}$ is an indicator for whether village j is in strata s, and S is the total number of strata. Because the strata s are within the three MLSFH study regions, the strata dummies also control for all region-specific differences. Standard errors are clustered at the level of the randomization, i.e., at the village level.

a) Population survival: We start by testing whether the BenKnow treatment had a positive effect on population survival expectations (Hypothesis 1). Table 2 documents a positive, sustained and statistically significant BenKnow treatment effect on the 2018 population-level survival probabilities for individuals who are healthy, are HIV+ or are sick with AIDS and on ART (columns 1, 2 and 4). In the treatment group, all of these subjective population-level survival probabilities increase by approximately 4 percentage points, displaying a 6.1% increase relative to the baseline survival probabilities for healthy, 6.6% for HIV+, and 7.1% for sick with AIDS and on ART. There is no treatment effect on the perceived survival of individuals who are sick with AIDS (not on ART), consistent with the fact that the BenKnow intervention videos emphasized the contributions of ART to recent increases in life expectancy. These results are important and suggest that respondents were able to understand and retain the information provided to them.

Somewhat surprisingly, there is no significant treatment effect on the subjective population-level survival probability unconditional on any particular health status (Column 5 in Table 2). A potential explanation for this result is that respondents understand that if more

[17] The age-group dummies correspond to the same 5-year age groups that were used in BenKnow for to provide age- and gender-specific life table survival information.

Table 2: **BenKnow treatment effects on survival expectations**

	Population Survival Probabilities:					Own Surv. Prob.	
	Conditional Prob. of surviving for individuals who are				Unconditional Surv. Prob.	Revision	
	Healthy	HIV+	Sick with AIDS	Sick with AIDS and on ART	(no health status specified)	Long	Short
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BenKnow treatment effect	0.043 (0.011)	0.041 (0.013)	0.017 (0.016)	0.035 (0.014)	-0.012 (0.011)	0.004 (0.014)	0.016 (0.013)
Observations	1,382	1,382	1,382	1,382	1,382	1,375	1,388
Mean	0.654	0.537	0.367	0.567	0.657	0.615	0.665

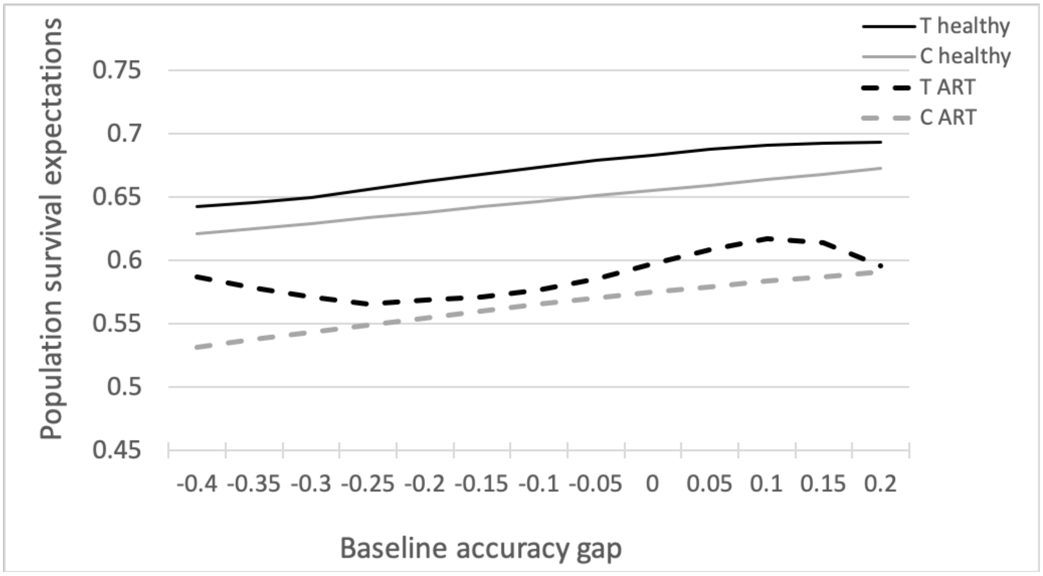
Notes: The table shows the coefficient of the Benknow Treatment effect on the updating of survival expectations from baseline to the 2018 follow-up. The first five subjective survival probabilities are based on questions about hypothetical individuals, of the same age and gender as the respondent, with the specified health status; see Section 3.3 for additional detail. The last two columns refer to 5 year own survival. Long refers to the updating from baseline to follow-up while Short refers to the update from baseline to the HTC stage. All analyses additionally control for age group, gender, years of schooling and randomization strata. Standard errors are clustered at the village level. Standard errors are clustered at the village level. Mean is the mean of the 2018 (follow-up) expectations.

HIV+ individuals survive, the HIV prevalence increases, which potentially compensates for the gains in overall population survival as long as there is differential survival between HIV– and HIV+ individuals, as is the case in our sample: Table 1 shows an average 8 percentage-point advantage of being healthy in terms of 5-year survival compared to being HIV+.[18]

The average treatment effect presented in Table 2 potentially combines a mixture of upward revisions among respondents whose prior beliefs were below the new statistical information, downward revisions among respondents whose prior beliefs were above the new statistical information and no revisions among respondents whose prior beliefs were very similar to the new statistical information. We therefore investigate whether there are heterogeneous treatment effects depending on the *accuracy* of prior beliefs, i.e., the accuracy gap = baseline unconditional subjective population survival minus objective population survival probability presented in the statistical information. A negative (positive) gap reflects an underestimation (overestimation) of prior beliefs relative to the objective measure. Figure 3 displays the results of simple non-parametric estimates of the mean follow-up population survival expectations conditional on the baseline accuracy gap (conducted separately for the treatment and the control group). Importantly, the posterior

[18] To illustrate the possibility of no change in unconditional population-level survival probability as a result of differential survival of HIV+ and HIV– individuals and corresponding changes in HIV prevalence, let $S^{pop} = p_{HIV}S^{pop+} + (1 - p_{HIV})\, S^{pop-}$ where S^{pop} is the survival expectations in the population and p_{HIV} is the expectations about the HIV prevalence. An increase in p_{HIV}, S^{pop+} and S^{pop-} may result in no increase in S^{pop}.

Figure 3: Population survival expectations at follow-up by baseline accuracy of the prior



Notes: The graph shows nonparametric estimates of the 2018 mean population survival using an Epanechnikov kernel function with a cross-validated optimal bandwidth. T (C) healthy refers to the survival expectations for healthy individuals in the treated (control) group. T (C) ART refers to the survival expectations for individuals sick with AIDS and on ART in the treated (control) group. Baseline accuracy gap is defined as the difference between prior survival expectations unconditional on health status and the objective survival rates used in the BenKnow intervention.

mean expectations of the treatment group is larger than that of the control group for *all* values of the baseline accuracy gap, implying a general upward revision of population survival risk among treated individuals irrespective of their prior accuracy. This is the case for the survival of individuals who are healthy, sick with AIDS on ART (Figure 3) and HIV+ (not shown). We test this result in a regression setting with all our usual controls in Table C.3 where we add to our main specification: (*i*) an interaction between treatment and an indicator for the intervention revealing "good news," i.e., a negative gap (odd columns); and (*ii*) an interaction between the treatment and the gap (even columns). These interaction terms are never precisely estimated, which confirms that the BenKnow treatment effects are not systematically different according to prior accuracy or to whether the BenKnow life-table information provided "good" or "bad" news. These findings suggest that the overall narrative of the BenKnow intervention about changing survival patterns in Malawi had more impact on individual's revision of population survival expectations than the numeric life-table information about age- and gender-specific survival probabilities.

b) Own survival: We now test whether the BenKnow treatment had a positive effect on own survival expectations (Hypotheses 2a and 2b). Column 6 of Table 2 shows the BenKnow treatment effect on the revisions to own survival expections between 2017 and 2018 for the 5-year time horizon. This is the analog of the treatment effect on population survival probabilities since the variables are measured at the same waves and refer to the same survival horizon. Importantly, there is *no effect* of the intervention on own survival expectations with a coefficient precisely estimated at zero (treatment effect for own survival is 0.004 (0.014) as opposed to 0.043 (0.011) for healthy population survival). We find similarly no treatment effect on the 10-year own survival expectations (Table C.4). Interactions of treatment with HIV status do not show statistically significant differences in revision (Table C.4).[19] There is also no treatment effect for respondent's expected age at death and their expected remaining life years (results not shown).

As discussed in our conceptual framework (Section 4), own survival expectations measured one year after the intervention may be influenced by both the BenKnow information and feedback effect from own behavior. The negative treatment effect on risky sex (Section 5.2) should have magnified the positive effect of the BenKnow intervention on own survival. Indeed, consistent with this behavioral change and as specified in Hypothesis 4, we do find a negative and precisely estimated treatment effect about the chance of being infected with HIV (Column 1 in Table 3) from baseline to the 2018 follow-up.[20] As of 2018, however, these revisions in the subjective probability of being HIV+ have not yet translated into gains in expected survival.

To gain a better understanding in the process through which respondents update own survival expectations in response to BenKnow, we can further leverage the expectations measured approximately two weeks after the BenKnow intervention. Within this short period, it is very unlikely that any feedback effect from behavior on own survival beliefs has occurred, so the treatment effect on short-run revisions of survival expectations identifies the effect of the BenKnow information only. Similar to the findings for the long-run revisions of survival expectations measured in 2018, the last column in Table 2 reveals no treatment effect. BenKnow neither affected short-run nor long-run revisions of own survival expectations. Our results are therefore not consistent with Hypotheses 2a and 2b.

This limited effect of the intervention on own survival expectations is puzzling, especially when contrasted with the sustained revisions of population survival expectations. We investigate the possible underlying reasons by looking at three different sources of heterogeneity for both the short and long-run revisions. First, we investigate whether there are heterogeneous treatment effects depending on the *accuracy of prior beliefs*, as we have done for population survival expectations. Individuals with downward-biased priors might update upward while individuals with upward-biased priors might update downward, resulting in a close to zero average treatment effect. However, Table C.5 shows no heterogeneous effect by prior accuracy or by receiving good news. A second explanation focuses on heterogeneity due to the *relevance* of information. The information we provided may be less relevant to the own survival expectations of people who feel they are different

[19]The interaction with HIV status is positive and large but the small sample size of HIV+ individuals do not provide sufficient statistical power to find significant differences in updating.

[20]The magnitude is of 4.2 percentage point, or 23% of baseline belief. We do not find statistically significant differences in the treatment effect between those tested HIV+ or HIV- (Table C.7). Similarly, Delavande and Kohler (2012) and Thornton (2008) find that learning about HIV status had limited effect on beliefs about HIV status among HIV+ individuals.

from the general population. However, even when restricting our sample for whom the information is likely to be relevant (e.g., the initial difference between own and population survival is small enough),[21] we still do not find a positive treatment effect (Table C.6).

The third explanation is related to the extent of *private information* about own survival. Individuals with more private information should have tighter priors about their own survival and any new information would lead to only limited updating. Unfortunately, we do not have direct measurement of private information or the tightness of the prior. We nevertheless take advantage of the panel aspect of the data to construct a proxy. We hypothetize that individuals who repeatedly report survival probabilities equal to 0 or 1 during 2006–17 have more private knowledge about their health,[22] and therefore construct a binary indicator for reporting extreme beliefs (0 or 1) at least half of the time in the past waves of the MLSFH either for the 5-year or 10-year survival (individuals with less than 3 observations are excluded). When looking at the treatment effects excluding the 20% of the sample who have "private information" according to this definition (Table C.6), we identify a precisely estimated treatment effect of 4 percentage points for the 10-year time horizon. The point estimates are positive, albeit smaller in magnitude and not statistically significant, for the 5-year time horizon. We acknowledge that this indicator is crude but interpret these results as suggestive evidence of the importance of private information in the lack of updating of own survival expectations.

c) HIV transmission risk: We now test whether the BenKnow treatment has a positive effect on the subjective probability of contracting HIV associated with having multiple partners (Hypothesis 3). Because HIV transmission risk expectations were not elicited in the 2012 and 2017 MLSFH mature adult surveys, these analyses use 2010 expectations as baseline. Column 4 in Table 3 documents a positive and precisely estimated treatment effect on the subjective probability that one would become HIV+ when having multiple sex partners. The magnitude of the treatment effect is 5 percentage point, or 6.5% of the average baseline beliefs.[23] There is however no treatment effect on the subjective probability Π of contracting HIV if married to a HIV+ spouse (Column 3 in Table 3). This suggests that there has been no change in the perception of the "technology of transmission of HIV" when holding constant the partner's HIV status.[24] Indeed, we did not anticipate the infor-

[21] To directly compare own and population survival, we construct a baseline population survival as follows: $(1 - f_I)\, S_I^{pop-} + f_I S_I^{pop+}$, i.e. we fix the HIV prevalence in the population to the respondent's subjective risk of being HIV+.

[22] For example, a terminally ill respondent is likely to report a zero chance of survival in 5 or 10 years and is unlikely to move her prior based on the BenKnow information.

[23] Note that the 2010 subjective transmission risks are not well balanced between treatment and control groups (Table C.8). We therefore assess the robustness of the main results in the paper in two different specifications that ensure balance of the 2010 subjective transmission risks. First we drop a village pair that cause most of the imbalance (Table C.8). Second, we reweight the sample using entropy weights to balance the sample on transmission risk. In both cases, the treatment effects on expectations and sexual behavior are very similar to the ones from our current specification (Table C.9).

[24] Derksen and van Oosterhout (2019) show that individuals in Malawi are relatively uninformed about the consequences of ART on viral load and its associated reduction in HIV transmission risk. Similar results are

Table 3: BenKnow treatment effect on expectations about HIV status and HIV transmission risk conditional on sexual behaviors

	Probability of being HIV+		Prob. of HIV infection if sex with		
	own (1)	spouse (2)	HIV+ partner (3)	multiple partners (4)	$p^1 - p^0$ (5)
BenKnow treatment effect	-0.042 (0.013)	-0.023 (0.018)	0.017 (0.020)	0.048 (0.016)	0.053 (0.016)
Observations	1454	1240	1417	1418	1298
Mean	0.196	0.206	0.505	0.565	0.474

Notes: The table shows regression coefficients for the BenKnow treatment effect on the updating of beliefs from baseline to the 2018 follow-up. Probability of being HIV+ is the updating from 2017 to 2018 in the subjective probability of being currently HIV+ for the respondent (own) and the spouse. HIV+ partner is the update from 2010 MLSFH survey to 2018 in the probability of becoming infected with HIV when having sex with an HIV+ spouse over a year. Multiple partners is the updating from 2010 MLSFH survey to 2018 in the probability of becoming infected with HIV when having sex with multiple partners over a year. $p^1 - p^0$ is the updating in the difference in the probability of becoming infected with HIV when having multiple sex partner and having sex with spouse only. $p^0 = f^s\Pi$ is the product of the probability of the spouse being HIV+ at baseline and the transmission risk of having sex with an HIV+ partner. All analyses additionally control for age group, gender, years of schooling and randomization strata. Standard errors are clustered at the village level. Mean is the mean of the 2018 (follow-up) expectations.

mation on population survival to lead to revision about Π. Moreover, the treatment effect on the probability of the spouse being HIV+ is negative but not statistically significant (column 2). Consistent with these, there is negative treatment effect on $p^1(\Pi, L^{HIV}) - p^0(\Pi)$ (column 5 of Table 3), which is what is relevant for behavior as emphasized in our theoretical framework.[25]

Because the HIV risk associated with having multiple partners $p^1(\Pi, L^{HIV})$ is an increasing function of both the HIV transmission technology Π and the local HIV prevalence L^{HIV}, the positive treatment effect on $p^1(\Pi, L^{HIV})$ combined with no treatment effect on Π suggests that, as hypothesised in section 4, individuals perceive that the pool of potential sexual partners includes more HIV+ individuals, or has become "riskier." Unfortunately, we do not have data on perceived local HIV prevalence in 2017 and 2018 to directly test this hypothesis. But the treatment effects on population survival expectations suggest that it is likely to be the case. As discussed in the conceptual framework, a larger relative increase in the survival of HIV+ compared to HIV$-$ implies an increase in the HIV prevalence. We observe such a larger relative increase in Table 2, regardless of whether individuals use the survival of HIV+ or the survival of individual sick with AIDS and on ART.[26] This relative increase may even be larger if individuals believe that the gains in survival for HIV+ are larger than that for HIV- among younger cohorts, where their sex partners also belong,

found from studies in South Africa, even among younger and more educated populations (Bor et al. 2018).

[25]Our theoretical framework emphasizes that it is the relative transmission risk between risky and safe sex $(p^1 - p^0)$ that matters for behavior. We construct as $p^0 = f^s \times \Pi$, where f^s is the probability of the spouse being HIV+ at baseline and Π is the transmission risk of having sex with an HIV+ partner.

[26]Respondents may correctly infer from the BenKnow videos that gains in survival for HIV+ individuals followed from the expansion of ART which now covers the majority of individuals sick with AIDS.

as younger persons are less affected by non-HIV-related morbidity. Finally, the increase in the survival of HIV+ persons might simply be particularly salient to respondents who may link it to HIV prevalence, due to availability bias (Tversky and Kahneman 1973) or the tendency to overestimate the probability of negative events (Harris, Corner and Hahn 2009).

5.2 Sexual behaviors

In this section we investigate whether the above change in perceived transmission risk led to changes in sexual behavior. The Sexual Risk Indices 1–3 (SRI1–SRI3; see Section 3.3) are our primary categorical outcome variables for identifying BenKnow effects on sexual behaviors. Specifically, we estimate an ordered probit model for the 2018 Sexual Risk Index $a_{ij(2018)}$ for individual i in village j as

$$P(a_{ij(2018)}) = \Phi\left(\beta T_j + \sum_k \delta_k a^k_{ij(2017)} + X_{ij}\gamma + \sum_{s=1}^{S} \tau_s I_{j\epsilon s}\right), \tag{4}$$

where, as in our previous analyses, T_j is a dummy equal to 1 if village j is assigned to the BenKnow treatment group, τ_s are strata fixed effects, $I_{j\epsilon s}$ is an indicator for whether village j is in strata s and S is the total number of strata and X_{ij} include individual baseline characteristics. The model also includes dummies $a^k_{ij(2017)}$ for each category k of the 2017 sexual risk index to control for baseline sexual behaviors. Standard errors are clustered at the village level.

We show additional results for pregnancy and marriage. For these binary outcomes, we use linear probability models in a specification similar to equation (4). For marriage, we control for baseline marital status but we do not have a baseline for pregnancy.

Panel A in Table 4 reveals a key policy result: the BenKnow health-information intervention significantly reduced the propensity to engage in risky sexual behavior across all three indices of risky sex (SRI1–SRI3), as is evidenced by a negative and precisely estimated treatment effect. To better assess the magnitude of the effect, Panel B of Table 4 provides the predicted probabilities of sexual risk taking based on Panel A, Column 3. It shows that the intervention had a large impact on risky sex, and that it was effective at changing behavior both at the extensive margin (being sexually active) and intensive margin (number of partners and condom use). For example, the predicted probability of having multiple partners with no condom is 7.6% in the control group and 6.4% in the treatment group, a reduction of 1.2 percentage points or 19%. Similarly, the predicted probability of not having sex is 33.3% in the control group and 36.1% in the treatment group, an increase of 3 percentage point or 8%. Focusing on HIV– respondents, we get a 12% reduction in the predicted probability of having multiple partners with no condom and a 7% increase in abstinence (Table C.10).

Table 4: Predicted probabilities of sexual risk taking, by BenKnow assignment

Panel A: Treatment Effects			
	Sexual Risk Index (SRI)		
	Had sex	**Number of partners (0,1,2+)**	**Sex and condom (no sex, 1 partner, 2+ w/ condom, 2+ w/o condom)**
	(1)	(2)	(3)
BenKnow treatment effect	-0.140	-0.156	-0.159
	(0.067)	(0.057)	(0.056)
Observations	1,479	1,479	1,479

Panel B: Predicted Probabilities			
	BenKnow Assignment		
	Control	Treatment	Difference
No sex	.333	.361	.028
Single partner	.579	.564	-.015
Multiple partners with condom	.013	.011	-.002
Multiple partners without condom	.076	.064	-.012

Notes: Panel A shows the coefficient of the BenKnow treatment effect using the ordered probit specification in Eq. (4). Sexual Risk Indices are defined as: Had Sex: 0 = not sexually active in the last 12 months, 1 = sexually active in the last 12 months; Number of Partners: 0 = not sexually active in the last 12 months, 1 = sex with spouse only, 2 = sex with multiple partners; Sex and Condom: 0 = not sexually active in the last 12 months, 1 = sex with spouse only, 2 = sex with multiple partners and condom at last intercourse, 3 = sex with multiple partners and no condom at last intercourse. Predicted probabilities in Panel B for each of the four categories are based on column (3) of Panel A. All analyses additionally control for age group, gender, years of schooling and randomization strata. Standard errors are clustered at the village level.

Splitting the sample by gender (Table C.10) reveals that while men act on both margins as a response to treatment, women only adjust their extensive margin: The BenKnow intervention reduced the average predicted probability of having multiple partners by 3.4 percentage points for men and 0.4 points for women. There are no significant interactions of the treatment effect with HIV status (Table C.11, bearing in mind that the number of HIV+ respondents in our sample is small). Our main results hold even if we exclude polygamous men, which constitute 6.7% of our sample (Table C.12).

5.2.1 Misreporting in sexual behavior

Misreporting of sexual behavior is a possible concern for the interpretation of our key findings on sexual risk taking. To evaluate the robustness of our results to misreporting, we follow Hausman, Abrevaya and Scott-Morton (1998) to correct for misclassification error in a binary choice model (i.e. when a response is reported in the wrong category). This strategy was adopted in a similar context by De Paula, Shapira and Todd (2014) and Delavande and Kohler (2016). We assume that individuals report truthfully when they engage in safe sex practices and that there is a constant probability α_1 of misreporting safe sex when engaging in risky sex. This probability α_1 is estimated together with the other coefficients of the model.[27] We conduct separate analyses for two different binary indicators of risky sex: (i) being sexually active and (ii) having multiple partners. Our results are reported in Table C.13. Column 2 shows the treatment effect on being sexually active under the assumption that individuals misreport about being sexually active, while Column 4 presents the results for having multiple sex partners under the assumption that individuals misreport about multiple sex partners.[28] Both specifications show a negative treatment effect, statistically significant at the 10% level. The magnitude of the BenKnow effect is larger than in the same specification without misreporting (shown in Columns 1 and 3), suggesting that misreporting leads to a downward bias of the treatment effect. Based on this model, we find a predicted probability of misreporting of having multiple partners of 9.4%.

5.2.2 Pregnancies

Our key finding about the BenKnow treatment effect on sexual behaviors is further corroborated by using an objective measure of sexual activity: pregnancies. MLSFH mature adults, i.e., the population to whom BenKnow intervention was targeted, are generally too old to become pregnant. Instead, our robustness tests based on pregnancy outcomes focuses on younger members of the MLSFH cohort who have been interviewed in 2019 (one year after the 2018 MLSFH-MAC follow-up on which our primary results are based).[29]

The primary mechanism allowing us to identify BenKnow treatment effects on pregnancies among female MLSFH respondents younger than 45 years (and who were therefore not eligible for enrollment in the BenKnow study) is as follows: if MLSFH mature adults have sex with younger spouses or partners in their villages, as a substantial fraction in all likelihood does, then changes in sexual behaviors among mature adults in response to BenKnow can potentially reduce pregnancy risks among women $<$ 45 years old. Specifically, since only 2 years have passed between the 2017 BenKnow intervention and the 2019 MLSFH survey, we expect a negative treatment effect on being pregnant in 2019 or having a baby less than a year old, while there should not be any treatment effect on having an infant who is 1 year or older.

[27] We estimate the model with Maximum Likelihood and find the coefficients to minimize the objective function: $L(\alpha_1, b) = \frac{1}{n}\sum_{i=1}^{n} y_i ln((1-\alpha_1)\Theta(x_i'b) + (1-y_i)ln(\alpha_1\Theta(x_i'b))$. This is a modification of the Maximum Likelihood of a probit with the added misreporting probability α_1.

[28] For having sex, the set of controls include gender, age, schooling and village pair fixed effects. For multiple partners, we substitute pair effects with region fixed effects. Standard errors are always clustered at the village level.

[29] The 2019 sample includes respondents less than 45 years old, plus some older respondents that were excluded from the original mature adults sample because they did not meet the MLSFH-MAC eligibility criteria of having completed both the 2008 and 2010 MLSFH surveys; see Kohler et al. (forthcoming) for additional details.

Table 5: BenKnow treatment effects on pregnancies or recent births among women aged < 45 years

	Respondent is pregnant or has baby aged $<$ 1 year (1)	Respondent has infant aged 1–2 years (2)	Respondent has infant aged 3–4 years (3)
BenKnow treatment effect	-0.037 (0.016)	0.023 (0.023)	-0.001 (0.021)
Observations	1022	1022	1022
Mean	0.158	0.163	0.194

Notes: The table shows regression coefficients for the BenKnow treatment effect on births and pregnancies using an OLS specification. The sample includes all women in reproductive age (<45) who participated in the 2019 MLSFH survey. The dependent variable in column 1 is a dummy for being currently pregnant or having a baby less than 1 year old at the time of the interview in the 2019 MLSFH survey. Dependent variables in columns 2 and 3 are dummy variables for having a baby of the specified age range. All analyses additionally control for age group, years of schooling and randomization strata. Standard errors are clustered at the village level. The mean of each dependent variable is shown at the bottom of the table.

Table 6: BenKnow treatment effects on marriage

	Being married in 2018			Divorced in 2018
	(1)	(2)	(3)	(4)
BenKnow treatment effect	0.016 (0.007)	0.069 (0.018)	-0.003 (0.007)	0.003 (0.005)
Sample	All	Not married in 2017	Married in 2017	Married in 2017
Observations	1,479	389	1,087	1,087
Mean	0.731	0.069	0.971	0.017

Notes: The table shows regression coefficients for the BenKnow treatment effect on the likelihood of being married. Estimates are based on a linear probability model. Outcome variable $y_{ij(2018)}$ is being married (yes/no) in 2018, controlling for marital status (married yes/now) $y_{ij(2017)}$ in 2017. Divorced includes divorced and separations. All analyses additionally control for age group, years of schooling and randomization strata. Standard errors are clustered at the village level. The mean of each dependent variable is shown at the bottom of the table.

Our results from a linear probability model in Table 5 confirm this hypothesis and provide additional support for the robustness of key results on sexual risk taking. Specifically, Column 1 shows the treatment effect on being currently pregnant or having a baby less than a year old for women in the 2019 survey and displays a precisely estimated negative treatment effects of 3.7 percentage points. Reassuringly, we do not find any significant treatment effects for infants 1–2 years or 3–4 years old (Columns 2 and 3).

5.2.3 Marriage

As discussed in Section 4, it is possible that the BenKnow intervention affected marriage rates during 2017–18. Column 1 of Table 6 shows a positive BenKnow treatment effect of 1.6 percentage points on the probability of being married in 2018 controlling for 2017 marital status. Splitting the sample according to 2017 marital status shows that the results is entirely driven by transition into marriages for unmarried respondents (Columns 2 and 3). Indeed, there is no effect on being divorced in 2018 for those who were married in 2017 (Column 4).[30] If we look at sexual activity by marital status, we see fewer singles having sex in the treatment group, and more abstinence within and outside marriage (Table C.15). In addition to its substantive relevance, the positive BenKnow treatment effect on marriage is another potential robustness check of our main result on self-reported sexual behavior, as marriage is unlikely to suffer from reporting bias and respondents are likely to perceive marriage as a HIV-risk reduction strategy.

5.3 Discussion, Interpretation and Other Outcomes

The in-depth analysis of the BenKnow treatment effects on subjective expectations in Section 5.1 allow us to understand the mechanisms that lead individuals to adopt safer sexual behavior. As anticipated, we find a positive treatment effect on population survival expectations (Hypothesis 1). In contrast, our results do not support the hypothesis that this led to an improvement in own survival expectations (Hypotheses 2a and 2b), and as an implication, the negative treatment effect on risky sex cannot be driven by an overall improvement in own survival expectations.

Instead of a confirmation of Hypotheses 2a+b, we find a positive treatment effect on the HIV transmission risk associated with risky sex (Hypothesis 3). This transmission risk was not directly targeted by the intervention, and despite being already over-estimated prior to the BenKnow intervention (Delavande and Kohler 2016), it was further heightened by the BenKnow health information. The increase in the perceived transmission risk of risky sex is also consistent with the positive treatment effect of the survival expectations of HIV+ vs. HIV– individuals (Hypothesis 1), as this effect on survival makes the pool of sexual partners more likely to include HIV+ individuals.

An important conclusion from our analysis, made possible only by the availability of expectations data, is therefore that the reduction in risky sex caused by the BenKnow intervention is driven by the increase in perceived transmission risk associated with having multiple partners. The positive treatment effect on marriage, which is concentrated among unmarried individuals, is also consistent with an increase in the risk among the pool of partners, as marriage may be a risk-reduction strategy for unmarried individuals

[30] Moreover, analyses by gender reveals that the treatment effects results come from single women getting married, where our sample included very few unmarried men in 2017 whose marriage transitions could be affected by the BenKnow intervention (Table C.14).

who want to commit to a faithful relationship with a low-risk partner.

In light of these findings on population survival expectations and risky sexual behaviors, one might wonder whether the BenKnow intervention had broader effects on well-being or other life-cycle behaviors. Importantly, we do *not* find any treatment effect on subjective well-being, and scores of physical and mental health (Table C.16), suggesting that safer sexual activity did not reduce respondents' well-being in the short/medium term (1 year). We also find no effect on the frequency of sex conditional on having sex (table not shown). In contrast, we do find evidence that the BenKnow intervention increased some forward-looking life-cycle behaviors, such as savings and investments (Table C.16), which can benefit other household members. Future follow-ups are necessary to show if the BenKnow intervention had long-term well-being implications.

Finally, it is useful to compare the magnitudes of our treatment effects to other studies that examine somewhat comparable outcomes, although samples will always be different. When Delavande and Kohler (2016) simulate an information campaign on mortality risk on the whole MLSFH sample, they find that under the assumption that revised beliefs would be the weighted average of prior beliefs and the provided information, the average predicted probability of having multiple partners would decrease by 3.5 percentage points for men and 0.3 points for women, which is nearly identical to the present findings. Godlonton, Munthali and Thornton (2016) estimates the effect of receiving information about the partial protection of male circumcision against HIV transmission risk among a sample of young men (average age=32) in Malawi. They find essentially no effect among circumcised men, and safer sex practices among uncircumcised men measured one year after the intervention (for example, a 26% reduction in sex acts per month, a 17% decrease in number of partners, a 65% increase in condom use, but no effect on abstinence). Our intervention led to a 22% decrease in the propensity to have multiple partners among males (using result from Table C.10), and a 6% reduction in the number of partners if we use an OLS specification similar to Godlonton, Munthali and Thornton (2016).[31] The age difference between the sample might explain the difference on the effect of abstinence (8% decrease in abstinence in the last year in our study). Kerwin (2018) focuses on an intervention providing information about the (mostly overestimated) HIV transmission risk from unprotected sex with an infected partner in Malawi among younger respondents (average age=29). About one month after the information provision, he finds an average increase of 10% for having sex in the last week, although his results point to heterogeneity in behavioral response and evidence of fatalism among respondents who held high prior beliefs. Regarding pregnancy, Dupas (2011*a*) finds that providing information in school on the relative risk of HIV infection by partners' age led to 28% decrease in teen pregnancy incidence (62% for pregnancies from relations with older partners) within a year in Kenya, which is

[31] We find a treatment effect of -.070 (.035) if we run an OLS specification similar to equation (4) using 2018 number of partners in the last 12 months as outcome, controling for 2017 number of partners, and excluding the 4 males who report more than 4 partners.

larger than the 23% decrease in our sample of reproductive age women over a two-year period.

6 Conclusions

While the centrality of health-related expectations for a broad range of health and other life-cycle behaviors is undisputed, there is evidence that misperceptions are common in LICs. In particular, many individuals are overly pessimistic about survival risks. In such contexts, survival expectations are a potentially modifiable determinant of health behaviors that can be targeted by health interventions. Our BenKnow study among mature adults in rural Malawi provides the first RCT-based evidence about possibilities to (*i*) improve the accuracy of population survival expectations by providing information about current population mortality risks, and (*ii*) test the hypothesis that more accurate expectations improve health decision-making.

Importantly, the BenKnow intervention had a positive treatment effect one year after its implementation on population survival expectations for healthy individuals, HIV+ individuals and HIV+ individuals on ART. These population survival expectations turned out to be important inputs for the formation of other relevant health risks. In particular, and consistent with HIV+ people being thought to live longer, which implies an increase in HIV prevalence in the pool of potential sexual partners, we found a positive treatment effect on the HIV transmission risk associated with having multiple partners. This renders risky sexual behavior more costly in terms of HIV infection risks. However, and contrary to our own priors, we did not find BenKnow treatment effect on own survival expectations, neither in the short-term nor after one year, possibly because of private information about one's own health status.

Related to the change in perceived transmission risk, BenKnow increased the likelihood of sexual abstinence, reduced the likelihood of having multiple sex partners and increased the 1-year likelihood of marriage (particularly among unmarried women). The magnitudes of these BenKnow treatment effects are conceptually plausible and substantively relevant.

Overall, our findings highlight the importance of incorporating detailed subjective expectations data in field experiments, as our study would not have been able to identify the pathways through which BenKnow affected behavior in the absence of such data. Our study also illustrates that, even if a specific health-information intervention is effective in terms of affecting the hypothesized outcomes, the actual pathways through which the intervention affects these outcomes may be quite complex as expectations about health risks are interrelated and not equally malleable. Information about the pathways, however, is critical for assessing the scope of potential scale-up of interventions, and an understanding of mechanisms is essential for future fine-tuning of study designs and information of follow-up, replication and/or effectiveness studies.

From a policy point of view, our analyses lend support to the development and further testing of cost-effective health-information programs focused on population survival expectations. Such BenKnow-inspired interventions are highly pertinent in HIV-affected countries in sub-Saharan Africa, where mortality levels and disease conditions have changed swiftly and non-monotonically in recent years, and may extend to other areas where survival risks are likely distorted due to rapid changes in socioeconomic development or health, or in populations affected by major epidemics—including possibly Covid19—or political upheavals.

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A Online Appendix A: Expectations Questions

2018Main Questionnaire. Chewa RESPONDENT ID:[_____________________________] 17-42

Section 12: Expectations Questions

INTERVIEWER: Recount the number of peanuts and check that you have 10 peanuts in the plate [__]. As you provide the explanation below, add the peanuts into the plate to illustrate what you say.

"I will ask you several questions about the chance or likelihood that certain events are going to happen. There are 10 peanuts in the cup. I would like you to choose some peanuts out of these 10 peanuts and put them in the plate to express what you think the likelihood or chance is of a specific event happening. One peanut represents one chance out of 10. If you do not put any peanuts in the plate, it means you are sure that the event will NOT happen. As you add peanuts, it means that you think the likelihood that the event happens increases. For example, if you put one or two peanuts, it means you think the event is not likely to happen but it is still possible. If you pick 5 peanuts, it means that it is just as likely it happens as it does not happen (fifty-fifty). If you pick 6 peanuts, it means the event is slightly more likely to happen than not to happen. If you put 10 peanuts 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 peanuts 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. If you think that you will win slightly more than 7 games but less than 8 games on average, then you can break the peanut in half and put 7 ½ peanuts on the plate.

INTERVIEWER: Report for each question the NUMBER OF PEANUTS put in the PLATE. After each question, replace the peanuts in the cup (unless otherwise noted).

Interviewer: Remind respondent that he/she can put ½ bean if respondent wants to pick value between two whole peanuts (e.g., respondent thinks 1 and 1/2 peanuts (1.5) is the best answer). If respondent is not able to break the peanut in ½, help him/her with this.

For question X1: If respondent puts 10 (or 0) peanuts, prompt "Are you sure that this event will almost surely (not) happen?" CIRCLE 1 in column P if you prompted the respondent, and report the final answer only.

X1	*Pick the number of peanuts that reflects how likely you think it is that…*	# of peanuts in plate	Prompt for 0 or 10?
	A person of your sex and age in your community will die within 5 years.	[____]	1

For the subsequent questions, no longer prompt for "0" and "10" answers

X2	*Pick the number of peanuts that reflects how likely you think it is that…*	# of peanuts in plate
a)	*you are infected with HIV/AIDS now*	[____]
b)	INTERVIEWER: for polygamous men, ask for most recent spouse *your spouse or romantic partner is infected with HIV/AIDS now* (INTERVIEWER: If no spouse or romantic partner, write 66)	[____]

X3 Consider a healthy man/woman in your village who currently does not have HIV. Pick the number of peanuts that reflects how likely you think it is that he will become infected with HIV...	# of peanuts in plate
c) *within the next 12 months if he/she is married to someone who is infected with HIV/AIDS*	[____]
d) *within the next 12 months if he/she has several sexual partners in addition to his/her spouse*	[____]

I want you to think how likely it is that you will die in the near future. We believe that there is nothing bad that will happen to you. But something bad might happen in the near future years to come, even though you prevent it to happen. If you don't want, you can refuse to answer these questions.

INTERVIEWER: If respondent refuses to answer, skip to GS1

Pick the number of peanuts that reflects how likely you think it is that you will:	# OF PEANUTS in plate
X7 *Pick the number of peanuts that reflects how likely you think it is that you*	
a) *will die within a five-year period beginning today* (LEAVE PEANUTS ON PLATE)	[____] if 10 → SKIP to X8a
Add the number of peanuts that reflecs how likely you think it is that you: b) *will die within a ten-year period beginning today* (IT IS POSSIBLE TO ADD ZERO ADDITIONAL PEANUTS)	[____]

Finally, I would like you to consider the likelihood that somebody else dies as time goes by. I am going to ask you about an imaginary person living in the same context like you, and I am going to describe him/her to you.

INTERVIEWER: For each of questions X8a to X8d start with an empty plate and 10 peanuts. Do not leave peanuts on plate.

Pick the number of peanuts that reflects how likely you think it is that one of the following persons will die within a five-year period beginning today:	# of peanuts in plate
X8a For men: *A man your age who is healthy and does not have HIV?* For women: *A woman your age who is healthy and does not have HIV?*	[____]
X8b For men: *A man your age who is infected with HIV?* For women: *A woman your age who is infected with HIV?*	[____]
X8c For men: *A man your age who sick with AIDS?* For women: *A woman your age who is sick with AIDS?*	[____]
X8d For men: *A man your age who is sick with AIDS and who is treated with antiretroviral treatments (ART)?* For women: *A woman your age who "is" sick with AIDS and who is treated with antiretroviral treatments (ART)?*	[____]

B Online Appendix B: Information Intervention

B.1 Statistical Information

Figure B.1: Benefits-of-Knowledge Health-information Intervention: Health information sheet providing life-table-based information about 5-year and 10-year mortality probabilities for a woman aged 60-64 years old.

Table B.1: Life table probabilities of dying for BenKnow health-information intervention

	Probability of dying			
	Men		Women	
Age	within 5 years	within 10 years	within 5 years	within 10 years
< 45	0.06	0.13	0.04	0.08
45-49	0.07	0.15	0.05	0.1
50-54	0.08	0.18	0.06	0.13
55-59	0.1	0.23	0.07	0.17
60-64	0.14	0.31	0.11	0.25
65-69	0.2	0.43	0.16	0.37
70-74	0.28	0.58	0.24	0.53
75-79	0.41	0.71	0.38	0.68
80+	0.51	0.76	0.49	0.74

The table reports mortality probabilities for each demographic group that were conveyed during the Benefits-of-Knowledge Health-information Intervention using informations sheets like the one shown in Figure B.1. Lifetable survival probabilities were obtained Global Burden of Disease Collaborative Network. Global Burden of Disease Study 2016 (GBD 2016) Results. Seattle, United States: Institute for Health Metrics and Evaluation (IHME), 2017. Available from http://ghdx.healthdata.org/gbd-results-tool

B.2 Intervention protocol

The Benefits of Knowledge: Mortality risk, Mental health and Life-cycle behavior

Protocol and Questionnaire for Health Information Intervention

Section 1---Background Information Pre-Intervention

When the survey team came to your house the other day, they asked you some questions about the chances that some people or you might die as time goes by using 10 peanuts.

BK0 *Do you remember those questions?*	Yes……………….1 No…………………2

Let's look at your answers together.

INTERVIEWER: Verify the number of peanuts that respondent put when previously interviewed. Put the corresponding number of peanuts in the cup for 5 years probabilities and the corresponding number of peanuts in the cup for 10 years probabilities. Show the respondent the cup with [M9_X7A] peanuts for the 5 years probabilities and the cup with [M9_X7B] peanuts for the 10 years probabilities. Do not remove the peanuts from the cups and keep them in front of the respondent during the whole time of the interview!

*You allocated [M9_X7A] peanuts, meaning [M9_X7A] chances out of 10, when asked about the chances that you might die in the next **5 years**. [Interviewer: lay out M9_X7A peanuts for 5-year mortality risk on flat surface]*

*You allocated [M9_X7B] peanuts, meaning [M9_X7B] chances out of 10, when asked about the chances that you might die in the next **10 years**. [Interviewer lay out M9_X7B peanuts for 10-year mortality risk on flat surface, below the M9_X7A peanuts]*

BK1 *Have you noticed lately that people in Malawi living in villages like yours tend to live longer than they used to 5 or 10 years ago?*	Yes ….. …………….1 No .... 2→ continue with videos following the exact sequence below; start with Video 1 (Story 1)
BK2 *How did you notice that people tend to live longer than they used to 5 or 10 years ago?* ***[check all answers that apply]*** *Interviewer: probe if the respondent does not provide initially a response.*	I go to fewer funerals..1 I noticed that fewer of my friends and relatives are dying ....2 I notice that people are dying when they are older ……….3 AIDS treatment has become available nearby..4 Health services have improved, and this helps individuals..5 Other [_________________________________]................6

Section 2---Videos

[CONTINUE WITH VIDEOS:]

*I would like to show you a video showing that people in Malawi are living longer nowadays than 5 or 10 years ago. These videos have been recorded by **actors** and the information in these videos is consistent with recent health and mortality trends in Malawi.*

Video 1 (Story 1---Davie the carpenter):

A middle-aged man, working it his carpenter's shop, talks: Hi, my name is Davie and I have a bit of land where I grow maize. I also know how to work with wood. I am lucky because both my parents are still alive. They are both in their 70ies and are doing well. They are taking care of themselves: they have enough food, they are in good health and they don't need to go often to the hospital and they actively participate in village activities. They also teach important things about life to me and my children. They knew that they could live longer than their parents and with the little they were earning they bought some livestock to support themselves in their old days. My brothers and I also help them sometimes. My aunties and uncle also died very old. They were more than 65. And I see a lot of other families in our village with old family members that are still alive. My grand-parents were not so lucky and they were dead when they were my age. Yes, I really notice that people are living longer nowadays. And it is a good thing for everyone.

Interviewer: continue with Video 2 --Rose

Video 2 (Story 2 -- Rose):

A middle-aged woman, working in her tailoring shop , talks: Hi, my name is Rose. I work in the field to plant cassava. When I have time, I do a bit of tailoring. I am married and I have four children who also help me in the field. The younger two go to school if they do not help at home. Five years ago, my husband got tested for HIV and he found out that he was HIV-positive. This was really a shock, and I was worried about the future of the family. How could we manage if my husband died soon? However, we have been lucky because my husband has had access to antiretroviral treatment (ART) in the local clinic. He takes his medicine regularly as the doctor explained him and I make sure he does not forget. He also often goes to the clinic for refill and check-ups. He looks really healthy and fit and does not show any sign of the disease. We do not know what will happen but we are very grateful for the availability of treatment. Ten years ago, my brother had HIV and he became very sick very quickly and died rapidly. Nowadays, there is more hope for people with HIV thanks to the availability of treatment. They can expect a longer life.

Interviewer: continue with Video 3 – the old man

Video 3 (Story 3 – old man):

An old man seating at home: I am lucky because I am more than 60 years old and I am still alive and feel healthy. I am not the only luck one. My neighbor next door is more than 70. And think about the popular musician Giddes Chalamanda. He is over 85 years old, and is still performing for the people. Last year, he even made is long-held dream of going to America come true, giving several shows across the USA. My parents were not so lucky because they died when they were in their 40ies. I think things are better nowadays. The kids, they do not die so frequently anymore. They get their immunization and many sleep under bed nets. They do not get sick so often. The adults, they do not die from HIV so rapidly anymore. The treatments, they really help. Also, people are not so hungry anymore and they eat more. When I was a kid, we were often hungry. My children and grand-children, they have almost always their meal on the table. It helps to build your health and keep you strong and prevent you from being unwell. Yes, things have changed quite a lot and people are less sick and live longer.

END OF VIDEO

Section 3--- Provision of Updated Mortality Information

[INTERVIEWER: SELECT THE MORTALITY INFORMATION SHEET CORRESPONDING TO THE RESPONDENT'S AGE AND SEX. USE THE INFORMATION ON THIS SHEET WHEN WE REFER TO 'MORTALITY INFO SHEET' BELOW]

Our research team has looked at some recent data showing how many individuals in Malawi are dying, and how long individuals your age and sex are likely to live. From these findings, it is possible to estimate how likely a person of your age and sex will die within five or ten years.

We would like to illustrate this to you with some pictures. In these pictures, blue persons indicate people who are alive, and red persons indicate people who have died.

*We begin with 10 hypothetical persons who are about your age and are of the same sex. These 10 persons are alive today, and they live in Malawi in a similar context as you do. You can see these 10 persons in this figure that shows 10 blue, or alive, persons [INTERVIEWER: SHOW **FIRST GRAPH** ON THE MORTALITY INFO SHEET].*

*We can now look five years into the future, and ask how many of the persons in the first figure will still be alive **5 years from today**. As you see on this picture [SHOW SECOND GRAPH "5 YEARS FROM TODAY" ON THE MORTALITY INFO SHEET], some of the persons will have died, and are shown in **red**, and others will still be alive, and are shown in **blue**, five years from today. How many persons are in red in this graph tells the chance out of 10 that a person your age and sex will die within the next **five** years: the more people we show in red (or the more red a person is), the higher is the risk of dying.*

Based on our knowledge today, we predict that [READ RED LINE IN 5-YEARS FROM TODAY SECTION] within 5 years from today, while [READ BLUE LINE IN 5-YEARS FROM TODAY SECTION] within 5 years from today.

*We can also look ten years into the future, starting today, and how many of the persons in the first figure will still be alive **10 years from today**. As you see on this picture [SHOW THIRD GRAPH "10 YEARS FROM TODAY" ON THE MORTALITY INFO SHEET], some of the persons will have died, and are shown in **red**, and others will still be alive, and are shown in **blue**, ten years from today. How many persons are in red in this graph tells you is the chance out of 10 that a person your age and sex will die within the next **ten** years. The more people we show in red (or the more red a person is), the higher is the risk of dying.*

Based on our knowledge today, we predict that [READ RED LINE IN "10-YEARS FROM TODAY" SECTION] within 10 years from today, while [READ BLUE LINE IN "10-YEARS FROM TODAY" SECTION] within 10 years from today.

Of course, nobody can predict what will happen to a specific individual, but this information can tell you about what is likely to happen if we look at a large group of people of your age and sex. And this information is helpful for you to think how likely you might die within the next 5 or 10 years. So, let's summarize this information: if we look at 10 persons your age and sex:

- *[READ RED LINE IN "5-YEARS FROM TODAY" SECTION] within 5 years from today, while [READ BLUE LINE IN "5-YEARS FROM TODAY" SECTION] within 5 years from today; and*
- *[READ RED LINE IN "10-YEARS FROM TODAY" SECTION] within 10 years from today, while [READ BLUE LINE IN "10-YEARS FROM TODAY" SECTION] within 10 years from today*

So based on this information, if I were to pick the number of peanuts that reflects how likely it is that a person your age and sex would die within 5 years, I would put **[INTERVIEWER: PICK THE NUMBER OF BEANS THAT CORRESPONDS TO THE NUMBER OF RED PEOPLE ON THE FIGURE WITH "5-YEARS FROM TODAY" MORTALITY INFO]** *peanuts on the plate.*
<u>*Interviewer: Put the number of beans infront of the cup with the 5-years chances of dying. Do not remove the peanuts but leave on the ground. So the respondent can see original answer in the cup, and new information on the ground until the end of the interview.*</u>

So based on this information, if I were to pick the number of peanuts that reflects how likely it is that a person your age and sex would die within 10 years, I would put **[INTERVIEWER: PICK THE NUMBER OF BEANS THAT CORRESPONDS TO**

THE NUMBER OF RED PEOPLE ON THE FIGURE WITH "10-YEARS FROM TODAY" MORTALITY INFO] *peanuts on the plate.*

Interviewer: Put the number of beans infront of the cup with the 5-years chances of dying. Do not remove the peanuts but leave on the ground. So the respondent can see original answer in the cup, and new information on the ground until the end of the interview.

***[Interviewer:** The following is an example how to use ½ peanuts and whole peanuts if the figures are partially colored in red. 1) If the instructions on the mortality info sheet say "less than 1 person will have died" put ½ a peanut; 2) If the instructions on the mortality info sheet say "Between 2 and 3 persons will have died" or "About 2 and 3 persons will have died" then put 2½ peanut. In all other cases put a whole peanut (for example, if instructions say "almost [#] persons will have died", "about 1 person will have died", "approximately[#] persons will have died", "almost [#] persons will have died", "slightly more [#] persons will have died".*

BK3: *Do you understand this information?*	Yes ....1 → SKIP BK3a No............2. → go back to beginning of Section 3 above, and explain again to respondent and ask BK3a;
BK3a. *Do you understand this information?*	Yes ....1 No.......................2
BK3b. Do you think this information reflects correctly what happens to people of your age and sex dying in your community nowadays?	Yes, reflects correctly...1 Yes, reflects somewhat...2 No, does not reflect correctly..3 Dont' Know...4

Of course, depending on your health and depending on your own family and economic context, you might be more or less likely to die than the average person your age and sex in a large group.

Now, I would like to ask you again about what you think about the chances that you might die in the next five or ten years. Look at the peanuts that you had put earlier for the chances that you will die within 5 years and 10 years. Based on what I have told you, and based on what you know about your own health, family and economic context please answer again the following questions below. Remember that you can break a peanut in ½ and put ½ peanut in addition to the whole peanuts if you want to pick a value between two whole peanuts.

Interviewer: Provide respondent with the empty 3rd cup in front of him/her. Give respondent 10 peanuts. Remind respondent that he/she can put ½ bean if respondent wants to pick value between two whole peanuts (e.g., respondent thinks 1 and 1/2 peanuts (1.5) is the best answer). If respondent is not able to break the peanut in ½, help him/her with this. If respondent used ½ peanut, do not substitute with a whole peanut.

Pick the number of peanuts that reflects how likely you think it is that you	**# OF PEANUTS in plate**

BK_X7a: *will die within a five-year period beginning today* **(LEAVE PEANUTS ON PLATE)**	[_____] **if 10 → ask BK_X8a, or BK_X8b, or BK_X8c, or BK_X8d and if the answer is yes and the respondent does not revise his/her answer then continue to BK4.**

BK_X8a: If BK_X7a>M9_X7A: Your answers show that you now think that the chance of dying within the next 5 years are larger than what you said before I gave you the information. Is that what you had in mind?	Yes 1 No 2 If No, go to **BK_X7a2** If Yes, go to **BK_X7b**
BK_X8b: If BK_X7a<M9_X7A: Your answers show that you now think that the chance of dying within the next 5 years are smaller than what you said before I gave you the information. Is that what you had in mind?	Yes No If No, go to **BK_X7a2** If Yes, go to **BK_X7b**
BK_X8c: If BK_X7a=M9_X7A: Your answers show that you now think that the chance of dying within the next 5 years are equal to what you said before I gave you the information. Is that what you had in mind?	Yes No If No, go to **BK_X7a2** If Yes, go to **BK_X7b**
Pick the number of peanuts that reflects how likely you think it is that you	# OF PEANUTS in plate
BK_X7a2: will die within a five-year period beginning today **(LEAVE PEANUTS ON PLATE)**	[_____] if 10 go to BK4 or BK5 depending if they changed their answer compared to the initial number of peanuts in the main questionnaire

Add the number of peanuts that reflects how likely you think it is that you: **BK_X7b.** *will die within a ten-year period beginning today* **(IT IS POSSIBLE TO ADD ZERO ADDITIONAL PEANUTS)**	[_____]

BK_X8d: If BK_X7b>M9_X7B: Your answers show that you now think that the chance of dying within the next 10 years are larger than what you said before I gave you the information. Is that what you had in mind?	Yes No If No, go to **BK_X7b2** If Yes, go to BK4
BK_X8e: If BK_X7b<M9_X7B: Your answers show that you now think that the chance of dying within the next 10 years are smaller than what you said before I gave you the information. Is that what you had in mind?	Yes No If No, go to **BK_X7b2** If Yes, go to BK4
BK_X8f: If BK_X7b=M9_X7B: Your answers show that you now think that the chance of dying within the next 10 years are equal to what you said before I gave you the information. Is that what you had in mind?	Yes No If No, go to **BK_X7b2** If Yes, go to BK4

Pick the number of peanuts that reflects how likely you think it is that you	**# OF PEANUTS in plate**
BK_X7b2: *will die within a ten-year period beginning today* **(LEAVE PEANUTS ON PLATE)**	[_____] go to BK4 or BK5 depending if they changed their answer compared to the initial number of peanuts in the main questionnaire

Interviewer: Confirm if the respondent has changes the number of beans on the plate compared to his/her initial answer. If the respondent did NOT change his/her answer, continue with question BK4. If the respondent did change his/her answer, continue with question BK5.

BK4 Why did you not want change your answer: **(select all that apply)**	I already knew that people live longer so I did not learn anything new …1 I do not believe the information you gave me ....2 The information you provided was not very clear .... 3 Nobody can predict their mortality.. 4 Other [___________________________________]................................. 5
BK5. Why did you change your answer? **(select all that appy)**	I did not know that people live longer …………………………………… 1 I believe the information you gave me ……………………………………2 The information you provided to me was very convincing ………………3 Other ……………………………………………………………………………..4

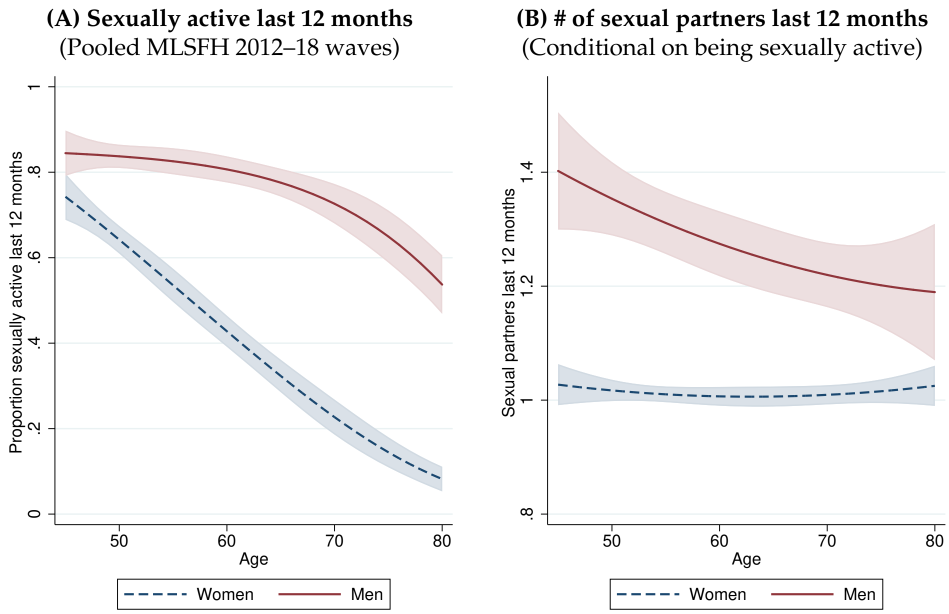
Finally, I would like you to consider the likelihood that somebody else dies as time goes by. I am going to ask you about an imaginary person living in the same context like you, and I am going to describe him/her to you.

INTERVIEWER: Empty the 3rd cup infront of the respondent. For each of questions X8a to X8d start with an empty plate and 10 peanuts. Do not leave peanuts on plate. If the respondent used ½ peanut, replace it after asking the question with one whole peanut and make sure that the respondent starts with 10 whole peanuts.

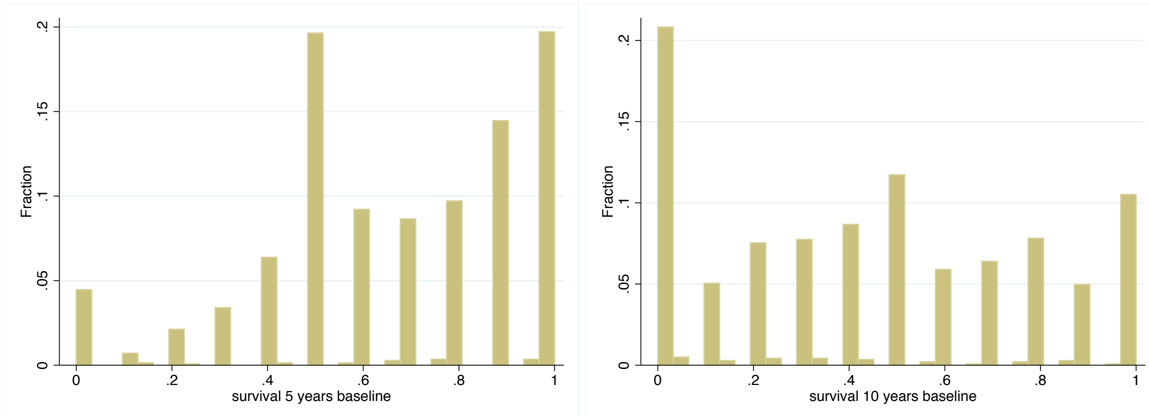
Pick the number of peanuts that reflects how likely you think it is that one of the following persons will die within a five-year period beginning today:	**# of peanuts in plate**
BK_X8a **For men:** *A man your age who is healthy and does not have HIV?* **For women:** *A woman your age who is healthy and does not have HIV?*	[_____]
BK_X8b **For men:** *A man your age who is infected with HIV?* **For women:** *A woman your age who is infected with HIV?*	[_____]
BK_X8c **For men:** *A man your age who sick with AIDS?* **For women:** *A woman your age who sick with AIDS?*	[_____]
BK_X8d **For men:** *A man your age who sick with AIDS and who is treated with antiretroviral treatments (ART)?* **For women:** *A woman your age who sick with AIDS and who is treated with antiretroviral treatments (ART)?*	[_____]

C Online Appendix C: Additional Tables and Figures

Figure C.1: Sexual behaviors and sexual risk taking among MLSFH mature adults



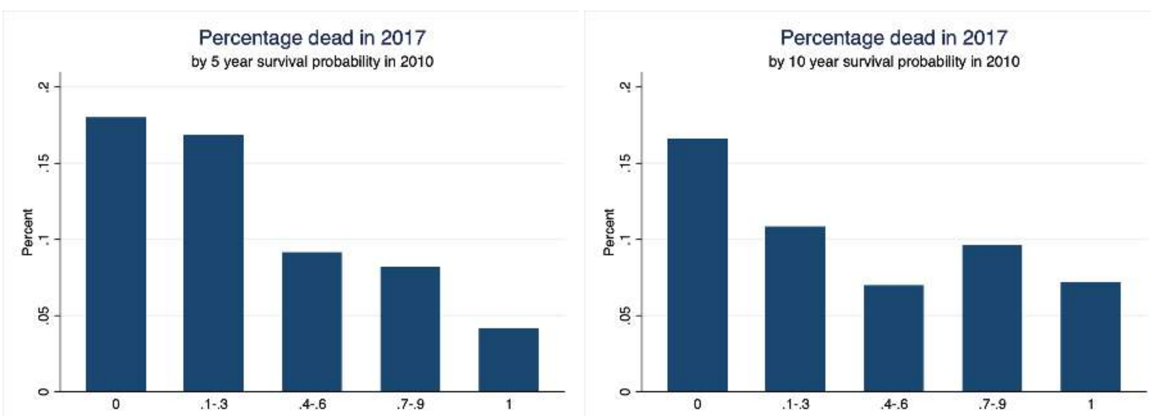
Notes: Marginal means (with 95% confidence intervals) obtained by regressing the outcome variables, sexual active in last 12 months (Panel A) and number of sexual partners in last 12 months (Panel B) on a quadratic function of age, separately by sex. Analyses are pooled across the 2012, 2013, 2017 and 2018 MLSFH mature adults surveys.



(a) 5 years **(b) 10 years**

Figure C.2: Subjective own survival probabilities at baseline.

Panel (a) shows a histogram of the 5-year own subjective survival probability at the 2017 Intervention baseline. Panel (b) shows a histogram of the 10-year own subjective survival probability at the 2017 Intervention baseline.



(a) 5 years **(b) 10 years**

Figure C.3: Predictive power of own subjective survival probabilities.

The figures show the percentage of respondents who are dead in 2017 by different levels of subjective own survival probabilities elicited in 2010. The left figure uses 5 year survival probabilities while the right figure uses 10 year survival probabilities.

Table C.1: Subjective survival expectations as predictors of expected age at death and expected remaining life years (2018)

	(2) Expected age at death	(3) Expected remaining life years
Predictor: 5-year survival expectations		
Subj. survival probability	5.94	6.27
(5 years)	(1.20)	(1.19)
Observations	1,580	1,580
Predictor: 10-year survival expectations		
Subj. survival probability	5.85	6.04
(10 years)	(0.99)	(0.99)
Observations	1,578	1,578

Notes: Based on 2018 MLSFH mature adults. Questions were phrased as: Expected age at death: "How long do you expect to live? That is, until what age?". Expected remaining life years is the difference between expected age at death minus the current age. Analyses additionally control for age group, gender and schooling. Standard errors are clustered at village level.

Table C.2: Predictors of 5-year subjective survival probabilities in 2017 among MLSFH mature adults

	Subj. 5-year survival probability			
	(1)	(2)	(3)	(4)
# of persons suspect have died from AIDS in past 12 months[a]	-0.0075			
	(0.0025)			
# of funerals attended last month		0.0013		
		(0.0043)		
# of deaths among children, spouses and parents in last 5 years			-0.0062	
			(0.013)	
Household affected by death/illness of adult household member or someone providing support for family				-0.032
				(0.013)
Observations	1,428	1,531	1,531	1,531

Notes: Analyses additionally control for age group, gender and years of schooling. Standard errors are clustered at village level. (*a*) Question is worded as: Overall, how many people known to you do you suspect have died from AIDS in the past 12 months?

Table C.3: BenKnow treatment effects on population survival expectations: Heterogeneity by baseline accuracy gap

	Healthy		HIV-		AIDS	
	(1) good news	(2) gap	(3) good news	(4) gap	(5) good news	(6) gap
Treatment	0.056	0.059	0.071	0.067	0.038	0.026
	(0.033)	(0.023)	(0.035)	(0.025)	(0.039)	(0.039)
Treatment × characteristics	-0.021	-0.066	-0.047	-0.114	-0.043	-0.068
	(0.043)	(0.090)	(0.047)	(0.095)	(0.048)	(0.125)
Observations	1272	1272	1268	1268	1269	1269
	ART		**Unconditional**			
	(7) good news	(8) gap	(9) good news	(10) gap		
Treatment	0.039	0.033	-0.004	-0.020		
	(0.035)	(0.031)	(0.027)	(0.018)		
Treatment × characteristics	-0.010	0.001	-0.026	0.022		
	(0.046)	(0.104)	(0.036)	(0.062)		
Observations	1267	1267	1300	1300		

Notes: The table shows regression coefficients for the BenKnow treatment effect on population subjective survival probabilities and interactions of treatment with measures of accuracy of prior beliefs. Gap is the baseline unconditional subjective population survival minus the objective population survival probability presented in the statistical information. Good news is a dummy equal to 1 if the gap is negative. Characteristic corresponds to good news in odd columns and to gap in even columns. Each regression includes also the characteristic not interacted with treatment. All subjective survival probabilities are based on questions about hypothetical individuals, of the same age and gender as the respondent, with the specified health status; see Section 3.3 for additional detail. All analyses additionally control for age group, years of schooling and randomization strata. Standard errors are clustered at the village level.

Table C.4: BenKnow treatment effects on own survival expectations

	Subjective probability of surviving							
	Long run (measured in 2018)				**Short run** (measured post-intervention 2017)			
	5 years		10 years		5 years		10 years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BenKnow treatment effect	0.004	-0.008	0.018	0.007	0.016	0.019	0.014	0.028
	(0.014)	(0.014)	(0.016)	(0.016)	(0.013)	(0.014)	(0.016)	(0.017)
HIV+		-0.070		-0.023		-0.003		0.059
		(0.052)		(0.065)		(0.041)		(0.050)
Treatment effect × HIV+		0.096		0.042		-0.002		-0.102
		(0.064)		(0.080)		(0.061)		(0.080)
Observations	1375	1340	1375	1340	1388	1366	1388	1366

Notes: The table shows regression coefficients for the BenKnow treatment effect on own subjective survival probabilities. In the first four columns, the dependent variables are the updating of each probability from baseline to the 2018 follow-up. In the last four columns, the dependent variables are the update of each probability from baseline to the HTC stage. HIV+ is a dummy for being tested positive during the HTC exercise. All analyses additionally control for age group, years of schooling and randomization strata. Standard errors are clustered at the village level.

Table C.5: BenKnow treatment effects on own survival expectations: Heterogeneity by baseline accuracy gap

	Short run				**Long run**			
	5 years		**10 years**		**5 years**		**10 years**	
	(1) good news	(2) gap	(3) good news	(4) gap	(5) good news	(6) gap	(7) good news	(8) gap
Treatment	0.014	0.007	-0.008	0.016	-0.010	0.010	-0.010	0.023
	(0.037)	(0.030)	(0.047)	(0.035)	(0.038)	(0.027)	(0.049)	(0.034)
Treatment × characteristics	0.001	0.036	0.047	0.044	-0.002	-0.081	0.017	-0.070
	(0.047)	(0.109)	(0.057)	(0.119)	(0.047)	(0.094)	(0.059)	(0.116)
Observations	1256	1256	1254	1254	1234	1234	1231	1231

Notes: The table shows regression coefficients for the BenKnow treatment effect on own subjective survival probabilities and interactions of treatment with measures of accuracy of prior beliefs. Short run refers to the updating from baseline to the HTC stage while long run to the 2018 follow-up. Gap is the baseline unconditional subjective population survival minus the objective population survival probability presented in the statistical information. Good news is a dummy equal to 1 if the gap is negative. Characteristic corresponds to good news in odd columns and to gap in even columns. Each regression includes also the characteristic not interacted with treatment as well as age group, years of schooling and randomization strata. Standard errors are clustered at the village level.

Table C.6: BenKnow treatment effects on own survival expectations: Heterogeneity by relevance and tightness of the prior

	Relevance				Extreme prior			
	Short run		Long run		Short run		Long run	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	5 years	10 years	5 years	10 years	5 years	10 years	5 years	10 years
treatment	0.007	0.015	0.014	0.027	0.020	0.040	0.007	0.036
	(0.015)	(0.018)	(0.013)	(0.017)	(0.016)	(0.019)	(0.014)	(0.018)
Observations	921	919	911	907	982	981	976	973

Notes: The table shows regression coefficients for the BenKnow treatment effect on the updating in own subjective survival probabilities for individuals more likely to consider the information provided relevant for their own survival. The first four columns only include individuals for whom the difference between baseline 5-year own survival and the baseline population survival is less than 20ppt. Baseline population survival is constructed as: healthy survival * HIV probability + HIV survival * (1-HIV probability). The second four columns exclude individuals who expressed extreme beliefs (0 or 1) at least half of the time in the past waves of the MLSFH either for 5-year or 10-year survival or they have less than 3 past observations. Short run refers to the update from baseline to the HTC while long run refers to the update from baseline to the 2018 MLSFH round. All analyses additionally control for age group, years of schooling and randomization strata. Standard errors are clustered at the village level.

Table C.7: BenKnow treatment effect on expectations about being HIV+ (in 2018) and expectations about HIV transmission conditional on sexual behaviors

	Probability of		Prob. of contracting HIV if sex with			
	being HIV+		HIV+ partner		multiple partners	
	(1)	(2)	(3)	(4)	(5)	(6)
BenKnow treatment effect	-0.042	-0.034	0.017	0.019	0.048	0.039
	(0.013)	(0.014)	(0.020)	(0.020)	(0.016)	(0.017)
HIV+		0.002		0.043		0.020
		(0.070)		(0.055)		(0.063)
Treatment effect × HIV+		-0.070		-0.105		0.039
		(0.084)		(0.075)		(0.072)
Observations	1454	1417	1417	1383	1418	1384

Notes: The table shows regression coefficients for the BenKnow treatment effect on the updating of beliefs over HIV-related probabilities from baseline to the 2018 follow-up. HIV probability is the subjective probability of being currently HIV+. HIV+ is a dummy for being tested positive during the HTC exercise. HIV+ partner is the update from baseline MLSFH survey in 2010 to the follow-up survey in 2018 in the probability of becoming infected with HIV having sex with an HIV+ spouse over a year. Multiple parrtners is the update from baseline MLSFH survey in 2010 to the follow-up survey in 2018 in the probability of becoming infected with HIV having sex with multiple partners over a year. All analyses additionally control for age group, years of schooling and randomization strata. Standard errors are clustered at the village level.

Table C.8: Balance in 2010 perceived HIV transmission risk

	Control	Obs	Treatment	Obs	P-value
Panel A: all respondents					
Sex with spouse	0.787	731	0.762	705	0.033
Sex with multiple partners	0.760	731	0.731	704	0.007
Panel B: drop a pair					
Sex with spouse	0.787	679	0.772	655	0.208
Sex with multiple partners	0.757	679	0.737	654	0.070

Notes: The table shows the balance between treatment and control group for the transmission risks variables measured in 2010. p-value shows the p-value of a t-test where the null hypothesis is that the difference in means between treatment and control group is zero. Panel A shows results for all respondents while panel B shows results excluding individuals living in the second biggest village pair which causes most of the imbalance.

Table C.9: Robustness tests for imbalance in perceived transmission risk

	Risky sex	Population survival		Own survival	HIV expectations	
		healthy	HIV	5 years	$p^1 - p^0$	HIV prob
Drop pair	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.164	0.037	0.047	-0.001	0.030	-0.038
	(0.011)	(0.046)	(0.014)	(0.015)	(0.013)	(0.014)
Observations	1377	1320	1318	1283	1316	1354
Entropy weights	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.039	0.042	0.015	0.010	0.032	-0.044
	(0.011)	(0.014)	(0.012)	(0.016)	(0.017)	(0.014)
Observations	1379	1377	1349	1346	1298	1409

Notes: The top panel shows regression coefficients for the BenKnow treatment effect on selected outcomes excluding individuals living in the second biggest village pair which causes most of the imbalance. The bottom panel shows regression coefficients for the BenKnow treatment effect on selected outcomes reweighting the sample using entropy weights to balance treatment and control group on transmission risk with having sex with multiple partners. Healthy and HIV refer to the updating in population survival probabilities. 5 years refers to the updating in own survival probabilities. Risky sex is a dummy variable taking value 0 if sexually passive, 1 if having sex with the spouse only, 2 if having multiple sexual partners and using condom during the last intercourse, 3 if having multiple sexual partners and not using condom during the last intercourse. $p^1 - p^0$ is the difference in transmission risk betweeen having sex with multiple partners and having sex with the spouse only. HIV prob is the update in the subjective probability of being HIV+ from baseline to the 2018 follow-up. All analyses additionally control for age group, years of schooling and randomization strata. Standard errors are clustered at the village level.

Table C.10: Predicted probabilities of sexual risk taking, by BenKnow assignment: subgroups

HIV– only	BenKnow Assignment		
	Control	Treatment	Difference
No sex (SRI3 = 0)	.334	.356	.022
Single partner (SRI3 = 1)	.581	.569	-.012
Multiple partners with condom (SRI3 = 2)	.01	.009	-.001
Multiple partners without condom (SRI3 = 3)	.075	.066	-.009

Men only	BenKnow Assignment		
	Control	Treatment	Difference
No sex (SRI3 = 0)	.166	.206	.04
Single partner (SRI3 = 1)	.685	.679	-.006
Multiple partners with condom (SRI3 = 2)	.025	.021	-.004
Multiple partners without condom (SRI3 = 3)	.124	.095	-.029

Women only	BenKnow Assignment		
	Control	Treatment	Difference
No sex (SRI3 = 0)	.373	.409	.036
Single partner (SRI3 = 1)	.617	.584	-.033
Multiple partners with condom (SRI3 = 2)	.002	.001	-.001
Multiple partners without condom (SRI3 = 3)	.009	.006	-.003

Notes: The table shows the predicted probabilities of being in each risky sex state calculated using the ordered probit model with four different states separately for selected subgroups. The top panel includes only HIV- respondents, the mid panel include only men and the bottom panel includes only women.

Table C.11: **BenKnow treatment effects on sexual behaviors: HIV status interactions**

	Sexual Risk Index (SRI)					
	Had sex		**Number of partners (0,1,2+)**		**Sex and condom (no sex, 1 partner, 2+ w/ condom, 2+ w/o condom)**	
	(1)	(2)	(3)	(4)	(5)	(6)
BenKnow treatment effect	-0.140	-0.136	-0.156	-0.135	-0.159	-0.136
	(0.067)	(0.077)	(0.057)	(0.067)	(0.056)	(0.066)
HIV+		0.007		0.168		0.149
		(0.343)		(0.268)		(0.264)
Treatment effect × HIV+		-0.253		-0.445		-0.421
		(0.408)		(0.350)		(0.337)
Observations	1,479	1,440	1,479	1,440	1,479	1,440

Notes: The table shows regression coefficients for the BenKnow treatment effect on risky sexual behavior using an ordered probit specification. Estimates are based on (ordered) probit specification in Eq. (4). Sexual Risk Indices are defined as: Had Sex: 0 = not sexually active in the last 12 months, 1 = sexually active in the last 12 months; Number of Partners: 0 = not sexually active in the last 12 months, 1 = sex with spouse only, 2 = sex with multiple partners; Sex and Condom: 0 = not sexually active in the last 12 months, 1 = sex with spouse only, 2 = sex with multiple partners and condom at last intercourse, 3 = sex with multiple partners and no condom at last intercourse. All analyses additionally control for age group, years of schooling and randomization strata. Standard errors are clustered at the village level.

Table C.12: BenKnow treatment effects on sexual behaviors: excluding polygamous men

	Sexual Risk Index (SRI)		
	(1) **Had sex**	(2) **Number of partners (0,1,2+)**	(3) **Sex and condom (no sex, 1 partner, 2+ w/ condom, 2+ w/o condom)**
BenKnow treatment effect	-0.140	-0.133	-0.135
	(0.070)	(0.062)	(0.061)
Observations	1380	1380	1380

Notes: The table shows regression coefficients for the BenKnow treatment effect on risky sexual behavior using an ordered probit specification for individuals who are not polygamous. Estimates are based on (ordered) probit specification in Eq. (4). Sexual Risk Indices are defined as: Had Sex: 0 = not sexually active in the last 12 months, 1 = sexually active in the last 12 months; Number of Partners: 0 = not sexually active in the last 12 months, 1 = sex with spouse only, 2 = sex with multiple partners; Sex and Condom: 0 = not sexually active in the last 12 months, 1 = sex with spouse only, 2 = sex with multiple partners and condom at last intercourse, 3 = sex with multiple partners and no condom at last intercourse. All analyses additionally control for age group, years of schooling and randomization strata. Standard errors are clustered at the village level.

Table C.13: BenKnow treatment effects on sexual behaviors: Misreporting of sexual behavior

	Sex active		Multiple partners	
	(1)	(2)	(3)	(4)
BenKnow treatment	-0.160	-0.211	-0.220	-0.237
	(0.066)	(0.113)	(0.125)	(0.135)
Misreporting		0.015		0.094
Observations	1479	1479	1479	1479

Notes: The table shows regression coefficients for the BenKnow treatment effect on risky sexual behavior using a probit specification. Columns 1 and 3 are probit models while columns 2 and 4 are probit models allowing for misreporting following Hausman, Abrevaya and Scott-Morton (1998). In particular, the model allows for the possibility of false negatives (report safe sex while having risky sex). The row Misreporting shows the estimated probability of misreporting. Sexual Risk Indices are defined as: Sex active: 0 = not sexually active in the last 12 months, 1 = sexually active in the last 12 months; Multiple partners: 0 = 0 or 1 sexual partner in the last 12 months, 1 = more than 1 sexual partner in the last 12 months. All analyses additionally control for age group, years of schooling and randomization strata (col 1 and 2) or region fixed effects (col 3 and 4). Standard errors are clustered at the village level.

Table C.14: BenKnow treatment effect on marital status by gender

Men only	Outcome: being married in 2018			Divorced in 2018
	(1)	(2)	(3)	(4)
BenKnow treatment	0.010	0.278	-0.007	0.005
	(0.008)	(0.322)	(0.007)	(0.005)
Sample	All	Not married in 2017	Married in 2017	Married in 2017
Observations	590	16	554	554

Women only	Outcome: being married in 2018			Divorced in 2018
	(1)	(2)	(3)	(4)
BenKnow treatment	0.018	0.065	0.001	0.002
	(0.010)	(0.018)	(0.012)	(0.011)
Sample	All	Not married in 2017	Married in 2017	Married in 2017
Observations	886	353	525	525

Notes: The table shows regression coefficients for the BenKnow treatment effect on the likelihood of being married separately for men and women. Estimates are based on a linear probability model. Outcome variable $y_{ij(2018)}$ is being married (yes/no) in 2018, controlling for marital status (married yes/now) $y_{ij(2017)}$ in 2017. Divorced includes divorced and separations. All analyses additionally control for age group, years of schooling and randomization strata. Standard errors are clustered at the village level.

Table C.15: Predicted probabilities of sexual risk taking and marriage, by BenKnow assignment

	BenKnow Assignment		
	Control	Treatment	Difference
Married, no sex	.093	.107	.014
Single, no sex	.239	.248	0.09
Married, sex	.630	.631	.001
Single, sex	.038	.014	-.024

Notes: The table shows the predicted probabilities of being in each marriage and sex state calculated using a multinomial logit model with four different states for selected subgroups. Standard errors are clustered at the village level.

Table C.16: BenKnow treatment effects on subjective health, wellbeing, and savings and investments

	(1) **Subjective Wellbeing**	(2) **SF12 Physical Score**	(3) **SF12 Mental Score**	(4) **Savings and Investments**
BenKnow treatment effect	-0.032	-0.006	-0.005	0.072
	(0.055)	(0.031)	(0.049)	(0.020)
Observations	1,478	1,466	1,466	1,450

Notes: The table shows regression coefficients for the BenKnow treatment effect on subjective health and wellbeing. SF12 physical and mental score are constructed using a 12 item questionnaire on general health, physical activity and includes emotional health. Subjective wellbeing is based on the question "How satisfied are you with your life, all things considered?," with responses ranging from 1 = very unsatisfied to 6 = very satisfied. Savings and investments is a factor score constructed using the inverse hyperbolic sine transformation of monetary savings, the inverse hyperbolic sine transformation of expenditure on agricultural tools, seeds and fertilizers and the number of animals owned by the respondent. Analyses control for baseline levels. All analyses additionally control for age group, years of schooling and randomization strata. Standard errors are clustered at the village level.