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Topics in Household Decision-Making

Risk Preferences and Investments in Children: Evidence from Mexico

HIV Testing and Belief Revision: What Do You Learn About Your Past and Future?

Knowledge of HIV-Negative Status and Household Decision-Making: Experimental Evidence from Malawi

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Economics

by

Veronica Tatiana Sovero

2013

ABSTRACT OF THE DISSERTATION

Topics in Household Decision-Making:

Risk Preferences and Investments in Children: Evidence from Mexico

HIV Testing and Belief Revision: What Do You Learn About Your Past and Future?

Knowledge of HIV-Negative Status and Household Decision-Making: Experimental Evidence from Malawi

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Veronica Tatiana Sovero

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Professor Moshe Buchinsky, Chair

Outcomes for children depend importantly on parental decisions regarding inputs. This relationship is perhaps most obvious in developing countries where families face liquidity constraints and income uncertainty. To better understand potential risk sharing mechanisms within the household, I first present theoretical evidence of the relationship between a parent's risk aversion and child quality in the context of a collective household model. I then estimate the effect of an experimental measure of risk aversion on a child's well-being using the Mexican Family Life Survey. I find that a mother and father's risk aversion increase investments in male children and decrease investments in female children, which is consistent with the patterns of old age support in Mexico.

In my second chapter, I examine whether HIV testing leads to revisions in the subjective likelihood of being HIV positive as well as the likelihood of surviving across various time horizons. This study is based on the Malawi Diffusion and Ideational Change Project (MDICP), which allows me to use randomized financial incentives as instrumental variables for the decision to learn one's HIV status. I find that women who learn their HIV negative status believe they are negative at the time of testing but appear to overestimate their likelihood of having contracted HIV in the two-year period after learning their HIV status.

My third chapter examines the relationship between learning ones HIV negative status and decisions made within households in the MDICP. Using the financial incentives as instrumental variables for the decision to learn one's HIV status, we find that there is no effect on marital stability two years after a woman learns her HIV negative status, but that the marriage is less likely to stay intact if the husband discovers he is HIV negative. We also find a significant increase in the share of expenditures that are spent on childrens schooling and a decrease in the share spent on childrens medical expenditures. This paper illustrates that HIV testing can be an effective policy tool for increasing the incentives to invest in childrens welfare and human capital.

The dissertation of Veronica Tatiana Sovero is approved.

Dora Costa

Kathleen McGarry

Sarah Reber

Moshe Buchinsky, Committee Chair

University of California, Los Angeles

2013

I dedicate this dissertation to my dad, who was a tremendous help.

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Preface

This dissertation explores three separate topics in household decision-making in developing countries. The first chapter presents a collective household model of risk sharing with a public good. I then estimate the effect of a parent's risk preferences on investments in children. I would like to thank Moshe Buchinsky, Kathleen McGarry, as well as seminar participants for their helpful advice.

In Chapter 2, I examine how individual's subjective beliefs about their HIV status and mortality respond to HIV testing. I relax the assumption that reported beliefs are a cardinal measure of probabilities. I would like to thank Moshe Buchinsky and Kathleen McGarry for their feedback, as well as seminar participants for helpful advice.

In Chapter 3, I present joint research with Katherine Eriksson analyzing the effect of learning one's HIV negative status on household decision-making. We would like to thank Moshe Buchinsky and Susan Watkins for research help, as well as seminar participants for helpful advice.

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Chapter 1

Risk Preferences and Investments in Children: Evidence from Mexico

1.1 Introduction

Outcomes for children depend importantly on parental decisions regarding inputs. This relationship is perhaps most obvious in developing countries where families face liquidity constraints and income uncertainty. In Mexico, poor households have little access to formal insurance markets to insure risk and rely heavily on family members. In response to income uncertainty, parents may favor some children over others, boys over girls, for example. In this paper I develop a model examining the relationship between parental risk aversion and investments in children. In a static setting, there is no investment motive for child expenditures and children are too young to contribute to household income in the current period. As a result, expenditures on children are purely altruistic. I find that a child's consumption is more shielded from income risk when parents are more risk averse with respect to their child's consumption than their own consumption. Furthermore, the effect of each parent's risk preferences is weighted by their marginal willingness to pay for the public good, so the parent with the higher marginal willingness to pay will have a greater influence on the child's exposure to income risk.

A parent's risk preferences may also contribute to health disparities between male and female children. While there is no reason to have a gender preferences in a static setting, it is possible that gender differences in child consumption can arise from intertemporal risk sharing motives. I extend my risk sharing model to include two time periods to allow for an investment motive for child expenditures. Parents invest in their children's human capital in the first period; in return, children transfer resources to their parents in the second period. The amount of the transfer is positively related to the child's human capital. If there are gender differences in the returns to human capital, risk averse households would smooth boy's consumption more than girl's consumption to insure themselves again future negative income shocks. Importantly, this result is achieved without having to assume differences in parent's preferences for boys and girls.

I then estimate the effect of an experimental measure of a mother and father's risk aversion on their children's health using the Mexican Family Life Survey (MXFLS). The MXFLS is a unique dataset that includes a module on risk preferences and anthropometric data. Risk preferences are elicited by having respondents choose between hypothetical gambles. A potential concern with this measure is that decisions regarding hypothetical outcomes may not be representative of a person's true risk preferences. While this claim is difficult to test, there are many studies that validate experimental measures of risk aversion by examining outcomes where there is a clear theoretical relationship between risk preferences and the outcome. Binswanger (1981) conducts an experiment with real payoffs to measure risk aversion among rural farmers in India. He finds that the experimental measure of risk aversion is correlated with the riskiness of the farmer's agricultural decisions such as fertilizer use, sowing time, and irrigation investment. Surveys in developed countries that elicit risk preferences, such as the Health and Retirement Survey (HRS), have been used to examine the relationship between risk tolerance, asset allocation, and savings. The method of eliciting risk preferences is similar to the MXFLs, where individuals are asked to choose between pairs of hypothetical gambles. Kimball, Sahm, and Shapiro (2009) find that differences in the experimental measure of risk tolerance can explain differences in asset allocations across households. To check the validity of the risk preferences elicited in the MXFLS, I restrict my estimation sample to individuals who understand probability.

The paper most similar to my empirical work is by Hamoudi and Thomas (2006). The authors examine the effect of a mother and father's risk preferences on household composition and intergenerational transfers using data from the MXFLS Preferences Pilot Study. The Preferences Pilot Study consists of a subsample of the MXFLS where individuals are presented with gambles with small actual payoffs. Hamoudi and Thomas (2006) find some evidence that mothers who were risk loving have children who weigh less whereas fathers who were risk loving had taller children. My paper differs from Hamoudi and Thomas in several ways. I use risk preferences elicited from hypothetical gambles and have the advantage of being able to use the entire MXFLS sample. Instead of using the coefficient of variation as a measure of risk aversion, I construct a series of dummy variables corresponding to the gambles an individual accepted and rejected. This creates a ranking of individuals by their level of risk aversion and allows me to control for nonlinearities in the relationship between risk aversion and the outcome of interest. Most importantly, I allow for interactions between a mother and father's risk preferences and allow for the effect of risk preferences to vary with the gender of the child.

One might expect that households who are more risk averse would would be better at smoothing the consumption of their children, but I find that mothers and fathers who are risk averse have girls who weigh less than girls whose parents who are less risk averse. The effects are larger when both parents are risk averse compared to when only one parent is risk averse. Interestingly, I find that a mother and father's risk aversion has the opposite affect on their son's weight, which suggests that a parent's risk preferences affect child quality through the intrahousehold allocation of resources. To examine whether there are differences between male and female children's quality within households, I employ a household fixed effects specification. My results indicate that parents who are risk averse prefer to focus household resources on their sons instead of their daughters. I then examine the direct effect of risk preferences on household resource allocations by estimating the effect of a mother and father's risk aversion on the share of household expenditures related to boy's and girl's schooling. My schooling expenditure share regressions confirm that households where both a mother and father are risk averse invest less in their daughter's human capital.

The theoretical model I propose suggests that risk preferences will play a role in how much a child's consumption is shielded from income shocks. To test this hypothesis, I estimate the effect of a parent's risk aversion on child schooling expenditures in communities that experienced a natural disaster. Approximately a third of the communities in the MFXLS experienced a drought, flood, or earthquake in the past year, which reduced average household income by approximately eighteen percent. I find that girl's schooling expenditure shares are lower in households where both parent's are highly risk averse compared to households where parents are less risk averse in communities that experienced a natural disaster. There is no difference between boy's schooling expenditure shares in households where parents are highly risk averse compared to household where parent's are less risk averse. Taken altogether, these findings suggest that households reallocate resources amongst members in response to income shocks, sometimes to the detriment of female children in the household.

My theoretical and empirical analysis bridges the emerging literature on risk sharing under income uncertainty with the literature on collective models with public goods. While there are many studies that examine risk sharing across households in developing countries[1], there has been limited empirical analysis of intrahousehold risk sharing. Dercon and Krishnan (2000) finds evidence that women in rural Ethiopia bear the brunt of household income shocks. The authors argue that these results are consistent with imperfect risk sharing within the household, but they do not allow for risk preference heterogeneity. Mazzocco (2004) finds evidence from the HRS that the savings behavior of couples varies with the

[1] See Mazzocco and Saini (2012) for a review of the relevant literature.

level of risk aversion of both the husband and wife, and shows that in a collective household, household members can share risk in two ways: income pooling to eliminate aggregate risk and insuring one another according to their risk preferences and bargaining power. The mutual insurance aspect of risk sharing is ignored when homogenous preferences are assumed. Mazzocco (2004) does not derive implications for public goods. To the best of my knowledge, my paper is the first to include public goods in a collective model of risk sharing.

Studies that examine household decision-making with respect to public goods have mainly focused on identifying differences between a mother and father's preferences for child expenditures. Duflo (2000) examines the effect of an old-age pension expansion in South Africa on children's height, where height represents accumulated investments in health care and nutrition. She finds that female children born after the reform are taller when a female pensioner lives in the same household, but there is no effect on boy's height. There is no effect for either sex's height when a male pensioner lives in the household. Reggio (2011) examines how an increase in a mother's bargaining power affects her child's labor supply using the Mexican Family Life Survey. While child labor itself is not necessarily a negative child quality outcome, it is associated with lower educational attainment and human capital accumulation (Psacharopoulos (1997)). Reggio finds that increases in a mother's bargaining power decreases labor supply for female children but has no effect on the labor supply of male children.

These empirical studies indicate that women have a greater preference for child expenditures than men, but there is limited research that explores preference heterogeneity within gender. A notable exception is Blundell, Chiappori, and Meghir (2005), who examine the theoretical underpinnings of the concept of mother's "caring more" within a collective model. They show that if private consumption and the public goods are normal goods, then a marginal increase in a household member's bargaining power will increase expenditure on the public good if and only if the household member's marginal willingness to pay for the public good is more sensitive to changes in his/her share of income. In other words, the household member has to be willing to spend more on the public good than private consumption for a marginal increase in income.

The remainder of the paper is organized as follows. Section 2 provides the theoretical framework for the relationship between a parent's risk preferences and child expenditures. Section 3 outlines the data I use in estimation, and includes details of how my risk aversion measure is constructed. Section 4 describes my empirical specification and results are reported in Section 5. Section 6 concludes.

1.2 Theoretical Framework

In this section I present a potential mechanism through which a parent's risk preferences influence expenditures on their children. Consider a collective household model where a mother and father must jointly decide how to allocate income for their own consumption and their child's consumption. The household faces income uncertainty and is assumed to make Pareto efficient decisions. In a static setting, I show that differences in the marginal utility of consumption of each type of good can lead to differences in a parent's risk aversion with respect to each good. In this framework, whether a parent is more risk averse relative to their child's consumption versus their own consumption is more important than the absolute levels of risk aversion. After deriving empirical implications from the static model, I then consider potential dynamic aspects of risk sharing. While there is no reason for parents to have gender preferences in a static context, I explain how differences in the return to human capital investments can lead to gender differences in child expenditures.

1.2.1 One Period Model

The following framework is based on the collective model in Browning, Chiappori, and Weiss (2011). I assume that the parent's utility is a strictly increasing, twice differentiable, concave function of the parent's consumption and the child's consumption. The household faces income uncertainty and must decide how to allocate income y_s between the mother, father, and child for every state s through a set of sharing rules. I define $\rho_m(y_s)$ and $K(y_s)$ as the shares of income that are allocated to the mother and child. The father is allocated the remainder: $y_s - \rho_m(y_s) - K(y_s)$. For notational simplicity I define $\rho_m \equiv \rho_m(y_s)$, $K \equiv K(y_s)$, and $\rho_f \equiv y_s - \rho_m - K$. Expenditure on children is assumed to be a public good. The household allocations are determined as the solution to the following problem:

$$\max_{\rho, K} \quad \sum_s \pi_s [U^m(\rho_m, K) + \lambda U^f(\rho_f, K)] \tag{1.1}$$

where U^m and U^f are the respective utility functions of the mother and father; the Pareto weight λ reflects the relative weight of the father in the household. I also assume that the individual consumption of each parent is separable from the public good, which leads to the following first order conditions:

$$U^m_{\rho_m} = \lambda U^f_{\rho_f} \tag{1.2}$$

where U^i_x is i's marginal utility of consumption with respect to x. This first order condition shows that the ratio of the marginal utilities of each parent is constant across all states of the world for *ex ante* efficient allocations. The first order condition for child expenditures is:

$$U^m_K + \lambda U^f_K = \lambda U^f_{\rho_f} \tag{1.3}$$

In this framework the household faces income uncertainty. Under what conditions is the child's consumption shielded from variation in household income? If the parent has different levels of risk aversion with respect to their own and their child's consumption there is the potential for mutual insurance. In other words, the parent can smooth the child's consumption by increasing or lowering their own consumption in response to income shocks. To derive the child's exposure to income risk I combine the first order conditions, which gives:

$$\frac{U_K^m}{U_{\rho_m}^m} + \frac{U_K^f}{U_{\rho_f}^f} = 1 \tag{1.4}$$

I then define the function F:

$$F = \frac{U_{\rho_m}^m}{MWP^m + MWP^f} - \lambda U_{\rho_f}^f \tag{1.5}$$

Using the Implicit Function Theorem on F, I get:

$$\frac{\partial K}{\partial y_s} = \frac{A_{\rho_f}^f - MWP^f A_{\rho_f}^f}{MWP^f A_{\rho_f}^f - A_{\rho_f}^f + MWP^f A_K^f + MWP^m A_K^m} \tag{1.6}$$

where MWP^i denotes i's marginal willingness to pay for the public good and A_x^i is i's absolute risk aversion with respect to x. See the Appendix for a more detailed derivation of equation (1.6). In words: expenditures on the public good are smoothed more when the father and mother's absolute risk aversion with respect to the public good increases. Furthermore, A_k^m and A_k^f are weighted by the mother and father's willingness to pay for the public good: the parent with a higher taste for public versus private consumption will have a greater effect on the child's marginal income risk. How does a parent's risk aversion with respect to private consumption affect the child's marginal income risk? Public good expenditures vary more with income when the father is more risk averse with respect to his own consumption. Equation 1.6 also shows that the difference between A_k^i and A_p^i affects how much a child is shielded from income risk. In particular, children will be more shielded from income risk when $A_k^i - A_p^i$ is larger. Conceptually, this means that a parent who is more risk averse with respect to their child's consumption versus their own may be more willing to smooth their child's consumption than a parent who is more risk averse with respect to their own consumption.

Extensions

I consider how a mother and father's risk preferences can have differential effects on their son's and daughter's consumption. To accommodate differential expenditures on sons and daughters, the static model of risk sharing can be augmented to include multiple public goods. In particular, consumption of male and female children would enter the parent's utility as distinct public goods. Under this specification, parents could have different levels of risk aversion with respect to female and male children, which would create gender differences in the child's exposure to income risk. This may not be a very realistic framework, because differential treatment of male and female children would have to arise from parents having different levels of altruism for their sons and daughters.

Alternatively, the one period model can be augmented to include a dynamic component to risk sharing. Consider a collective household that lives for two periods. The first period household utility function is the similar to the static model, where household resources are allocated between the mother, father, and children. The second period corresponds to when the child is an adult and the parents are elderly. Parents do not have to spend household resources on the child's human capital in the second period, but still derive utility from the child's quality. Parents cannot save income from period one, but adult children can contribute to the parent's income in the second period. This feature of the model reflects the importance of intergenerational transfers in Mexico. While there is no gender difference in the utility derived from the child's human capital in the first period, gender differences in child expenditures may arise if the return on human capital investments vary with the gender of the child. In particular, risk averse parents may have a preference for investing in their sons over daughters in order to insure themselves against second period income shocks.

I have presented a static and a dynamic model of risk sharing with a public good. Empirically, do these models have different implications? The static model predicts that a parent's risk aversion with respect to their own consumption should always have a negative effect on child quality, and there should be no differential effects by the gender of the child. On the other hand, there is no clear prediction for the effect of a parent's risk aversion on child quality in the dynamic setting. If a parent is more concerned with smoothing their consumption in the short term, then risk aversion should have a negative effect on their son's and daughter's quality, same as the static model. If the parent is more concerned with insuring him or herself against future income uncertainty, then risk aversion may have a positive effect on the child most likely to transfer resources to the parents as an adult. If adult sons are more likely to transfer resources to parents than adult daughters, then a parent's risk aversion could have differential effects on male and female children. Ultimately the effect of a parent's risk aversion on child quality is an empirical question. In the next sections I outline the data and estimation strategy for my analysis.

1.3 Data

I use data from the Mexican Family Life Survey (MXFLS) to estimate the effect of the mother and father's risk preferences on a child's height, weight, and body mass index (BMI). The MXFLS is a longitudinal study of approximately 8,400 Mexican households (Rubalcava, Luis and Teruel, Graciela (2008)). Data are collected on a wide range of demographic, economic, and health characteristics of the households over two survey waves (2002 and 2005). The MXFLS provides a unique opportunity to study this topic because it contains anthropometric data for parents and their children, along with a module on risk preferences in the 2005 wave. My estimation sample consists of children from the 2005 wave under the age of ten that have both parents present in the household. I restrict my sample to households with both parents present in order to control for both parent's risk preferences. Furthermore, the decision-making process of a single parent may differ from a couple's decision-making process. Table 1.1 presents summary statistics for mothers and fathers. Household in my analytic sample have a division of labor where fathers are the primary income earners and mothers are primarily in home production. In particular, 21 percent of women were in the labor force compared to 99 percent of men. Conditional on being the in labor force women's earnings are 25 percent less than men. The lower earnings of women could arise from gender disparities in hours worked or wages. On average, women in the sample have 7.3 years of education while men have 7.8 years of education, which could contribute to a gender wage gap.

Identifying an individual's level of risk aversion requires an understanding of probabilities, so individuals were first asked a question to test their understanding. They were asked: if a yellow chip and blue chip were in a bag, which chip would have a higher probability of being drawn? If the individual answered incorrectly the enumerator would explain why each chip had an equal probability of being drawn. Next, the individual was presented with a series of pairs of hypothetical gambles. Here is the scenario presented:

> *Now imagine a game of chance. In a bag there is a blue chip and a yellow chip and an amount of money written on each of them. Now you reach inside the bag, but you do not know yet which chip you will get. In Bag 1, if you get the blue chip or the yellow chip you receive 1,000 pesos. In Bag 2, if you get the blue chip you receive 500 pesos or 2,000 pesos if you get the yellow chip. Which bag would you choose?*

If the individual accepts the riskier choice (Bag 2), they are asked to choose between Bag 2 and a new bag with a riskier but higher expected payoff. This continues until the individual chooses the safer option or until the end of the module is reached, whichever comes first. If the individual chooses Bag 1, they are asked to choose between Bag 1 and a safer option. This continues until the individual chooses the riskier option or the end of the module is reached, whichever comes first. This sequence of questioning creates an upper and lower bound on an individual's level of risk aversion. I rank individuals based on the riskiest bet they would accept, which creates six levels of risk aversion. Figure 1.1 presents a flow chart of the questioning process. The chart also illustrates the sequence of choices each risk group makes. For example, individuals in the 5th most risk averse group would choose the riskier option in question 1 and the safer option in the follow up question whereas individuals in the 6th group would choose the riskier option in both scenarios.

Figure 1.2 presents the distribution of the mother and father's risk groups where risk aversion is decreasing with group number. While there is evidence from the United States that women tend to be more risk averse than men, the distribution of men and women's risk preferences are fairly similar to one another in the MXFLS. To compare the distribution of preferences to the distribution in the Health and Retirement Survey, I calculate the lower bound of the coefficient of relative risk aversion under the assumption of CRRA preferences. The distribution of the lower bound is presented in Figure 1.2. The majority of respondents in the MXFLS have very low levels of risk aversion compared to estimates from the HRS (Kimball, Sahm, and Shapiro (2009)), which suggests that either the functional form is misspecified or the distribution of preferences are not the same across the two populations. I use an ordinal measure of risk aversion in estimation to avoid having to make functional form assumptions about the utility function. I assume that the relative ranking of individuals according to the riskiness of the gambles chosen is a valid ordinal measure of risk aversion. Another concern about the validity of these elicited risk preferences is that individuals respond differently when presented with hypothetical gambles versus gambles with actual payoffs. Hamoudi and Thomas (2006) find a similar distribution of preferences from the MXFLS Preferences Pilot study, which uses gambles with small actual payoffs on a subsample of MXFLS respondents.

Do couples match along risk preferences? Having spouses with different levels of risk aversion can create opportunities for risk sharing within the household since a less risk averse parent could be willing to insure other household members against aggregate income shocks. Table 1.2 tabulates the risk preferences of women and their husbands. Couples are not perfectly assortatively matched across risk preferences, which can create opportunities for mutual insurance within the household. There is the concern whether all of the risk groups and their interactions would be separately identified in estimation, since several cells have very few observations. To increase cell counts I aggregate risk groups. More specifically, I aggregate risk groups 1 and 2, 3 and 4, and 5 and 6. I call these new groups m_1, m_2, and m_3 for the mothers, and d_1, d_2, and d_3 for the fathers[2]. The tabulation of a mother and father's risk preferences with the aggregated groups are presented in table 1.3. One can see that even with aggregated risk groups, some of the cells where the mother and father are highly risk averse still do not have very many observations, which would make identification of these coefficients difficult. As an alternative grouping, I divide the sample by their response to the first question of the module, which everyone answers. This question serves as a coarse screen to separate individuals into high and low levels of risk aversion. This grouping is the equivalent of classifying risk groups 1-4 as having high risk aversion, which I will call M_{high} and D_{high}, for mother's and father's, respectively. Similarly, I classify groups 5 and 6 as having low risk aversion, which I will call M_{low} and D_{low} for mother's and father's, respectively.

1.3.1 Children

In order to make a child's height and weight comparable across children of different ages and sexes, I standardize the data using the World Health Organization's sex-specific child growth standards (WHO Multicentre Growth Reference Study Group (2006)). The standards were estimated from a sample of healthy children from a variety of ethnic backgrounds and cultural settings. I convert the MXFLS height, weight, and BMI data into height-for-age, weight-for-age, and BMI-for-age Z-scores using the WHO growth standards as the reference group. Table 1.4 presents summary statistics by gender of the child. Boys, on average, are farther below the growth standard for height than girls. On the other hand, a girl's weight given height (BMI) is lower than boys, on average. If height were more determined by genetics than nutritional investments compared to weight, this would indicate that girls receive fewer resources than boys.

[2] I tried alternative groupings, and estimation results were unchanged.

1.3.2 Household Expenditures

My empirical analysis also includes estimating the effect of risk preferences on household level expenditures. Households were asked their expenditure on a variety of goods in the past week, month, quarter, or year depending on the frequency in which the good is usually purchased. For example, households report how much food they purchased in the last week and how much they spend on clothing in the past three months. I calculate the annual expenditure share of a good by multiplying the amount spent on the good times the frequency per year the good is purchased. To minimize the effects of outliers, I trim observations where expenditures in a particular category are more than double the 99th percentile of expenditures.

Table 1.5 presents summary statistics at the household level. The majority of household expenditures are on food and a relatively small amount of expenditures are school related. On average, boys schooling expenditure shares are 1.5 percent of annual expenditures while girls schooling expenditures are 1.4 percent of annual expenditures. There is a greater gender gap in the average expenditure per child: households spend 1.6 percent per school-aged girl compared to 1.8 percent per school-aged boy. Households invest more in boys than girls, which is consistent with the fact that labor force participation and earnings are significantly lower for women compared to men in the MXFLS. If boys were more likely to stay in the labor force and have more resources to transfer to their parents in their old age, the potential return on a child's human capital investment would be higher for boys than girls.

1.4 Estimation Strategy

1.4.1 Child Level Outcomes

I first estimate the effect of a mother and father's risk preferences on a child's weight for age Z-score. A child's weight represents the amount of health and nutritional resources given to the child, so increases in a child's weight should be associated with increased child expenditures. The equation used in estimation is as follows:

$$Zscore_i = \alpha_i X_i + \beta_p X_p + \theta_m M_{high} + \theta_d D_{high} + \delta(M_{high} * D_{high}) + \gamma_c + \varepsilon_i \tag{1.7}$$

Boys and girls are considered separately to allow for the effect of risk aversion to vary with the gender of the child. The dummy variables M_{high} and D_{high} correspond to mothers and fathers who picked the safe option in the first question of the risk module. The least risk averse mothers and fathers (M_{low} and D_{low}), who picked the risky option, are the reference groups. An important feature of equation 1.7 is that the marginal effect of the mother and father's risk aversion is allowed to vary depending on the risk aversion of the spouse. The key identifying assumption is that the direction of causality goes from risk preferences to child health. It may be possible that parents become more risk averse if their children are in poor health, but there is evidence from the HRS that risk preferences are fairly stable across survey waves(Kimball, Sahm, and Shapiro (2009)).

I include controls at the child level (X_i) and for each parent X_p ($p = m, d$). Child level controls include: a third order polynomial in age, number of siblings, and birth order. Since there is a genetic component to height and weight I control for the mother and father's height. I also assume that children are public good, which would make the child consumption decision a function of both the mother and father's preferences weighted by their relative bargaining power. I control for bargaining power by the level of income and education of each parent, where the parent with a higher education and income is likely to have more bargaining power in the household. In addition, there are community characteristics that contribute to a child's physical development, such as the availability of healthcare services and access to running water. To control for these factors, I include community fixed effects (γ_c).

With this specification, gender differences in the effect of risk aversion on child quality may be driven by differences across households. It's possible that a parent's risk aversion has the same effect on boys and girls in the same household, but some households that have only daughters spend less on their children than households that have only sons. Furthermore, there may be concerns about omitted variables that are affecting child quality. In particular, risk averse households may hold more precautionary savings or have informal insurance arrangements with extended family outside the household. Children may fare better in risk averse households because household level consumption is smoothed more than less risk averse households. To isolate the effect of risk aversion on differences in child quality within households, I employ a household fixed effects specification:

$$\begin{aligned} Zscore_i = \alpha_i X_i + \beta Female_i + \theta_{m_h}(Female_i * M_{high}) + \theta_{d_h}(Female_i * D_{high}) \\ + \delta_{m_h d_h}(Female_i * M_{high} * D_{high}) + \gamma_h + \varepsilon_i \end{aligned} \tag{1.8}$$

The mother and father's risk aversion is interacted with a dummy variable for whether the child is female. Child level controls include the gender of the child, a third order polynomial in age, and birth order. In this specification, the marginal effect of a parent's risk aversion on female children is relative to the male children in the household.

1.4.2 Alternative Measures to Weight

In addition to weight, I estimate the effect of risk preferences on other measures of a child's well being that are commonly used in the literature. More specifically, I use height for age as an alternative dependent variable. Height can be interpreted as a child's stock of nutritional and health care investments, while weight is more representative of the flow of resources. Weight would therefore be more responsive to short term changes in resources. Another alternative measure of well-being is a child's body mass index (BMI) for age Z-score, which is a measure of weight given height. BMI is a more informative measure of whether a child's weight is healthy given their height.

1.4.3 Household Outcomes

The anthropometric measures are an outcome of parental investments rather than a direct measure of the investments themselves. To examine whether risk preferences affect the allocation of resources to child specific goods, I estimate some household level outcomes. If a mother or father's risk aversion increases the share of resources allocated to children, then the same relationship should hold between the parent's risk preferences and the share of household expenditures on child specific goods. It is common in the literature to use children's clothing expenditures (Lundberg, Pollack, and Wales 1997), but this may not be relevant in a developing country context. I estimate the effect of risk aversion on a child specific good that is correlated with child quality, namely schooling related expenditures. I restrict my sample to households with at least one school-aged child (between the ages of 5-18). This is:

$$SchoolShare_h = \alpha_h X_h + \theta_m M_{high} + \theta_d D_{high} + \delta(M_{high} * D_{high}) + \gamma_c + \varepsilon_h \tag{1.9}$$

Controls are similar to the child health regressions and include the parent's educational attainment, labor income, and whether the mother participates in the labor force. I also include the number of adults and the number of school-aged boys and girls in the household. Schooling expenditures are reported by gender so I estimate the share of schooling expenditures by gender.

Equation 1.9 estimates the average differences in schooling expenditure shares by a parent's risk aversion, but how do schooling expenditures vary in response to a household income shock? The theoretical framework in Section 2 predicts that parents who are more risk averse would be less willing to smooth child expenditures if they are more risk averse with respect to their own consumption. To estimate how schooling expenditures vary in response to income variation, I utilize community level data from MXFLS. I classify a community as having experienced an income shock if the community head reported a drought, flood, or earthquake.

Controlling for educational levels, whether the community is rural, and municipality fixed effects, I find that annual household expenditures are 18 percent lower among households living in a community that experienced an income shock. Given this large drop in expenditures, are child expenditures lowered more in households where parent's are highly risk averse? To estimate how risk preferences affect schooling expenditure shares in response to an income shock, I split my sample by whether there was an income shock in the community. The preferred specification would be to pool the full sample and interact an indicator for an income shock with the parent's risk preferences, but there are multicollinearity concerns with the number of interactions that would have to be included. Since the shock is at the community level, I include municipality fixed effects instead of community fixed effects. I add controls for whether the community is rural and whether there is a secondary school present in the community.

1.5 Estimation Results

1.5.1 Child Level Outcomes

Table 1.6 presents estimated coefficients from equation (1) for girls, in column 1 and for boys, in column 2. The marginal effects of the mother and father's risk aversion are reported below the estimated risk coefficients. Note that all the marginal effects are relative to when the mother and father are in the least risk averse risk group. A mother's risk aversion has a positive effect on her son's weight for age z-score, but the magnitude of the effect depends on her husband's risk preferences. When both parent's are in the high risk aversion group, the marginal effect of a mother's risk aversion increases her son's weight for age z-score by .21 standard deviations. On the other hand, when the father is in the low risk aversion group, the marginal effect of a mother's risk aversion is still positive but insignificant.

While there are positive effects of a mother's risk aversion on her son's weight, her risk preferences have the opposite effect on her daughter's weight for age Z-score. A striking feature of this result is that the effect is almost exactly the same magnitude as in the boy's regressions. When the father is also in the high risk aversion group, a mother's risk aversion lowers her daughter's weight for age z-score by .23 standard deviations. Again, the effect diminishes when the father is not in the high risk aversion group. While I am not estimating differences between boy's and girl's weight in the same household, this pattern suggests that resources are being diverted from girls and given to boys when the mother and father are highly risk averse. I will show further evidence that supports this hypothesis in the within-household estimates and expenditure estimates. The father's marginal effects are not significant in either the boy's or girl's weight regressions.

Are there similar effects of risk aversion on height? Height regression results for girls are reported in column 1 of Table 1.7 and regression results for boys are presented in column 2 of the same table. Marginal effects are presented below the estimated coefficients. While risk preferences have a significant effect on weight, it appears that the effects of a parent's risk aversion are not large enough to affect a child's height. A mother and father's risk aversion does not have any significant effects on their son's or daughter's height for age Z-scores.

Given that height does not seem to be affected by a parent's risk preferences, I next turn to estimates of a child's weight given height, or BMI. BMI regression results for girls are reported in column 1 of Table 1.8 and regression results for boys are presented in column 2 of the same table.The marginal effects follow a similar pattern as in the weight regressions. For example, the marginal effect of a mother being risk averse lowers her daughter's weight for age Z-score by .20 standard deviations, but only when the father is also risk averse. There is no significant effect of the mother's risk aversion when the father in the low risk aversion group. For boys, neither the mother nor the father's risk aversion has a significant effect on BMI.

Household Fixed Effects

Estimates of weight for age Z-scores suggest that boys are healthier than girls in risk averse households. To test for differential treatment of boys and girls within households, I turn to estimates of the household fixed-effects specification. Results are presented in Table 1.9 for weight and Table 1.10 for BMI, respectively. Marginal effects are computed relative to the boys in the household. When both parents are highly risk averse, a mother's risk aversion decreases her daughter's BMI for age Z-score by .53 standard deviations compared to her son's BMI for age Z-score.The mother's marginal effect is smaller and insignificant when the father is in the low risk aversion group. Similarly, the marginal effect of the mother's risk aversion is negative in the weight regressions, but the coefficients are not significant. These results confirm that there are gender disparities in child health when parents are highly risk averse.

1.5.2 Household Expenditure Shares

If risk preferences affect child health through household resource allocations, then I would expect to find that risk averse parents spend a larger share of household resources on their sons versus their daughters. Regression results for girl's schooling expenditure shares are presented in column 1 of Table 1.12 and regression results for boy's schooling expenditure shares are presented in column 2 of the same table. Patterns from the anthropometric estimates persist in the schooling expenditure share estimates, which suggests that risk preferences affect a child's well being through the allocation of resources to the child. The marginal effect of a mother being in the high risk aversion group is associated with a .5 percentage point (25 percent) increase in the the share of boy's schooling expenditures when the father is also in the high risk aversion group. There is no significant effect when the father is in the low risk aversion group. The father's risk aversion has a similar effect as the mother's risk aversion. The marginal effect of a father being in the most risk averse group increases boy's schooling expenditure shares by .7 percentage points when the mother is also risk averse.

Estimates of girl's schooling expenditure shares indicate that a mother's risk aversion is associated with decreases in the share of resources spent on girls. In particular, the marginal effect of a mother's risk aversion decreases girl's schooling expenditure shares by .6 percentage points when the father is also in the high risk aversion group. The marginal effects diminishes to .2 percentage points when the father is in the low risk aversion group, but effect is not significant. The marginal effects of a father's risk aversion are also insignificant.

Income Shock Results

I have found evidence that risk averse parents allocate more resources, on average, to sons versus daughters. It appears that risk averse parents are acting out of self interest because they are investing more resources in the child that will have more resources available when the parents are elderly. In this population, men are more likely to participate in the labor force and have higher earnings than women, which would make sons a more appealing investment. Given that risk averse parents seem concerned with their own intertemporal consumption smoothing, does this mean that children in risk averse households are also more exposed to short term variations in income? Regression results of the child schooling expenditures by whether there was a natural disaster in the community are presented in Table 13.

In communities that experience a natural disaster, girl's schooling expenditures shares are lower in households where the mother is highly risk averse compared to households where the mother is less risk averse. On the other hand, there is no significant difference in boy's schooling expenditures by the parent's level of risk aversion. These results indicate that risk preferences may play a role in deciding which household member's consumption gets reduced when there is an income shock. Interestingly, risk aversion does not have a significant effect on girl's schooling expenditure shares among households that did not experience a natural disaster, which could indicate that there are enough resources for girl's schooling expenditures under normal conditions. On the other hand, there is evidence that parent's who are highly risk averse spend a larger share of expenditures on boy's schooling when there is no income shock, so there is still a preference for male children. There are some caveats to comparing the estimates between communities that experienced a shock versus no shock due to the lack of community fixed effects. In particular, there may be omitted variables that could be potentially correlated with community specific characteristics. As a result, comparisons across the two samples are merely suggestive evidence.

1.5.3 Robustness Checks

Alternative Groupings

By sorting parents into two levels of risk aversion, I identify the average effect of each group's risk aversion on the outcomes of interest. There may be heterogenous effects due to varying levels of risk aversion within groups. As an alternative specification, I estimate equation (1.7) to allow for more risk heterogeneity. I keep the same low risk aversion group as the reference group, and split the high risk aversion group into two subgroups. The most risk averse parents are risk groups 1 and 2, and the second most risk averse parents are risk groups 3 and 4. The new dummy variables are called m_1, m_2, and m_3 for mothers, and d_1, d_2, and d_3 for fathers. The least risk averse parents (m_3 and d_3) are the omitted groups (M_{low} and D_{low} in the previous specifications).

$$\begin{aligned} Zscore_i = {} & \alpha_i X_i + \beta_p X_p + \theta_{m_1} m_1 + \theta_{m_2} m_2 + \theta_{d_1} d_1 + \theta_{d_2} d_2 \\ & + \delta_{m_1 d_1}(m_1 * d_1) + \delta_{m_1 d_2}(m_1 * d_2) + \delta_{m_2 d_1}(m_2 * d_1) \\ & + \delta_{m_2 d_2}(m_2 * d_2) + \gamma_c + \varepsilon_i \end{aligned} \tag{1.10}$$

The drawback of this specification is that some of the risk groups have few observations, which limits the precision of the estimated effects.Table 1.13 presents weight regression results for boys and girls. The marginal effects are reported in Table 1.14 for each parent, and by the gender of the child. As expected, the marginal effects of a parent's risk aversion are greater when parents are separated into more risk levels. For example, a mother in the second most risk averse group (m_2) increases her son's weight for age Z-score by .5 standard deviations when the father is in the most risk averse group (d_1), by .2 standard deviations when the father is in the second most risk averse group (d_2), and by .17 standard deviations when he is in the least risk averse group (d_3). For fathers, the largest marginal effect is being in the most risk averse group (d_1) when the mother is in group m_2. In these cases, risk averse fathers lower their son's weight Z-score by .58 standard deviations.

Regression results for girl's BMI are presented in column 1 of Table 1.15 and regression results for boy's BMI are presented in column 2 of the same table. Marginal effects of the risk groups are presented in Table 1.16. For boys, neither the mother nor the father's risk aversion has a significant effect on BMI. On the other hand, both a mother and father's risk aversion has a negative effect on their daughter's BMI. The marginal effect of a mother being in the most risk averse group (m_1) lowers her daughter's BMI for age Z-score by .51 standard deviations when the father is in the second most risk averse group (d_2). A mother in the second most risk averse group (m_2) lowers her daughter's BMI for age Z-score by .21 standard deviations when the father is also in the second most risk averse group (d_2). A father's risk aversion has a significant negative effect on his daughter's BMI when the mother is in the most risk averse group (m_1). In particular, the marginal effect of the father being the the most risk averse group (d_1) lower's his daughter's BMI for age Z-score by .87 standard deviation when the mother is also in the most risk averse group. When the father is in the second most risk averse group (d_2) the effects are smaller: a father lowers his daughter's BMI for age Z-score by .76 standard deviations.

The schooling expenditure estimates follow a more clear pattern of the diminishing effect of a parent's risk aversion as the other parent becomes less risk averse. The marginal effect of a mother being the in the most risk averse group (m_1) raises the share of boy's schooling expenditures by 1.6 percentage points or 61 percent when the father is also in the most risk averse group (d_1). For girls, the marginal effect of a mother being in the most risk averse group lowers the schooling expenditure share by 3.1 percentage points when the father is also in the most risk averse group, and the marginal effect becomes less negative when fathers are less risk averse. Turning to the father's marginal effects, a father's risk aversion has a significant positive effect on both boys and girls schooling expenditure shares only when the mother is in the second most risk averse group (m_2). Otherwise a father's risk aversion has a negative effect when the mother is in the most risk averse group (m_1).

Validity of Risk Measure

Measuring risk aversion from hypothetical gambles requires the assumption that individuals can calculate the expected value of the gambles presented. My measure of risk aversion would not by a valid representation of a person's underlying risk preferences if the person did not understand the tradeoffs between different gambles. Individuals were asked: "A blue chip and yellow chip are in a bag. Which chip is more likely to be drawn at random?"I classify individuals as not having a good understanding of probability if they did not answer that the blue chip and the yellow chip had an equal probability of being drawn. I find that women who do not have a good understanding of probability disproportionately fall into the most risk averse group where every gamble is rejected. These women would be incorrectly categorized as being risk averse when in reality they do not have a good understanding of the expected value of the gambles. As a robustness check I re-estimate equation (1.10) by first excluding children whose mother does not understand probability, and then excluding children whose father does not understand probability. A limitation of this approach is that there may be a selection bias in the estimated coefficients. In particular, individuals who have a better understanding of probability are likely to be more educated, which could give them more bargaining power in the household. The parent with more bargaining power would have a greater influence on the child's share of resources, so the estimated risk coefficients could be picking up the effect of a shift in the bargaining power along with the effect of the parent's risk aversion.

The marginal effects on a parent's risk aversion on weight Z-scores are presented in Table 1.19 for children whose mother's understand probability and Table 1.20 for children whose father's understand probability. Conditional on understanding probability, mothers in the most risk averse group (m_1) increase their son's weight by 1.2 standard deviations when the father is also in the most risk averse group (d_1). The marginal effect of being in the most risk averse or second most risk averse group continues to have a negative effect on her daughter's weight when the father is also in those groups. When a father understands probability (Table 1.20) the marginal effect of being in the most risk averse (d_1) or second most risk averse group (d_2) has a positive effect on his son's weight when the mother is in the most risk averse group (m_1). The marginal effect of a father being in the most or second most risk averse group is negative for daughters when the mother is also in those groups. There is some overlap between the estimation samples of the father understanding probability and the mother understanding probability, so I estimate the marginal effects when both parents understand probability. When both parents understand probability (Table 1.21), there is a similar pattern to the signs of the marginal effects. Interestingly, the magnitudes of the coefficients are not as large in the estimation sample where both parents understand probability. This could reflect the fact that the mother has relatively higher bargaining power in Table 1.19, while the father has relatively higher bargaining power in Table 1.20. When both parents understand probability, any bargaining power effects are canceled out.

The marginal effects of the mother and father's risk aversion on BMI when the mother understands probability, the father understands probability, and both parents understand probability are reported in Tables 1.22, 1.23 and 1.24, respectively. The marginal effects are larger in absolute terms when restricting the samples to those who understand probability. For example, when the father understands probability (Table 1.23), being in the most risk averse group (d_1) lowers his daughter's BMI for age zscore by just over a standard deviation when the mother is also in the most risk averse group (m_1), whereas in the full sample (Table 1.16) this coefficient is -.87. When both parents understand probability (Table 1.24) a father's risk aversion has a significant negative effect on his daughter's BMI when the father and mother are in the most or second most risk averse groups.

The marginal effects of the mother and father's risk aversion on schooling expenditure shares when the mother understands probability, the father understands probability, and both parents understand probability are reported in Tables 1.25, 1.26 and 1.27, respectively. The marginal effects for both parents look similar across the different samples. A mother's risk aversion has a positive effect on the boy's schooling expenditure share and a negative effect on the girl's schooling expenditure share. A father's risk aversion has a negative effect on the girl's schooling expenditure share when a mother is in the most risk averse group and a positive effect when the mother is less risk averse.

1.6 Conclusion

Parents who are risk averse have a negative effect on their daughter's weight and BMI, but not their son's. My results also indicate that the marginal effect of a parent's risk aversion is dependent on the spouse's risk aversion; the marginal effects are larger when both parents are in the high risk aversion group. Parents who are risk averse seem to devote more resources to their sons than daughters, which is verified in my household expenditure share regressions. In particular, a smaller share of household resources are spent on girl's schooling when the mother and father are both risk averse, while a mother's risk aversion has a positive effect on boy's schooling expenditure shares. I find my results are robust to alternative groupings and sample restrictions based on whether the parents understand probability. In the context of the theoretical framework, these results suggest that gender differences are related to an intertemporal risk sharing motive. In Mexico, intergenerational transfers are an important source of income for the population over 65 (Wong and Espinoza (2002)). This population has very low pension coverage: over 75 percent of the elderly population does not receive any pension benefits (Noel-Miller and Tfaily (2009)). As a result, over a third of income comes from kin, usually children.

If children are a form of insurance against future income uncertainty, then risk averse parents would focus their resources on the child who is expected to have a higher future income. In other words, gender differences arise from economic factors rather than differences in parent's underlying preferences for male and female children. Rosenzweig and Schultz (1982) find similar effects when examining gender inequality in India. The authors show that intrafamily resource allocations are sensitive to changes in the economic prospects of men and women. Given that households in the MXFLS tend to have a division of labor where men are in the labor market and women are in home production, it's likely that human capital investments in boys would have a higher expected return (Thomas (1994)). While boys have greater earnings potential, they must also be more likely to transfer resources to parents compared to daughters. There is evidence that adult sons in Mexico are more likely to coreside with their parents versus parent-in-laws. Sons are also more likely to transfer money to parent's versus parent-in-laws (Noel-Miller and Tfaily (2009)). Since both a mother and father are more likely to benefit from their adult sons than daughters, these patterns can explain why a mother and father's risk preferences have similar effects on their children's quality.

Based on my empirical results there are a few policy relevant implications. Uncovering gender differences, or the lack thereof, in preferences for child investment is important from a policy perspective since there are many social programs that target women as beneficiaries. The underlying assumption is that that women would invest more in their children than men. One such program is the Programa de Educacion, Salud, y Alimentacion (PROGRESA), whose goal is to alleviate poverty and stimulate investments in children's education and health in poor households. Benefits are sizable (almost a quarter of household income), are paid to women, and are conditional on children in the household attending school. Rubalcava, Teruel, and Thomas (2006) find that the program improves child outcomes, but it is not clear whether the effect is due to the conditional aspect of the transfers or designating women as the recipients. To examine the relative importance of the conditional aspect of PROGRESA, de Brauw and Hoddinott (2011) exploit the fact that some beneficiaries did not receive the necessary forms to monitor school attendance . The authors find that school attendance was lower in households where attendance was not monitored, which suggests that the conditional aspect of the transfers plays a large role in the overall program effect.

My findings suggest that there is substantial heterogeneity in preferences for child expenditures among women that is related to their risk preferences. This heterogeneity would reduce the effectiveness of targeting women as beneficiaries of cash transfers. If a policymaker's goal were to improve female educational attainment, then it would be more effective to provide school vouchers instead of targeting cash to mothers. Increasing female educational attainment may also have an indirect effect on household resource allocations. In particular, if female educational attainment increases, then women might become a more valuable investment to parents. This, in turn, would help reduce the differential treatment of boys and girls in risk averse households.

1.7 Appendix

To derive each household member's marginal income risk, I apply the Implicit Function Theorem to F, where F is defined as:

$$F = \frac{U^m_{\rho_m}}{MWP^m + MWP^f} - \lambda U^f_{\rho_f} \tag{1.11}$$

and where $MWP^m = \frac{U^m_k}{U^m_{\rho_m}}$ and $MWP^f = \frac{U^f_k}{U^f_{\rho_f}}$. For the mother:

$$\frac{\partial \rho_m}{\partial y_s} = \frac{\frac{\partial F}{\partial y_s}}{\frac{\partial F}{\partial \rho_m}} \tag{1.12}$$

The denominator D in (1.12) is:

$$\begin{aligned}
D \equiv \frac{\partial F}{\partial \rho_m} &= U^m_{\rho_m \rho_m} - U^m_{\rho_m}\left[\frac{\partial MWP^m}{\partial \rho_m} + \frac{\partial MWP^f}{\partial \rho_m}\right] + \lambda U^f_{\rho_f} \\
&= U^m_{\rho_m \rho_m} + \lambda U^f_{\rho_f} - U^m_{\rho_m}\left[\frac{-U^m_K}{U^m_{\rho_m}}\frac{U^m_{\rho_m \rho_m}}{U^m_{\rho_m}} + \frac{U^f_K}{U^f_{\rho_f}}\frac{U^f_{\rho_f \rho_f}}{U^f_{\rho_f}}\right] \\
&= U^m_{\rho_m \rho_m} + \lambda U^f_{\rho_f} - U^m_{\rho_m}\left[MWP^m A^m_{\rho_m} - MWP^f A^f_{\rho_f}\right] \\
&= U^m_{\rho_m \rho_m} + \lambda U^f_{\rho_f} - U^m_{\rho_m} MWP^m A^m_{\rho_m} + U^m_{\rho_m} MWP^f A^f_{\rho_f}
\end{aligned} \tag{1.13}$$

Where U^i_{xx} is the second derivative of i's utility with respect to x. The numerator N is:

$$\begin{aligned}
N \equiv \frac{\partial F}{\partial y_s} &= U^m_{\rho_m\rho_m}\frac{\partial \rho_m}{\partial y_s} - U^m_{\rho_m}\left[\frac{\partial MWP^m}{\partial y_s} + \frac{\partial MWP^f}{\partial y_s}\right] \\
&\quad - \lambda U^f_{\rho_f\rho_f}\left(1 - \frac{\partial \rho_m}{\partial y_s} - \frac{\partial K}{\partial y_s}\right) \\
&= U^m_{\rho_m\rho_m}\frac{\partial \rho_m}{\partial y_s} - U^m_{\rho_m}\left[\frac{U^m_{KK}}{U^m_{\rho_m}}\frac{\partial K}{\partial y_s} - \frac{U^m_K}{U^m_{\rho_m}}\frac{U^m_{\rho_m\rho_m}}{U^m_{\rho_m}}\frac{\partial \rho_m}{\partial y_s}\right] \\
&\quad - U^m_{\rho_m}\left[\frac{U^f_{KK}}{U^f_{\rho_f}}\frac{\partial K}{\partial y_s} - \frac{U^f_K}{U^f_{\rho_f}}\frac{U^f_{\rho_f\rho_f}}{U^f_{\rho_f}}\left(1 - \frac{\partial \rho_m}{\partial y_s} - \frac{\partial K}{\partial y_s}\right)\right] \\
&\quad - \lambda U^f_{\rho_f\rho_f}\left(1 - \frac{\partial \rho_m}{\partial y_s} - \frac{\partial K}{\partial y_s}\right) \\
&= U^m_{\rho_m\rho_m}\frac{\partial \rho_m}{\partial y_s} - U^m_{\rho_m}\left[-MWP^m A^m_K\frac{\partial K}{\partial y_s} + MWP^m A^m_{\rho_m}\frac{\partial \rho_m}{\partial y_s}\right] \\
&\quad - U^m_{\rho_m}\left[-MWP^f A^f_k\frac{\partial K}{\partial y_s} + MWP^f A^f_{\rho_f}\left(1 - \frac{\partial \rho_m}{\partial y_s} - \frac{\partial K}{\partial y_s}\right)\right] \\
&\quad - \lambda U^f_{\rho_f\rho_f}\left(1 - \frac{\partial \rho_m}{\partial y_s} - \frac{\partial K}{\partial y_s}\right) \\
&= \left(U^m_{\rho_m\rho_m} + \lambda U^f_{\rho_f\rho_f} - U^m_{\rho_m}MWP^m A^m_{\rho_m} + U^m_{\rho_m}MWP^f A^f_{\rho_f}\right)\frac{\partial \rho_m}{\partial y_s} \\
&\quad + \left(\lambda U^f_{\rho_f\rho_f} + U^m_{\rho_m}MWP^m A^m_K + U^m_{\rho_m}MWP^f A^f_K + U^m_{\rho_m}MWP^f A^f_{\rho_f}\right)\frac{\partial K}{\partial y_s} \\
&\quad - U^m_{\rho_m}MWP^f A^f_{\rho_f} - \lambda U^f_{\rho_f\rho_f} \\
&= \left(\lambda U^f_{\rho_f\rho_f} + U^m_{\rho_m}MWP^m A^m_K + U^m_{\rho_m}MWP^f A^f_K + U^m_{\rho_m}MWP^f A^f_{\rho_f}\right)\frac{\partial K}{\partial y_s} \\
&\quad + D\frac{\partial \rho_m}{\partial y_s} - U^m_{\rho_m}MWP^f A^f_{\rho_f} - \lambda U^f_{\rho_f\rho_f}
\end{aligned} \tag{1.14}$$

Now that I have expressions for the numerator and denominator, Equation (1.12) can be rewritten as:

$$\begin{aligned}
\frac{\partial \rho_m}{\partial y_s} &= \frac{N}{D} \\
D\frac{\partial \rho_m}{\partial y_s} &= N \\
D\frac{\partial \rho_m}{\partial y_s} &= D\frac{\partial \rho_m}{\partial y_s} - U^m_{\rho_m} MWP^f A^f_{\rho_f} - \lambda U^f_{\rho_f \rho_f} \\
&\quad + \left(\lambda U^f_{\rho_f \rho_f} + U^m_{\rho_m} MWP^m A^m_K + U^m_{\rho_m} MWP^f A^f_K + U^m_{\rho_m} MWP^f A^f_{\rho_f}\right) \frac{\partial K}{\partial y_s}
\end{aligned} \tag{1.15}$$

The $D\frac{\partial \rho_m}{\partial y_s}$ terms cancel out, so I can now solve for $\frac{\partial K}{\partial y_s}$:

$$\begin{aligned}
\frac{\partial K}{\partial y_s} &= \frac{-U^m_{\rho_m} MWP^f A^f_{\rho_f} - \lambda U^f_{\rho_f \rho_f}}{\left(\lambda U^f_{\rho_f \rho_f} + U^m_{\rho_m} MWP^f A^f_{\rho_f} + U^m_{\rho_m} MWP^f A^f_K + U^m_{\rho_m} MWP^m A^m_K\right)} \\
&= \frac{A^f_{\rho_f} - MWP^f A^f_{\rho_f}}{MWP^f A^f_{\rho_f} - A^f_{\rho_f} + MWP^f A^f_K + MWP^m A^m_K}
\end{aligned} \tag{1.16}$$

Table 1.1: Summary Statistics of Parents of Children Under the Age of Ten

	Mother			Father		
	Mean	SD	N	Mean	SD	N
Height(cm)	154.4	7	1515	166.5	7.4	1515
Years of Education	7.3	3.7	1515	7.8	3.7	1515
Monthly income (if work)	3,019	3,673	313	4,000	3,793	1515
Works	0.21	0.4	1515	0.99	0.11	1515
Age	32.4	8	1515	35.5	9	1515
Risk group 1	0.092	0.29	1515	0.091	0.29	1515
Risk group 2	0.022	0.15	1515	0.019	0.14	1515
Risk group 3	0.09	0.29	1515	0.071	0.26	1515
Risk group 4	0.352	0.48	1515	0.357	0.48	1515
Risk group 5	0.075	0.26	1515	0.067	0.25	1515
Risk group 6	0.368	0.48	1515	0.395	0.49	1515
Understand equal prob	0.61	0.49	1515	0.65	0.48	1515
Number of children	2.57	1.39				

Group 1 has the greatest risk aversion, Group 6 the least

Table 1.2: Tabulation of Mother and Father's risk preferences (cell percentages)

		Father's Risk Groups						
		1	2	3	4	5	6	Row Total
Mother's Risk Groups	1	3.4	0.3	1	1.8	0.4	2.2	9.1
	2	0.2	0.1	0.2	0.9	0.1	0.7	2.3
	3	0.8	0.4	0.7	2.9	0.7	3.2	8.6
	4	1.9	0.7	1.9	19.6	1.8	9.5	35.3
	5	0.3	0.2	0.8	2.4	1.5	2.5	7.7
	6	1.9	0.6	1.9	8.8	2.1	21.8	37.1
Column Total		8.6	2.3	6.4	36.3	6.6	39.7	

Group 1 is the most risk averse, Group 6 is the least risk averse.

Table 1.3: Tabulation of Mother and Father's risk preferences using aggregated risk groups (cell percentages)

	d_1 (groups 1 and 2)	d_2 (groups 2 and 3)	d_3 (groups 5 and 6)	Row Total
m_1 (groups 1 and 2)	4	3.9	3.4	11.3
m_2 (groups 3 and 4)	3.8	25	15.2	43.9
m_3 (groups 5 and 6)	3	13.9	27.8	44.7
Column Total	10.9	42.8	46.3	

Table 1.4: Summary Statistics of Children Under the Age of Ten

	Boys			Girls		
	Mean	SD	N	Mean	SD	N
Weight for age Z-score	-0.05	1.4	1298	-0.03	1.3	1212
Height for age Z-score	-0.57	1.5	1298	-0.49	1.4	1212
BMI for age Z-score	0.44	2	1298	0.37	1	1212
Age (months)	71	37	1298	73	36	1212
Number of siblings	1.8	1.4	1298	1.7	1.4	1212

Table 1.5: Summary Statistics of Household Annual Expenditure Shares

	Mean	SD	N
Food	0.598	0.17	1460
Non-clothing personal goods, services, recreation	0.240	0.14	1460
Clothing, domestic goods, medicine	0.097	0.11	1460
Electronics, appliances, furniture, property	0.036	0.08	1460
Boy's schooling expenditure	0.015	0.03	1460
Girl's schooling expenditure	0.014	0.02	1460
Number of school aged children			
Boys	0.81	0.94	1460
Girls	0.88	0.99	1460

Table 1.6: Fixed effect regression of weight Z-scores on risk interactions

	(1) Girls	(2) Boys
M_{high}	0.015	0.134
	[0.105]	[0.108]
D_{high}	.150	-0.148
	[0.093]	[0.103]
$M_{high} * D_{high}$	-.245	0.079
	[0.156]	[0.155]
$\frac{\partial Z}{\partial M_{high}}$ if $D_{high} = 1$	-0.230**	0.213**
	[0.095]	[0.097]
$\frac{\partial Z}{\partial M_{high}}$ if $D_{high} = 0$	0.015	0.134
	[0.105]	[0.108]
$\frac{\partial Z}{\partial D_{high}}$ if $M_{high} = 1$	-0.095	-0.007
	[0.102]	[0.089]
$\frac{\partial Z}{\partial D_{high}}$ if $M_{high} = 0$	0.150	-0.148
	[0.093]	[0.103]
Observations	1,123	1,209
R-squared	0.108	0.1

The dependent variable is the child's Height-for-age Z-score. M_{high} and D_{high} are indicators for parents who chose the safe option in the first question of the risk module. M_{low} and D_{low} (parents who chose the risky option) are omitted as the reference groups in all regressions. Controls include a third order polynomial in age, birth order, height, income, and educational attainment of the mother and father, and community fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.7: Fixed effect regression of height Z-scores on risk interactions

	(1) Girls	(2) Boys
M_{high}	0.043	0.087
	[0.096]	[0.108]
D_{high}	-0.052	-0.108
	[0.090]	[0.162]
$M_{high} * D_{high}$	-.077	0.053
	[0.144]	[0.159]
$\frac{\partial Z}{\partial M_{high}}$ if $D_{high} = 1$	-0.034	0.141
	[0.093]	[0.115]
$\frac{\partial Z}{\partial M_{high}}$ if $D_{high} = 0$	0.043	0.087
	[0.096]	[0.108]
$\frac{\partial Z}{\partial D_{high}}$ if $M_{high} = 1$	-0.130	-0.055
	[0.096]	[0.110]
$\frac{\partial Z}{\partial D_{high}}$ if $M_{high} = 0$	-0.052	-0.108
	[0.090]	[0.162]
Observations	1,212	1,298
R-squared	0.117	0.130

The dependent variable is the child's Height-for-age Z-score. M_{high} and D_{high} are indicators for parents who chose the safe option in the first question of the risk module. M_{low} and D_{low} (parents who chose the risky option) are omitted as the reference groups in all regressions. Controls include a third order polynomial in age, birth order, height, income, and educational attainment of the mother and father, and community fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.8: Fixed effect regression of BMI Z-scores on risk interactions

	(1) Girls	(2) Boys
M_{high}	0.024	0.080
	[0.103]	[0.104]
D_{high}	0.127	-0.047
	[0.087]	[0.149]
$M_{high} * D_{high}$	-0.232**	-0.052
	[0.366]	[0.150]
$\frac{\partial Z}{\partial M_{high}}$ if $D_{high} = 1$	-0.208**	0.028
	[0.083]	[0.098]
$\frac{\partial Z}{\partial M_{high}}$ if $D_{high} = 0$	0.024	0.080
	[0.103]	[0.104]
$\frac{\partial Z}{\partial D_{high}}$ if $M_{high} = 1$	-0.105	-0.099
	[0.076]	[0.098]
$\frac{\partial Z}{\partial D_{high}}$ if $M_{high} = 0$	0.127	-0.052
	[0.087]	[0.150]
Observations	1,196	1,296
R-squared	0.023	0.033

The dependent variable is the child's BMI-for-age Z-score. M_{high} and D_{high} are indicators for parents who chose the safe option in the first question of the risk module. M_{low} and D_{low} (parents who chose the risky option) are omitted as the reference groups in all regressions. Controls include a third order polynomial in age, birth order, height, income, and educational attainment of the mother and father, and community fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.9: Household fixed effects regression of weight Z-scores on risk interactions

	(1)
$Female$	0.083
	[0.136]
$Female * M_{high}$	-0.260
	[0.217]
$Female * D_{high}$	-0.025
	[0.245]
$Female * M_{high} * D_{high}$	-0.074
	[0.324]
$\frac{\partial Z}{\partial M_{high}}$ if $D_{high} = 1$	-0.251
	[0.276]
$\frac{\partial Z}{\partial M_{high}}$ if $D_{high} = 0$	-0.177
	[0.168]
$\frac{\partial Z}{\partial D_{high}}$ if $M_{high} = 1$	-0.017
	[0.251]
$\frac{\partial Z}{\partial D_{high}}$ if $M_{high} = 0$	0.057
	[0.202]
Observations	1,592
R-squared	0.050

M_{high} and D_{high} are indicators for parents who chose the safe option in the first question of the risk module. M_{low} and D_{low} (parents who chose the risky option) are omitted as the reference groups in all regressions. Controls include a third order polynomial in age, birth order, and household fixed effects.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.10: Household fixed effects regression of BMI Z-scores on risk interactions

	(1)
$Female$	0.080
	[0.136]
$Female * M_{high}$	-0.069
	[0.243]
$Female * D_{high}$	0.306
	[0.223]
$Female * M_{high} * D_{high}$	-0.375
	[0.326]
$\frac{\partial Z}{\partial M_{high}}$ if $D_{high} = 1$	-0.525**
	[0.256]
$\frac{\partial Z}{\partial M_{high}}$ if $D_{high} = 0$	-0.149
	[0.201]
$\frac{\partial Z}{\partial D_{high}}$ if $M_{high} = 1$	-0.149
	[0.273]
$\frac{\partial Z}{\partial D_{high}}$ if $M_{high} = 0$	0.226
	[0.178]
Observations	1,679
R-squared	0.025

M_{high} and D_{high} are indicators for parents who chose the safe option in the first question of the risk module. M_{low} and D_{low} (parents who chose the risky option) are omitted as the reference groups in all regressions. Controls include a third order polynomial in age, birth order, and household fixed effects.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.11: Fixed Effects Estimates of Schooling Expenditure Shares

	(1) Girls	(2) Boys
M_{high}	-0.003	-0.001
	[0.003]	[0.002]
D_{high}	0.005	0.001
	[0.004]	[0.003]
$M_{high} * D_{high}$	-0.003	0.006
	[0.004]	[0.004]
$\frac{\partial S}{\partial M_{high}}$ if $D_{high} = 1$	-0.006**	0.005*
	[0.002]	[0.003]
$\frac{\partial S}{\partial M_{high}}$ if $D_{high} = 0$	-0.003	0.001
	[0.003]	[0.003]
$\frac{\partial S}{\partial D_{high}}$ if $M_{high} = 1$	0.001	0.007***
	[0.002]	[0.002]
$\frac{\partial S}{\partial D_{high}}$ if $M_{high} = 0$	0.005	0.006
	[0.004]	[0.004]
Observations	770	757
R-squared	0.074	0.071

M_{high} and D_{high} are indicators for parents who chose the safe option in the first question of the risk module. M_{low} and D_{low} (parents who chose the risky option) are omitted as the reference groups in all regressions. Controls include number of school-aged boys and girls, number of adults, income and education of of the mother and father, mothers LFP, and community fixed effects.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.12: Estimates of Schooling Expenditure Shares by Whether There Was a Natural Disaster

	Shock		No Shock	
	(1) Girls	(2) Boys	(3) Girls	(4) Boys
M_{high}	-0.005	0.008	-0.001	-0.003
	[0.004]	[0.005]	[0.004]	[0.004]
D_{high}	0.017*	0.014**	0.003	-0.001
	[0.009]	[0.006]	[0.004]	[0.004]
$M_{high} * D_{high}$	-0.009	-0.015*	-0.002	0.010*
	[0.008]	[0.008]	[0.006]	[0.006]
$\frac{\partial S}{\partial M_{high}}$ if $D_{high} = 1$	-0.014**	-0.007	-0.003	0.007*
	[0.007]	[0.006]	[0.004]	[0.004]
$\frac{\partial S}{\partial M_{high}}$ if $D_{high} = 0$	-0.005	0.008	-0.001	-0.003
	[0.004]	[0.005]	[0.002]	[0.004]
$\frac{\partial S}{\partial D_{high}}$ if $M_{high} = 1$	0.008	-0.001	0.001	0.009**
	[0.005]	[0.005]	[0.004]	[0.004]
$\frac{\partial S}{\partial D_{high}}$ if $M_{high} = 0$	0.017*	0.014**	0.003	-0.001
	[0.009]	[0.006]	[0.004]	[0.004]
Observations	221	215	508	496
R-squared	0.131	0.133	0.080	0.070

M_{high} and D_{high} are indicators for parents who chose the safe option in the first question of the risk module. M_{low} and D_{low} (parents who chose the risky option) are omitted as the reference groups in all regressions. Controls include number of school-aged boys and girls, number of adults, income and education of the mother and father, mother's LFP, municipality fixed effects, and whether the community is rural.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.13: Fixed effect regression of weight Z-scores on risk interactions

	(1) Girls	(2) Boys
m_1	0.2757	-0.026
	[0.311]	[0.262]
m_2	-0.0423	0.1685*
	[0.108]	[0.100]
d_1	0.1031	−0.5780**
	[0.230]	[0.244]
d_2	0.1620*	-0.0515
	[0.093]	[0.098]
$m_1 * d_1$	-0.724	0.4816
	[0.591]	[0.456]
$m_1 * d_2$	-0.5992	0.0034
	[0.386]	[0.252]
$m_2 * d_1$	-0.2389	0.3323
	[0.302]	[0.478]
$m_2 * d_2$	-0.1336	0.0285
	[0.163]	[0.136]
Observations	1,123	1,209
R-squared	0.108	0.1

m_3 and d_3 are omitted as the reference group in all regressions. Controls include a third order polynomial in age, birth order, height of the mother and father, income and education of the mother and father, and community fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.14: Marginal effects of Risk Aversion on Weight by Gender of Child and Parent

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial Z}{\partial m_1}$	0.456	-0.023	-0.0260	-0.448	-0.324**	0.275
	[0.286]	[0.194]	[0.262]	[0.355]	[0.131]	[0.311]
$\frac{\partial Z}{\partial m_2}$	0.501	0.197*	0.1685*	-0.281	-0.176	-0.042
	[0.436]	[.116]	[0.100]	[0.270]	[.116]	[0.108]
$\frac{\partial Z}{\partial m_3}$	-0.578**	-0.0515	0.000	0.103	0.162*	0.000
	[0.244]	[0.098]		[0.230]	[0.093]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial Z}{\partial d_1}$	-0.096	-0.575*	-0.578**	-0.621	-0.136	0.103
	[.367]	[.344]	[0.244]	[.4165]	[.132]	[0.230]
$\frac{\partial Z}{\partial d_2}$	-0.048	-0.023	-0.0515	-0.437	0.028	0.162*
	[.227]	[.084]	[0.098]	[.374]	[.122]	[0.093]
$\frac{\partial Z}{\partial d_3}$	-0.0260	0.1685*	0.000	0.276	-0.042	0.000
	[0.262]	[0.100]		[0.311]	[0.108]	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.15: Fixed effect regression of BMI for age Z-scores on risk interactions

	(1) Girls	(2) Boys
m_1	0.4625***	0.2218
	[0.160]	[0.244]
m_2	-0.0695	0.0582
	[0.118]	[0.111]
d_1	-0.1773	-0.3193
	[0.129]	[0.305]
d_2	0.2045*	0.0103
	[0.103]	[0.131]
$m_1 * d_1$	-0.6963***	-0.0008
	[0.261]	[0.360]
$m_1 * d_2$	-0.9681***	-0.4752
	[0.243]	[0.383]
$m_2 * d_1$	0.2329	0.1547
	[0.158]	[0.461]
$m_2 * d_2$	-0.1427	-0.0252
	[0.136]	[0.174]
Observations	1,196	1,276
R-squared	0.033	0.036

m_3 and d_3 are omitted as the reference group in all regressions. Controls include a third order polynomial in age, birth order, height of the mother and father, income and education of the mother and father, and community fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.16: Marginal effects of Risk Aversion on BMI by Gender of Child and Parent

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial Z}{\partial m_1}$	0.221	-0.253	0.223	-0.234	-0.506***	-0.114
	[.205]	[.274]	[0.244]	[.221]	[.149]	[0.284]
$\frac{\partial Z}{\partial m_2}$	0.213	0.033	0.058	0.163	-0.212**	0.075
	[.415]	[.127]	[0.111]	[.149]	[.097]	[0.098]
$\frac{\partial Z}{\partial m_3}$	-0.319	0.01	0.000	0.014	-0.071	0.000
	[0.305]	[0.131]		[0.224]	[0.093]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial Z}{\partial d_1}$	-0.320	-0.165	-0.149	-0.874***	0.056	0.014
	[.429]	[.225]	[0.179]	[.273]	[.138]	[0.224]
$\frac{\partial Z}{\partial d_2}$	-0.465	-0.015	-0.102	-0.764***	0.062	-0.071
	[.443]	[.099]	[0.183]	[.214]	[.109]	[0.093]
$\frac{\partial Z}{\partial d_3}$	0.235	0.052	0.000	-0.114	0.075	0.000
	[0.508]	[0.152]		[0.284]	[0.098]	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.17: Fixed effect regression of girls and boys schooling expenditure shares on risk interactions

	(1) Girls	[2] Boys
m_1	-0.0002	0.0082*
	[0.005]	[0.005]
m_2	-0.0033	-0.0025
	[0.002]	[0.002]
d_1	0.0227	-0.0085***
	[0.014]	[0.003]
d_2	0.0004	0.0028
	[0.003]	[0.004]
$m_1 * d_1$	-0.0306*	0.0080
	[0.016]	[0.007]
$m_1 * d_2$	-0.0106**	-0.0053
	[0.005]	[0.007]
$m_2 * d_1$	-0.0140	0.0222***
	[0.013]	[0.007]
$m_2 * d_2$	0.0031	0.0049
	[0.003]	[0.004]
Observations	771	758
R-squared	0.101	0.078

m_3 and d_3 are omitted as the reference group in all regressions. Controls include income and education of the mother and father, number of boys and girls in the household, and community fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.18: Marginal effects of Risk Aversion on Schooling Expenditure Shares by Gender of Child and Parent

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial S}{\partial m_1}$	0.016***	0.003	0.008*	-0.031**	-0.011***	0.000
	[0.005]	[0.005]	[0.005]	[0.013]	[0.002]	[0.005]
$\frac{\partial S}{\partial m_2}$	0.020***	0.002	-0.003	-0.017	-0.0002	-0.0033
	[0.006]	[.003]	[0.002]	[0.012]	[.003]	[0.002]
$\frac{\partial S}{\partial m_3}$	-0.008***	0.003	0.000	0.023	0.000	0.000
	[0.003]	[0.004]		[0.014]	[0.003]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial S}{\partial d_1}$	-0.001	0.014**	-0.008***	-0.008	0.009*	0.0227
	[.007]	[.006]	[0.003]	[.005]	[.005]	[0.014]
$\frac{\partial S}{\partial d_2}$	-0.003	0.008***	0.003	-0.010*	0.004*	0.0004
	[.005]	[.002]	[0.004]	[.005]	[.002]	[0.003]
$\frac{\partial S}{\partial d_3}$	0.008	-0.003	0.000	0.000	-0.003	0.000
	[0.005]*	[0.002]		[0.005]	[0.002]	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.19: Marginal effects of Risk Aversion on Weight by Gender of Child and Parent When Mother Understands Probability

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial Z}{\partial m_1}$	1.183*	0.175	-0.063	-0.162	-0.390***	0.364
	[0.606]	[0.183]	[0.420]	[0.716]	[0.130]	[0.220]
$\frac{\partial Z}{\partial m_2}$	0.224	0.231	-0.022	-0.302	-0.393**	-0.010
	[0.768]	[0.167]	[0.156]	[0.660]	[0.156]	[0.190]
$\frac{\partial Z}{\partial m_3}$	-0.678*	-0.167	0.000	0.104	0.161	0.000
	[0.377]	[0.146]		[0.582]	[0.139]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial Z}{\partial d_1}$	0.569	-0.431	-0.678*	-0.421	-0.187	0.104
	[0.652]	[0.495]	[0.377]	[0.370]	[0.236]	[0.582]
$\frac{\partial Z}{\partial d_2}$	0.071	0.086	-0.167	-0.592**	-0.222	0.161
	[0.370]	[0.115]	[0.146]	[0.286]	[0.151]	[0.139]
$\frac{\partial Z}{\partial d_3}$	-0.063	-0.022	0.000	0.364	-0.010	0.000
	[0.420]	[0.156]		[0.220]	[0.190]	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.20: Marginal effects of Risk Aversion on Weight by Gender of Child and Parent When Father Understands Probability

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial Z}{\partial m_1}$	0.855	0.355*	-0.255	-0.108	-0.228*	0.524*
	[0.551]	[0.200]	[0.462]	[0.426]	[0.124]	[0.306]
$\frac{\partial Z}{\partial m_2}$	0.340	0.125	0.105	-0.233	-0.235*	-0.179
	[0.690]	[0.168]	[0.133]	[0.537]	[0.125]	[0.168]
$\frac{\partial Z}{\partial m_3}$	-0.550	-0.137	0.000	-0.289	0.061	0.000
	[0.375]	[0.141]		[0.327]	[0.143]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial Z}{\partial d_1}$	0.560	-0.315	-0.550	-0.914**	-1.034***	-0.282
	[0.662]	[0.350]	[0.375]	[0.374]	[0.291]	[0.327]
$\frac{\partial Z}{\partial d_2}$	0.474	-0.117	-0.137	-0.691**	0.005	0.061
	[0.307]	[0.107]	[0.141]	[0.294]	[0.143]	[0.143]
$\frac{\partial Z}{\partial d_3}$	-0.255	0.105	0.000	0.524*	-0.179	0.000
	[0.462]	[0.133]		[0.306]	[0.168]	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.21: Marginal effects of Risk Aversion on Weight by Gender of Child and Parent When Both Parents Understand Probability

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial Z}{\partial m_1}$	1.117	0.421**	0.114	-0.025	-0.377*	0.448
	[0.781]	[0.186]	[0.227]	[0.843]	[0.198]	[0.289]
$\frac{\partial Z}{\partial m_2}$	-0.004	0.088	0.076	-0.550	-0.383**	0.065
	[0.981]	[0.203]	[0.175]	[0.631]	[0.188]	[0.208]
$\frac{\partial Z}{\partial m_3}$	-0.351	-0.055	0.000	0.068	0.167	0.000
	[0.493]	[0.178]		[0.556]	[0.165]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial Z}{\partial d_1}$	0.652	-0.431	-0.351	-0.405	-0.546**	0.068
	[0.553]	[0.573]	[0.493]	[0 .524]	[0.267]	[0.556]
$\frac{\partial Z}{\partial d_2}$	0.252**	-0.043	-0.055	-0.661**	-0.284*	0.167
	[0.119]	[0.133]	[0.178]	[0.300]	[0.164]	[0.165]
$\frac{\partial Z}{\partial d_3}$	0.114	0.076	0.000	0.448	0.065	0.000
	[0.227]	[0.175]		[0.289]	[0.208]	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.22: Marginal effects of Risk Aversion on BMI by Gender of Child and Parent When Mom Understands Probability

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial Z}{\partial m_1}$	0.418	-0.220	0.232	0.257	-0.651***	-0.049
	[.536]	[.290]	[0.209]	[0.276]	[0.182]	[0.279]
$\frac{\partial Z}{\partial m_2}$	-0.321	0.030	0.019	0.308	-0.428***	0.078
	[0.719]	[0.194]	[0.154]	[0.387]	[0.130]	[0.125]
$\frac{\partial Z}{\partial m_3}$	-0.331	-0.172	0.000	0.007	-0.146	0.000
	[0.204]	[0.231]		[0.555]	[0.186]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial Z}{\partial d_1}$	-0.171	-0.431	-0.331	-0.653***	-0.074	0.007
	[0.339]	[0.289]	[0.204]	[0.181]	[0.245]	[0.555]
$\frac{\partial Z}{\partial d_2}$	-0.747*	-0.063	-0.172	-0.850***	-0.098	-0.146
	[0.441]	[0.130]	[0.231]	[0.214]	[0.101]	[0.186]
$\frac{\partial Z}{\partial d_3}$	0.232	0.019	0.000	-0.049	0.078	0.000
	[0.209]	[0.154]		[0.279]	[0.125]	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.23: Marginal effects of Risk Aversion on BMI by Gender of Child and Parent When Dad Understands Probability

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial Z}{\partial m_1}$	0.366	-0.200	0.235	-0.101	-0.557***	0.045
	[0.427]	[0.322]	[0.508]	[0.236]	[0.165]	[0.186]
$\frac{\partial Z}{\partial m_2}$	-0.090	-0.058	0.052	0.001	-0.281*	-0.038
	[0.517]	[0.137]	[0.152]	[0.385]	[0.145]	[0.135]
$\frac{\partial Z}{\partial m_3}$	-0.289	-0.207	0.000	-0.300	-0.190	0.000
	[0.249]	[0.136]		[0.232]	[0.116]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial Z}{\partial d_1}$	-0.171	-0.194	-0.289	-1.065***	-0.163	-0.300
	[0.384]	[0.316]	[0.249]	[0.260]	[0.286]	[0.232]
$\frac{\partial Z}{\partial d_2}$	-0.591	-0.016	-0.207	-1.041***	0.034	-0.190
	[0.730]	[0.141]	[0.136]	[0.282]	[0.101]	[0.116]
$\frac{\partial Z}{\partial d_3}$	0.235	0.052	0.000	0.045	-0.038	0.000
	[0.508]	[0.152]		[0.186]	[0.135]	

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table 1.24: Marginal effects of Risk Aversion on BMI by Gender of Child and Parent When Both Parents Understands Probability

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial Z}{\partial m_1}$	0.552	-0.240	0.545*	0.250	-0.784***	0.016
	[0.737]	[0.320]	[0.274]	[0.298]	[0.166]	[0.209]
$\frac{\partial Z}{\partial m_2}$	-0.258	-0.128	0.054	0.019	-0.448***	0.007
	[0.877]	[0.275]	[0.196]	[0.278]	[0.163]	[0.131]
$\frac{\partial Z}{\partial m_2}$	-0.326	-0.215	0.000	-0.155	-0.248	0.000
	[0.285]	[0.220]		[0.437]	[0.208]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial Z}{\partial d_1}$	0.007	-0.306	-0.331	-0.656***	-0.507***	-0.155
	[0.423]	[0.382]	[0.204]	[0.188]	[0.191]	[0.437]
$\frac{\partial Z}{\partial d_2}$	-0.698	-0.090	-0.172	-0.913	-0.196	-0.248
	[0.803]	[0.154]	[0.231]	[0.245]	[0.095]	[0.208]
$\frac{\partial Z}{\partial d_3}$	0.545*	0.054	0.000	0.016	0.007	0.000
	[0.274]	[0.196]		[0.209]	[0.131]	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.25: Marginal effects of Risk Aversion on Schooling Expenditure Shares by Gender of Child and Parent When Mother Understands Probability

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial S}{\partial m_1}$	0.004	0.010	0.007	-0.038***	-0.021***	0.003
	[0.013]	[0.006]	[0.009]	[0.014]	[0.003]	[0.008]
$\frac{\partial S}{\partial m_2}$	0.023**	0.003	-0.007**	-0.025*	0.001	-0.007**
	[0.009]	[0.005]	[0.003]	[0.014]	[0.003]	[0.003]
$\frac{\partial S}{\partial m_3}$	-0.012	-0.0001	0.000	0.029*	-0.0016	0.000
	[0.009]	[0.005]		[0.015]	[0.004]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial S}{\partial d_1}$	-0.014	0.019**	-0.012	-0.011	0.011***	0.029*
	[0.014]	[0.008]	[0.009]	[0.006]	[0.003]	[0.015]
$\frac{\partial S}{\partial d_2}$	0.003	0.011**	-0.0001	-0.026**	0.007**	-0.002
	[0.010]	[0.004]	[0.005]	[0.008]	[0.003]	[0.004]
$\frac{\partial S}{\partial d_3}$	0.007	-0.007**	0.000	0.003	-0.007**	0.000
	[0.009]	[0.003]		[0.008]	[0.003]	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.26: Marginal effects of Risk Aversion on Schooling Expenditure Shares by Gender of Child and Parent When Father Understands Probability

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial S}{\partial m_1}$	0.018***	0.007	0.010	-0.043**	-0.016***	-0.001
	[0.009]	[0.009]	[0.006]	[0.020]	[0.004]	[0.005]
$\frac{\partial S}{\partial m_2}$	0.021***	0.004	-0.004*	-0.018	0.000	-0.003
	[0.007]	[0.004]	[0.002]	[0.017]	[0.005]	[0.003]
$\frac{\partial S}{\partial m_3}$	-0.014**	0.003	0.000	0.032*	-0.002	0.000
	[0.005]	[0.005]		[0.019]	[0.004]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial S}{\partial d_1}$	-0.006	0.011**	-0.014**	-0.009	0.017*	0.032*
	[0.011]	[0.005]	[0.005]	[0.007]	[0.009]	[0.019]
$\frac{\partial S}{\partial d_2}$	0.000	0.011***	0.003	-0.014**	0.003	-0.002
	[0.009]	[0.002]	[0.005]	[0.006]	[0.004]	[0.004]
$\frac{\partial S}{\partial d_3}$	0.010	-0.004*	0.000	-0.001	-0.003	0.000
	[0.006]	[0.002]		[0.005]	[0.003]	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1.27: Marginal effects of Risk Aversion on Schooling Expenditure Shares by Gender of Child and Parent When Both Parents Understand Probability

	Boys			Girls		
	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$	$d_1 = 1$	$d_2 = 1$	$d_3 = 1$
$\frac{\partial S}{\partial m_1}$	0.017	0.008	0.019***	-0.033***	-0.023***	-0.003
	[0.018]	[0.008]	[0.005]	[0.005]	[0.006]	[0.003]
$\frac{\partial S}{\partial m_2}$	0.021	0.004	-0.007***	-0.017***	0.000	-0.010***
	[0.015]	[0.005]	[0.002]	[0.006]	[0.004]	[0.003]
$\frac{\partial S}{\partial m_3}$	-0.020	0.004	0.000	0.019	-0.003	0.000
	[0.012]	[0.005]		[0.002]	[0.004]	
	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$	$m_1 = 1$	$m_2 = 1$	$m_3 = 1$
$\frac{\partial S}{\partial d_1}$	-0.022	0.008	-0.0202	-0.011	0.012**	0.019***
	[0.013]	[0.006]	[0.012]	[0.005]	[0.005]	[0.002]
$\frac{\partial S}{\partial d_2}$	-0.007	0.015***	0.004	-0.022***	0.007**	-0.003
	[0.007]	[0.003]	[0.005]	[0.005]	[0.003]	[0.004]
$\frac{\partial S}{\partial d_3}$	0.019***	-0.007***	0.000	-0.003	-0.010***	0.000
	[0.005]	[0.002]		[0.003]	[0.003]	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

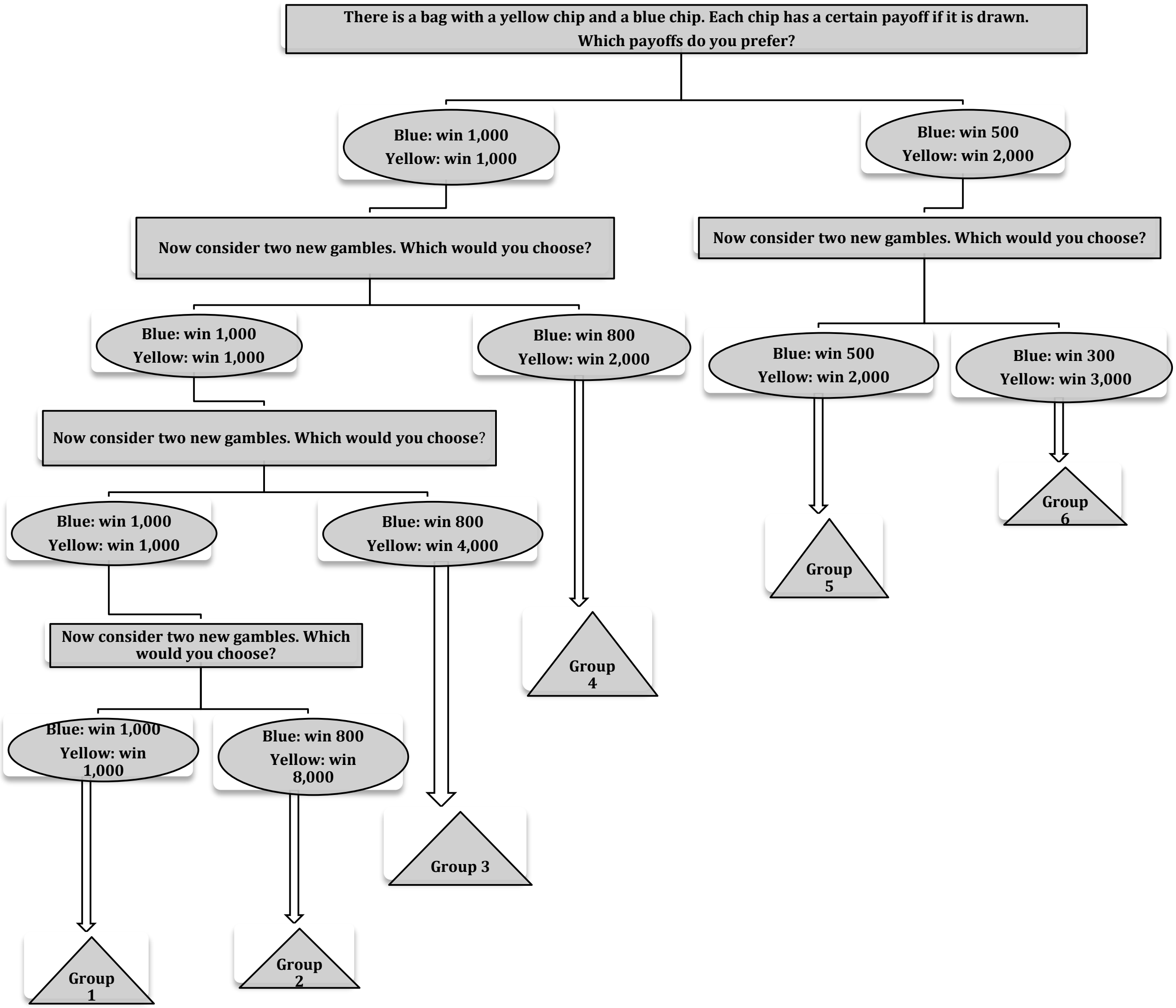

Figure 1.1: Flow chart of gambles presented

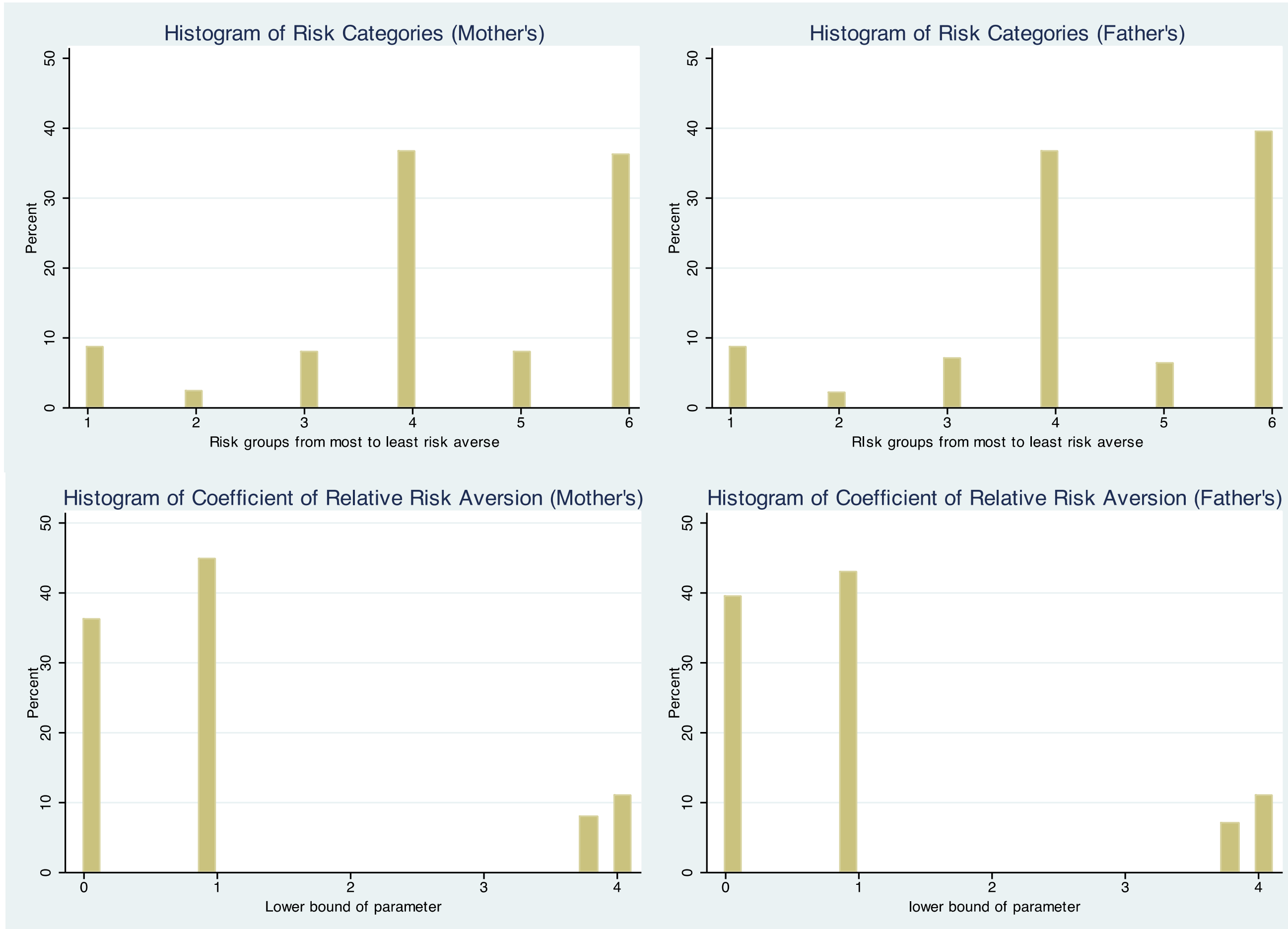

Figure 1.2: Histograms of risk groups and risk aversion coefficients for mothers and fathers

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Chapter 2

HIV Testing and Belief Revision: What Do You Learn About Your Past and Future?

2.1 Introduction

In regions where access to HIV testing is limited, individuals face the challenge of estimating their likelihood of being HIV positive and expected mortality. Years could pass between infection and displaying symptoms, which makes it difficult to accurately assess the source of infections (Anglewicz and Kohler (2009)). Anglewicz and Kohler note that there is a tendency for individuals to overestimate the risk factors associated with contracting HIV, which could lead to individuals choosing suboptimal levels of savings and investments for the future.

In this paper I examine whether HIV testing leads to revisions in the subjective likelihood of being HIV positive and the subjective likelihood of surviving across various time horizons. HIV testing should provide certainty about one's HIV status in the short term, but how individuals revise their likelihood of being HIV positive over time is an empirical question.

An HIV negative woman may have contracted HIV after learning her status, which means that reporting a nonzero subjective likelihood of being HIV positive could be consistent with believing the test result. On the other hand, if individuals do not believe the validity of the test result, then there may be no effect of testing on the subjective likelihood of being HIV positive and subjective mortality. Voluntary Counseling and Testing centers (VCT's) have been suggested as an HIV prevention strategy, so it would be of interest for policy purposes to evaluate how beliefs and behavior respond to testing.

In my estimation I use panel data from the Malawi Diffusion and Ideational Change Project (MDICP). Data collection began in 1998 with a sample of ever-married women and their co-resident spouses. Before the sample was offered testing in 2004, very few had already been tested already, but many believed they knew their status based on their behavior and that of their partner. Test results in 2004 were not available until four to six weeks after testing, so individuals had to make a decision to go to a small mobile clinic to receive their results and post-test counseling. The 2004 MDICP study was designed provide information that would permit controlling for the possible endogeneity of preferences for receiving results: randomized incentives of varying amounts were offered during pre-test counseling, and the location of the mobile clinics was randomized (Thornton (2008)).

Beginning in 2006, individuals were asked to report their likelihood of being HIV positive on a scale of zero to ten. Individuals also reported their expected mortality over one, five, and ten year horizons on a zero to ten scale. The average reported belief across HIV positive and negative women was 1.5 out of 10, whereas actual HIV rate in the sample was five percent. This suggests that individuals overestimate their likelihood of being HIV positive if one were to assume that a one corresponds to ten percent probability of infection, two corresponds to twenty percent probability, etc. In my estimation strategy I relax the assumption that the likelihood categories correspond to fixed probabilities. Instead, I argue that reported subjective likelihoods are an ordinal measure of the likelihood of being HIV positive or the likelihood of dying.

Using the randomizations of financial incentives as an instrumental variable for the decision to get test results, I find that HIV negative individuals who learn their status believe they have a higher likelihood of being HIV positive two years later compared to HIV negative women who do not find out their status. At the same time, I find that HIV negative individuals believe they are less likely to die over a ten-year period. It appears that women who learn their HIV negative status believe they are negative at the time of testing but overestimate their likelihood of having contracted HIV in the two-year period after learning their HIV status. HIV positive individuals who learn their status have higher beliefs about their current HIV status compared to HIV positive individuals who do not obtain their test results. However, learning one's HIV status does not have a significant effect on beliefs about mortality for HIV positive women. Since HIV positive women do not learn when they contracted HIV, this uncertainty could makes the effect of learning one's HIV positive status on expected mortality ambiguous.

A possible explanation for the limited response of beliefs about HIV status and mortality to HIV testing may be that individuals have very strong priors about their HIV status. It has been suggested that individuals may not fully believe the negative test results if they strongly believe they are at risk of contracting HIV (Sterck (2012)). If a woman is sure that her husband is at very high risk of being HIV positive and believes that the transmission rate is high, then she will believe that she must be HIV positive. She will think that the test is a mistake because she is overestimating the transmission rate associated with having sex with an HIV positive partner. Conversely, HIV positive individuals may not fully believe they are HIV positive if they believe their spouse must be infected by now if they were truly HIV positive. In the Appendix I develop a model where individuals update their beliefs about being HIV positive in a Bayesian manner. In this framework an individual's beliefs about his or her likelihood of being HIV positive may be unresponsive to testing if the individual has strong priors about their HIV status before testing. This result can have important implications for policymakers who wish to use HIV testing as a tool for minimizing the spread of HIV. In particular, individuals may have to be tested multiple times in order to fully believe their actual HIV status.

This paper is related to to the literature that evaluates the validity of self-reported beliefs regarding health and mortality. In a developed country context, there is evidence that subjective mortality expectations vary with risk factors in the expected direction (Hurd and McGarry (1995)). Using subjective mortality expectations in the Health and Retirement Study, the authors show that the average mortality expectations of individuals are close to the actual average mortality in the population. There has been skepticism about whether individuals in developing countries understand probabilistic questions and whether subjective beliefs are useful predictors of future behavior. For example, if individuals do not understand how to answer their likelihood of being HIV positive or their likelihood of dying in the future, then reported beliefs would not have any predictive power over future decision-making. Delavande, Gine, and McKenzie (2011) review several studies in developing countries where individuals are given visual representations of probabilities such as allocating beans or stones to different possible states. They find that elicited probabilistic expectations followed the basic properties of probability and that individuals rarely give degenerate distributions.

In Malawi, de Paula, Shapira, and Todd (2010) estimate the effect of belief revision about the likelihood of being HIV positive on the number of sexual partners. While they find that a change in the reported likelihood of being HIV positive leads to a change in risky behavior among men, they do not evaluate how individuals revise their beliefs in respond to HIV testing. Furthermore, self reported beliefs about HIV status might be correlated with unobservable characteristics that drive risky behavior, so it's not clear if the authors establish a causal link between beliefs about HIV status and behavior.

Shapira (2013) incorporates a woman's beliefs about her likelihood of being HIV positive into a dynamic model of the fertility decisions of women. He finds that women who believe they have a low likelihood of being HIV positive increase their fertility. Shapira does not control for the endogeneity of the decision to get test results, which is documented by

Thornton (2008). She finds that individuals who engage in less risky sexual behavior and have a lower self reported likelihood of being HIV positive return to a clinic to find out their HIV status, which would bias the effect of testing on beliefs downwards. To identify the effect of HIV testing on condom purchases two months later, Thornton randomizes the size of financial incentives offered to individuals to return to a clinic to find out their test results. Due to the short time frame of analysis, she was not able to examine the effect of testing on long term decision-making such as fertility. Thornton does not address beliefs in detail, but finds some evidence that testing has a greater effect on individuals who were surprised by their test results. Thornton assumes that HIV positive individuals with low priors and HIV negative individuals with high priors were the individuals who where surprised by their test results.

Gong (2011) investigates the effect of HIV testing on risky behavior in East Africa. He measures risky behavior by sexually transmitted infections, which is an outcome of risky behavior. Gong randomizes HIV testing over a sample of individuals seeking HIV services, which calls into questions the external validity of the study. In joint work with Katherine Eriksson (2013) we use Thornton's instrumental variable for learning one's HIV status to examine the effect on testing on a representative sample of the ever-married population in Malawi. We find that individual's preferences regarding fertility and investments in children are dependent on their HIV status. In particular, women who learn they are HIV negative increase their fertility and educational expenditures on their children.

Delavande and Kohler (2012) examine the effect of HIV testing on beliefs and find that there is no significant effect of testing for HIV positive women. There is a positive effect of testing on the subjective likelihood of being HIV positive among HIV negative individuals. The authors use a linear specification, which assumes that the reported likelihood categories corresponded to probability intervals of fixed width. Previous studies have noted that HIV negative individuals are overestimating their subjective likelihood of being HIV positive if the likelihood categories are assumed to correspond to 10% probability intervals. Furthermore, Delavande and Kohler (2009) do not look at the effect of testing on subjective mortality, so they cannot distinguish whether individuals do not fully believe the test results or whether they are overestimating their risk in the time between testing and reported their beliefs.

In Section Two I describe the dataset that I use in estimation and provide descriptive statistics about self reported beliefs. I find that individuals understand how HIV is transmitted and understand probabilistic questions. In section three I estimate the effect of finding out one's HIV status on beliefs two years later. In section four I discuss possible explanations of the estimation results. In particular, I discuss if the effect of testing on beliefs about HIV status and beliefs about mortality are consistent with one another. The next step of research is to look at the sequence of testing, beliefs, and behavior. I conclude by proposing a simple model that can be used in future research.

2.2 Data

The Malawi Diffusion and Ideational Change Project (MDICP) created a panel data set with surveys in 1998, 2001, 2004, 2006, and 2008. The initial sample in 1998 consisted of ever-married women and their co-resident spouses. I will be using the 2004 and 2006 survey waves in estimation. Three districts in Malawi were selected to participate: Rumphi in the northern region, Mchinji in the central region, and Balaka in the southern region. In all regions most individuals are subsistence farmers, but there is variation in their predominant religion and HIV rates. Rumphi and Balaka are primarily Christian, while Balaka is primarily Muslim. In my estimation sample of women aged 18-50, Balaka has the highest HIV rate (12%), while Rumphi has the lowest (5%). The data includes the usual socio-demographic variables along with information about sexual activity and beliefs regarding HIV. Summary statistics of the estimation sample are reported in Table 2.1. Fifty-seven percent of women in the sample have at least a primary education, and twenty-seven percent are in a polygamous marriage. On average, women have had about two sexual partners in their lifetime. This could be due to previous marriages or extramarital partners.

2.2.1 HIV Testing

After the 2004 survey wave was completed, nurses were sent to respondent's homes to conduct HIV testing. 91 percent of the survey respondents consented to an HIV test. Results were not immediately available, so individuals had to go to a voluntary testing and counseling (VCT) center 2-4 months after testing to learn their status. In a field experiment, Thornton offered individuals a randomized financial incentive to go to a VCT center. Respondents were offered a voucher between zero and three dollars, which was redeemable upon showing up at a VCT center to find out their test results. The average value of the voucher was one dollar, which is equivalent to about a day's wage. Individuals who returned to a VCT center were told their status and received counseling about HIV prevention methods. In my estimation sample, 73% went to a VCT center to find out their HIV status.

When considering the effect of testing on beliefs two years later, it's possible that individuals do not remember that they found out their status. Individuals were asked if they had ever found out the results to an HIV test, and surprisingly only 78 percent of individuals who got their test results in 2004 report ever having gotten a test result. Although HIV testing was not widely available, 46 percent of individuals who did not find out their HIV status in 2004 report having found out their HIV status in the past. If individuals had been tested in the past, then the 2004 test result may not be completely new information. In particular, the test result would provide information about their HIV status in the time period between the two tests.

2.2.2 Beliefs

Beginning with the 2006 survey, women were asked to report their likelihood of being HIV positive on a scale of zero to ten. A histogram of the beliefs of HIV negative women in 2006 is shown in Figure 1. The reported beliefs represents a mixture of women who found out their HIV status in 2004 and women who did not find out their status in 2004. A majority of HIV negative women report a belief of zero, but thirty eight percent report non-zero beliefs. The average reported belief for HIV negative women is twelve percent, or 1.2 on a scale of zero to ten. One and a half percent of the HIV negative women in this sample contracted HIV, so for a small number of women their status did in fact change. Figure 2 shows that the distribution of beliefs of HIV positive women is fairly spread out. On average, HIV positive women report an average belief of 35 percent, which is higher than the average beliefs of HIV negative women but not as high as one might expect a priori. About 14 percent of HIV positive women report a likelihood 100 percent, but more HIV positive women report a likelihood of zero. Why do some HIV positive women who find out their test results report a low likelihood of being HIV positive two years later? Most individuals understand that there is no cure for HIV, so a woman who tests positive for HIV should believe she has HIV two years later. Possible explanations include some women not believing in the validity of the test results, or believing they may have been cured. Because HIV can be asymptomatic for several years, individuals may not be convinced that they are in fact HIV positive two years after testing. In the estimation section I will examine whether there is any significant belief revision due to testing.

Interpretation of response categories

The assumption that the response categories correspond to probabilities of zero percent, ten percent, twenty percent, etc. does not appear to fit the data well. The average reported belief across HIV positive and negative women was 1.5 out of 10 whereas actual HIV rate in the sample was five percent. Although the goal of the survey is to elicit probabilities, there are limitations in using a discrete response set to estimate an event with a very low probability of occurring. For example, does a woman with a two percent chance of having HIV report a different likelihood than a woman with a four percent chance of having HIV? The HIV rate is increasing with reported beliefs as reported in Table 2.2, which suggests that reported beliefs should be interpreted as an ordinal measure of the likelihood of having HIV.

What observable characteristics are correlated with the subjective likelihood of being HIV positive? Table 2.3 reports summary statistics of the women in the 2006 MDICP, separately by HIV status. Some notable differences between women who are HIV positive and negative are the number of lifetime sexual partners and marital status. In particular, women who are HIV positive report having 3.1 sexual partners on average compared to 1.9 for HIV negative women. Women who are HIV positive are also less likely to be currently married than HIV negative women on average. A woman may use these differences to construct her subjective likelihood of being HIV positive. For example, a women who has had more sexual partners may be more likely to believe she is HIV positive. I run a linear regression to examine the correlation between potential risk factors associated with HIV and the reported likelihood of being HIV positive. Results are reported in Table 2.4. Variables that differ across HIV positive and negative women have significant effects on the subjective likelihood of being HIV positive. Although the rates of polygamy are similar for HIV positive and negative women, the regression results suggest that individuals who are in a polygamous marriage are more likely to believe that they are HIV positive.

2.2.3 Mortality

Most individuals in the sample are aware of the risk factors associated with contracting HIV. To examine whether individuals understand the effect of HIV on mortality, individuals were asked the likely mortality of four hypothetical women of the same age: A healthy women who does not have HIV, a woman who has HIV, a woman who is sick with AIDS, and a woman who is sick with AIDS and is treated with antiretrovirals. The average responses are reported below in Table 2.5. On average, the expected mortalities of the hypothetical women are ranked correctly across all time horizons. In other words, individuals believe that a woman who has HIV is more likely to die a woman who does not have HIV, and a woman with AIDS is more likely to die than a woman who has HIV and a woman who does not have HIV.

On average, individuals understand the negative effects of HIV on mortality, so how does this knowledge affect beliefs about their own mortality? Individuals were asked on a scale of one to ten the likelihood they would be alive in one year, five years, and ten years. Individuals were not allowed to decrease their likely mortality over longer time horizons. For example, a women who reports a likelihood of two that she will die in a year must answer two or greater for her likelihood of dying in five and ten years. Figure 3 shows beliefs about mortality by HIV status over one, five, and ten years. The left hand column compares HIV negative women over different time horizons and the right hand column compares HIV positive women over different time horizons. Each row compares women of different HIV status over the same time horizon. The distribution of beliefs shifts to the right over longer time horizons for both HIV positive and negative women. Within a given time horizon, the distribution of beliefs falls on the higher end of the likelihood scale for HIV positive women compared to the distribution of beliefs for HIV negative women. These histograms suggest that being HIV positive is correlated with having a higher subjective likelihood of dying in the future.

2.3 Empirical Strategy

It appears that individuals in the MDCIP understand the basic principals of probability, and that beliefs about the likelihood of having HIV are correlated with actual status and risky behavior. In this section I use several specifications to estimate the effect of learning one's HIV status on beliefs two years later. Individuals in the MDICP were administered HIV tests immediately after the 2004 survey wave. I regress the 2006 beliefs on the 2004 test results for ever-married women between the ages of 15 and 50:

$$Beilef_i = \alpha + \beta_1 GotResult_i + \beta_2 X_i + \varepsilon_i \tag{2.1}$$

X_i incudes additional controls such as age, the number of lifetime sexual partners, whether the woman is in a polygamous marriage, and regional dummies. Variation in the receipt of test results is due to the fact that individuals had to return to a clinic a few months after testing to find out their test result and receive counseling. As a result, not all individuals who were tested in 2004 found out their results. Because there is likely a selection bias, I use the randomized financial incentives offered by Thornton to construct instrumental variables for learning one's HIV status. In particular, I use whether the individual received any incentive, the size of the incentive, and the size of the incentive squared as instrumental variables. The first stage regression is:

$$GotResult_i = \alpha + \beta_1 IncentiveAny_i + \beta_2 IncentiveAmt_i + \beta_3 IncentiveAmt_i^2 + \varepsilon_i \tag{2.2}$$

I run separate regressions for HIV positive and negative women to allow the estimated coefficients to vary by HIV status. An alternative specification is to run a regression that pools HIV positive and negative individuals. In this specification, the effect of finding out ones HIV status is allowed to vary by HIV status but other coefficients are restricted to be equal. [1] The first stage equations for the pooled sample include interactions between the incentives and HIV status:

$$\begin{aligned} GotResult_i = \alpha &+ \beta_1 IncentiveAny_i + \beta_2 IncentiveAmt_i + \beta_3 IncentiveAmt_i^2 \\ &+ \beta_4 (IncentiveAny_i * HIV_i) + \beta_4 (IncentiveAmt_i * HIV_i) \\ &+ \beta_4 (IncentiveAmt_i^2 * HIV_i) + \varepsilon_i \end{aligned} \tag{2.3}$$

[1] The concern with this specification is that there are few observations of HIV positive individuals, which could lead to multicollinearity issues between the HIV positive indicator and $HIV * GotResults$.

$$\begin{aligned} GotResult_i * HIV_i = \alpha &+ \beta_1 IncentiveAny_i + \beta_2 IncentiveAmt_i + \beta_3 IncentiveAmt_i^2 \\ &+ \beta_4(IncentiveAny_i * HIV_i) + \beta_4(IncentiveAmt_i * HIV_i) \\ &+ \beta_4(IncentiveAmt_i^2 * HIV_i) + \varepsilon_i \end{aligned} \tag{2.4}$$

And the second stage also include HIV status:

$$Belief_i = \alpha + \beta_1 GotResult_i + \beta_2(GotResult_i * HIV_i) + \beta_3 HIV_i + \beta_4 X_i + \varepsilon_i \tag{2.5}$$

If HIV positive women believe their test results, then the effect of learning their HIV positive status would be expected to be positive and significant. If the effect of learning one's HIV positive status is close to zero, then this may mean women already have an accurate perception of there exposure to HIV, so testing did not provide much additional information. Alternatively, a zero effect could also mean that HIV positive women to do not believe the test results. The predicted effect of learning one's HIV negative status is less straightforward because a woman's status could have changed in the two years post-testing. If a woman does not believe her status changed and believed the test results then learning one's HIV negative status should have a negative effect of the subjective likelihood of being HIV positive. On the other hand, if an HIV negative woman believes her test result but believes her exposure to HIV in the post-testing period has increased then learning one's negative status may have a positive effect on the subjective likelihood of being HIV positive.

First stage regressions are reported in Table 2.6 for both specifications. The F statistic of the instruments is fairly large with the exception of the $GotResult * HIV$ regression. The F statistic is larger when running separate regressions for HIV positive and negative women. The second stage can be estimated by a linear or nonlinear regression. An ordered probit model would be more appropriate if reported beliefs are an ordinal measure rather than a cardinal measure of the likelihood of having HIV. As discussed in the data section, average reported beliefs do not correspond well to the actual HIV rate if belief categories are interpreted as probability intervals of equal size. Instead, beliefs provide a ranking of individuals: those with higher reported beliefs think they are more likely to have HIV than individuals with lower reported beliefs.

2.3.1 Nonlinear Regression Results

To estimate an ordered probit with an endogenous regressor I use the two-stage conditional maximum likelihood estimator (2SCML) proposed by Rivers and Vuong (1988). An advantage of this estimator is that the inclusion of the error term in the second stage provides a test for the endogeneity of the instrumented variable. Results are reported in the Table 2.7 below. Column 1 reports the regression results of the pooled HIV positive and negative sample, and columns 2 and 3 report results from running separate regressions by HIV status. There is no significant effect of testing on beliefs when HIV positive and negative individuals are pooled together. When running separate regressions for HIV positive and negative women the effect of finding out ones HIV status (both positive and negative) is now significant. The change in coefficients is likely due to the fact that the coefficients on most of the covariates are different for the HIV positive and HIV negative regressions, which suggest that the appropriate specification is to run separate regressions. Table 2.8 reports the marginal effect of finding out ones HIV status from regressions 2 and 3 at the mean of the dependent variable.

HIV positive individuals who find out their status are 52 percent less likely to report a zero likelihood of being HIV positive and 17 percent more likely to report a likelihood of ten, both of which are significantly different from zero at the five percent level. Surprisingly, HIV negative individuals who find out their status believe they have a higher likelihood of being HIV positive two years later than HIV negative individuals who do not find out their status, although this effect is not as large in magnitude as the HIV positive results. Women who find out their negative status are 14 percent less likely to report a zero likelihood of being HIV positive, which is significant at the five percent level. The effect of testing on reporting non-zero likelihoods is small for each likelihood category, so it appears the largest effect is that women are less likely to report a belief of zero. It is possible that interacting with the medical community increases a woman's awareness of her exposure to HIV risk factors in the two year post-testing, which leads to women reporting some nonzero likelihood of being HIV positive.

Because there are relatively few observations in the high end of the likelihood scale, I group together individuals in the six to ten range and run an ordered probit regression with the fewer categories (0,1,2,3,4,5,6 and above). Results are reported in Table 2.9. The effect of finding out ones HIV status remains positive for both HIV positive and negative individuals when running separate regressions for HIV positive and negative individuals. The marginal effect of finding out ones HIV status when running separate regressions for HIV positive and negative women is reported in Table 2.10. HIV positive women who find out their status are 53 percent less likely to report a likelihood of zero and 26 percent more likely to reports a likelihood of 6 and above. HIV negative women who find out their status are 14 percent less likely to report a likelihood of zero compared to HIV negative women who do not find out their status.

2.3.2 Linear Regression Results

As a robustness check I report the results of linear two-staged least squared regressions. The results of the pooled second stage regression are reported in column 1 of Table 2.11, which can be used to compare to the results found by Delavande and Kohler (2009). In the pooled linear specification, the effect of finding out ones status is positive and significant for HIV negative women, and positive and insignificant for HIV positive women. My point estimates are slightly higher than in Delavande and Kohler, but my sample is only women whereas Delavande and Kohler include both men and women. Column 2 and 3 report results when running separate regressions for HIV positive and negative women. For HIV negative women, finding out ones status is associated with a .6 increase in the expected likelihood of being HIV positive on a scale of zero to ten, which is significant at the 10 percent level.

For HIV positive women, finding out ones status is associated with a 4.64 increase in the expected likelihood of being HIV positive. These results are similar to the ordered probit regression results.

To summarize, the linear and nonlinear regression results suggest that there is a positive effect of getting test results on the subjective likelihood of being HIV positive for HIV negative women. In other words, individuals who receive an HIV-negative test result are more likely to think they are HIV positive two years after testing than individuals who are HIV-negative and did not get their test results. There is a larger increase in beliefs for HIV positive women who find out their status compared to HIV positive women who do not find out their status.

2.3.3 Expected Mortality

In this section I estimate the effect of learning ones HIV status on the reported likelihood of dying over the next year, the next five years, and the next ten years. The estimated equations are similar to the beliefs regressions but with a few different covariates. I include covariates relative to socioeconomic status such as educational level and marital status since it is well documented that actual mortality is highly correlated with socioeconomic status (Hurd and McGarry (1995)). For there to be a negative relationship between testing and expected mortality an HIV negative individual must believe that she was HIV negative at least as of two years ago when the test results were given. If individuals do not believe the validity of the test results then there should be no effect of testing on expected mortality. Results of the ordered probit regressions are reported in Table 2.12. For HIV negative individuals, the effect of learning ones status becomes more negative over longer time horizons. The marginal effect of learning one's HIV status over the different time horizons is reported in Table 2.13 Over a ten year horizon, women who find out they are HIV negative are less likely to report likelihoods on the high end of the scale. More specifically, these women are less likely to report a likelihood above six compared to HIV negative women who do not learn their status.

There is no significant effect of learning ones HIV status for HIV positive women across all time horizons, which is likely due to the small sample size. Because these estimates lack precision, any effect of HIV testing would have to be very large in order to be detected. Another concern is that there are very few observations per likelihood category. As a robustness check, I estimate ordered probit regressions with fewer likelihood categories to eliminate thinly populated categories. The observation count of each likelihood category is presented in Table 2.14. I define three new groups: Group 1 includes women who report a zero to two on the old likelihood scale, Group 2 includes women who report a three to five, and Group 3 report a 6 and up.

Regression results with the new groups are presented in Table 2.15 and marginal effects are presented in Table 2.16. The pattern of the marginal effects remains consistent when compared to the ungrouped regression results. In particular, HIV negative women who learn their status are more likely to fall in the lowest likelihood group for the one and five year time horizons. Interestingly, women who learn their HIV status are more likely fall in the middle group rather than the lowest group on the ten year scale. This pattern could be consistent with the theory that women who learn they are HIV negative attach a higher likelihood to having contracted HIV in the period post-testing. In other words, women revise their subjective mortality downward over the short term because they learn they were HIV negative as of two years ago. On the other hand, women don't revise their subjective likelihood of dying over a longer time horizon as much because they may have contracted HIV after learning their test result. The details of this argument are discussed in the following section.

2.4 Discussion

My regression results suggest that women who find out they are HIV negative have a higher reported belief about their current HIV status than women who do not find out they are HIV negative. Despite believing they have a higher likelihood of being HIV positive, women who find out they are HIV negative revise their expected mortality downwards relative to women who do not find out they are HIV negative. How does one reconcile the beliefs results with the expected mortality results? The results seem to be related to the two year lag between when HIV test results were available (2004) and when individuals were asked the likelihood they had HIV (2006). Due to the lag, reported beliefs are a composition of the individuals interpretation of the test result and their perceived exposure to HIV in the two year period post-testing. Assuming that they believe the validity of their negative test result, individuals must be overestimating their recent potential exposure to HIV when estimating their current likelihood of having HIV.

The following framework can be used to explain how individuals who find out they are HIV negative believe they have a higher likelihood of being HIV positive two years later. There are three time periods: the current period (t), the period after HIV testing but before the current period (t-1) and the time period prior to HIV testing (t-2). The probability an individual is HIV positive at time t is a function of the probability they contracted HIV in the two previous periods:

$$P_t = P_{t-1} + (1 - P_{t-1}) * P_{t-2} \tag{2.6}$$

An individual who got their test result in period t-2 knows that they were HIV negative at least until that time period so the probability having contracting HIV during that time period is zero. Individuals who did not get their test result have some probability they contracted HIV in period t-2.

$$P_t = \begin{cases} P^1_{t-1} & \text{if Got Result=1} \\ P^0_{t-1} + (1 - P^0_{t-1}) * P^0_{t-2} & \text{if Got Result=0} \end{cases}$$

If P^1_t is greater than P^0_t, then P^1_{t-1} must be weakly greater than P^0_{t-1} because all probabilities are non-negative:

$$\begin{aligned} P^1_t &> P^0_t \\ P^1_{t-1} &> P^0_{t-1} + (1 - P^0_{t-0}) * P^0_{t-2} \\ \Rightarrow P^1_{t-1} &\geq P^0_{t-1} \end{aligned} \tag{2.7}$$

In other words, individuals who get their test result must be overweighing the risk of contracting HIV in the two-year period post-testing.

An alternative explanation is that the subjective likelihood of being HIV positive represents an individuals perceived risk of contracting HIV as opposed to representing the probability of having contracted HIV in the past. A negative test is a signal of her underlying risk of contracting HIV, and she uses this information to update her perceived risk. To examine whether there is more concern about contracting HIV among individuals who found out their HIV negative status, I estimate the effect of learning one's HIV negative status on how worried an individual is about contracting HIV. Individuals were asked how worried they were about contracting HIV and given three response categories: none, low, and high. Ordered probit regression results of HIV negative women are reported in Table 2.17. Individuals who find out they are HIV negative report being more worried about contracting HIV, which is significant at the ten percent level. In terms of the marginal effects, women who learn their HIV negative status are sixteen percent less likely to report not being worried at all about contracting HIV. By returning to a clinic to find out their test results and receive counseling about HIV, individuals may be more aware of the risk factors that are related to contracting HIV. The counseling could serve as a reminder that HIV is present in the community and that a woman may have had some level of exposure to HIV.

How can there be negative effects on expected mortality if women who learn they are HIV negative believe that they are more likely to have HIV? If an HIV negative woman who received her test results now believes she may be HIV positive, she knows her status must have changed in the past two years. An individual who did not obtain her test results and is unsure of her HIV status would have to consider a larger timeframe in which HIV infection may have occurred. Although they may have similar beliefs about their current likelihood of being HIV positive, the expected elapsed time from infection would be shorter for individuals who found out they were HIV negative in 2004. Therefore expected mortality should be lower for an individual who learns she is HIV negative as of 2004. When comparing HIV negative women who learn and and do not learn their HIV status, the difference in expected mortality is stronger over a longer time horizon. Contracting HIV negative effect may not have an effect on mortality for several years. Table 2.5 in the data section shows that the difference in subjective mortality between HIV positive and negative individuals is increasing over the length of the time horizon, which suggests that individuals believe the mortality effects of HIV are more likely to happen farther into the future.

HIV positive results

HIV positive women who learn their status revise their beliefs upward relative to HIV positive women who do not learn their status. These results suggest that HIV positive women believe their test results and understand that their HIV status cannot change from positive to negative. In other words, a woman who is HIV positive should be certain of her HIV status two years later. Despite having a higher reported likelihood of being HIV positive, there is no significant difference in expected mortality between HIV positive women who learn their status compared to HIV positive women who do not learn their status. Why is there no difference? While her future status is certain, an individual who finds out she is HIV positive does not know at what point she became HIV positive. The positive test result ensures that she will have a higher expected mortality at some point in the future, but it is not clear when. Due to this uncertainty, a woman who thinks she may be HIV positive should think she is less likely to die than a woman who knows she is HIV positive but doesnt know when she became HIV positive, but this difference may be small. Since there are relatively few HIV positive women in the sample there is not enough power to detect a small change in the likelihood of dying due to testing.

2.5 Conclusion

I find that HIV negative individuals who learn their status are more likely to believe they are HIV positive two years after testing compared to HIV negative individuals who do not learn their status. Despite believing they are more likely to be HIV positive in the current period, individuals who learn their status believe they are less likely to die in the next ten years. HIV positive individuals believe they have a higher likelihood of being HIV positive compared to HIV positive individuals who do not learn their status, but there is no significant difference in beliefs about the likelihood of dying in the future. Unlike some previous studies, which have not instrumented for the decision to get test results, I argue that my identification strategy provides a causal link between testing and beliefs.

Future research can utilize these findings to model how individuals update their beliefs about their HIV status and mortality for welfare analysis and estimating counterfactuals. For example, one could estimate a structural model of belief formation in order to test whether there are welfare gains if individuals are more certain of their HIV status. A policy relevant question that can be addressed through a dynamic model is how individuals update their beliefs in response to new information such as HIV testing. It would be of interest to estimate how additional testing and counseling will affect individuals beliefs about their HIV status. For example, would an HIV positive individual continue to revise her beliefs upwards if she were to be retested? If she does, then this suggests that individuals may need to receive multiple tests in order to fully believe their HIV status. In the Appendix I present a preliminary model that can motivate future structural work.

2.6 Appendix

In this model it is possible for individuals to update their beliefs in a Bayesian manner, yet still be relatively unresponsive to testing. Beliefs (b) will be defined as the probability an individual thinks she is HIV positive. Prior to testing, I assume beliefs are a beta distribution with shape parameters α and β:

$$p(b) = \frac{1}{B(\alpha, \beta)} b^{\alpha-1}(1-b)^{\beta-1}, \quad 0 \leq b \geq 1, \alpha > 0, \beta > 0 \tag{2.8}$$

From the properties of the beta distribution it follows that the expected value of beliefs is also a function of α and β:

$$E(b) = \frac{\alpha}{\alpha + \beta} \tag{2.9}$$

After testing is made available individuals have additional information about their HIV status, which can be used to update their beliefs. Out of the total number of tests taken (t) there are p positive test results. By Bayes rule, the posterior probability distribution of beliefs is the likelihood function of the test results times the prior probability density function and then normalized:

$$p(b \mid t, p) = \frac{1}{B(\alpha + p, \beta + t - p)} b^{\alpha-1}(1-b)^{\beta-1} b^{p-1}(1-b) + t - p, \quad 0 \leq b \geq 1, \alpha > 0, \beta > 0 \tag{2.10}$$

Conveniently, posterior beliefs are also a Beta distribution with new shape parameters:

$$p(b \mid t, p) \sim Beta(\alpha + p, \beta + t - p) \tag{2.11}$$

The expected value of posterior beliefs is also shifted by the number of positive test results and overall test results:

$$E(b \mid t, p) = \frac{\alpha + p}{\alpha + \beta + t} \tag{2.12}$$

The evolution of beliefs after testing depends on the starting value of the shape parameters. In other words, an individual's priors will affect how much they adjust their posterior beliefs after testing. I will discuss two hypothetical individuals to illustrate this point. The shape parameters of each individual are presented below:

	α	β	t	E[b]	$E[b \mid t]$
Individual 1	2	6	4	$\frac{2}{2+6} = \frac{1}{4}$	$\frac{2}{2+6+4} = \frac{1}{6}$
Individual 2	1	3	4	$\frac{1}{1+3} = \frac{1}{4}$	$\frac{1}{1+3+4} = \frac{1}{8}$

Individual 1 and individual 2's beliefs are drawn from beta distributions with different shape parameters. The expected value of beliefs is the same for both individuals prior to testing. Suppose both individuals are HIV negative and undergo HIV testing. If both individuals are tested 4 times, the expected value of individual 1's posterior beliefs is 1/6 while the expected value of individual 2's posterior beliefs is 1/8. Individual 1 would have to take 4 additional HIV tests for the expected value of his beliefs to equal Individual 2s beliefs.

What does this example tell us? Holding the ratio between the alpha and beta shape parameters constant, the magnitude of the shape parameters can be interpreted as how strongly an individual weights prior beliefs when faced with new information. If individuals have very strong priors, then testing would have a relatively small affect on posterior beliefs.

Table 2.1: Summary Statistics of Women in 2006 MDICP

	Mean	Std. Dev.
Age	32.56	8.33
Primary Education	0.57	0.49
Polygamous	0.27	0.45
Married	0.93	0.26
Total # Sex partners	1.96	1.17
Got HIV test result in 2004	0.73	0.44
Region=mchinji	0.28	0.45
Region=balaka	0.37	0.48
Region=rumphi	0.35	0.48
Likelihood of having HIV*	1.40	2.26
Likelihood of dying in next 1yr*	2.10	1.92
Likelihood of dying in next 5yrs*	4.10	2.24
Likelihood of dying in next 10yrs*	5.98	2.32

*Individuals were asked to give a likelihood on a scale of zero to ten

Table 2.2: HIV Rates by Subjective Likelihood of Being HIV Positive

Belief	%HIV pos	Std. Dev.	N
0	0.03	0.17	485
1	0.05	0.21	85
2	0.03	0.17	65
3	0.16	0.37	44
4	0.12	0.33	25
5	0.09	0.29	64
6 and up*	0.21	0.41	39
Total	0.05	0.23	807

*likelihood categories above 6 were aggregated due to the lack of observations

Table 2.3: Summary Statistics of Women in 2006 MDICP by HIV Status

	HIV Positive		HIV Negative	
	Mean	Std. Dev.	Mean	Std. Dev
Age	31.75	7.40	32.62	8.39
Primary Education	0.50	0.50	0.58	0.49
Polygamous	0.25	0.44	0.28	0.45
Married	0.75	0.44	0.94	0.24
Total # Sex partners	3.14	1.48	1.88	1.09
Got HIV test result in 2004	0.64	0.48	0.74	0.44
Region=mchinji	0.29	0.46	0.28	0.45
Region=balaka	0.52	0.50	0.36	0.48
Region=rumphi	0.20	0.40	0.36	0.48
Likelihood of having HIV*	3.57	3.41	1.24	2.07
Likelihood of dying in next 1yr*	2.78	1.83	2.06	1.92
Likelihood of dying in next 5yrs*	5.31	2.42	4.02	2.20
Likelihood of dying in next 10yrs*	6.52	2.21	5.95	2.32
Number of observations	44		763	

*Individuals were asked to give a likelihood on a scale of one to ten

Table 2.4: Linear regression of self-reported beliefs

Age	0.1589**
	[0.070]
Age squared	-0.0026**
	[0.001]
Number of Children	0.0335
	[0.031]
Primary Education	0.0904
	[0.170]
Number of Sex Partners	0.3359***
	[0.102]
Polygamous	0.8235***
	[0.186]
Region=Michinji	0.5712***
	[0.212]
Region=Balaka	0.1955
	[0.199]
HIV positive	1.7483***
	[0.489]
Constant	-2.3026**
	[1.136]
Observations	807
R-squared	0.112

Robust standard errors in brackets
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2.5: Beliefs about Mortality Likelihood of Hypothetical Women on a Scale of Zero to Ten

	Woman who is healthy and no HIV	Woman who is infected with HIV	Woman who is sick with AIDS	Woman who is sick with AIDS and treated with ARV
Individual will die within one year	2.0 (1.7)	4.5 (1.8)	7.0 (2.0)	4.5 (1.9)
Individual will die within five years	4.1 (2.0)	7.0 (2.0)	9.1 (1.3)	6.9 (1.9)
Individual will die within ten years	6.0 (2.1)	8.6 (1.6)	9.8 (0.5)	8.7 (1.6)

*Standard deviations in brackets

Table 2.6: First stage regression of the decision to get test results

	(1)	(2)	(3)	(4)
	Full Sample		HIV Negative	HIV Positive
Age	0.0013	0.0003	0.0010	0.0123
	[0.002]	[0.000]	[0.002]	[0.012]
Primary Education	-0.0220	-0.0044	-0.0183	-0.1373
	[0.031]	[0.007]	[0.033]	[0.128]
# Sex partners	-0.0202	0.0010	-0.0228	0.0490
	[0.017]	[0.004]	[0.018]	[0.078]
Polygamous	0.0197	0.0077	0.0127	0.2038
	[0.031]	[0.007]	[0.032]	[0.155]
Region=Mchinji	0.0930**	0.0156*	0.0812**	0.4274***
	[0.039]	[0.009]	[0.040]	[0.156]
Region=Balaka	0.0722*	0.0016	0.0729*	0.2635
	[0.040]	[0.008]	[0.042]	[0.174]
HIV Positive04	0.0089	0.3632**	0.0000	0.0000
	[0.144]	[0.144]	[0.000]	[0.000]
Any Incentive	0.2776***	-0.0022	0.2793***	-0.3007
	[0.063]	[0.004]	[0.063]	[0.284]
Incentive^2	-0.0000***	-0.0000	-0.0000***	-0.0000***
	[0.000]	[0.000]	[0.000]	[0.000]
Incentive	0.0026***	0.0000	0.0025***	0.0100***
	[0.001]	[0.000]	[0.001]	[0.003]
Any*HIV Positive	-0.2782	0.0497		
	[0.259]	[0.252]		
Incentive^2*HIV	-0.0000*	-0.0000**		
	[0.000]	[0.000]		
Incentive*HIV	0.0051*	0.0071**		
	[0.003]	[0.003]		
Constant	0.3250***	-0.0146	0.3415***	-0.2613
	[0.081]	[0.012]	[0.083]	[0.338]
Observations	807	807	763	44
F-stat of instruments	38.2	6.9	64	13.3
R-squared	0.256	0.759	0.252	0.419

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

Table 2.7: Subjective likelihood of being HIV positive, ordered probit regression results

	(1) Full Sample	(2) HIV Negative	(3) HIV Positive
Age	-0.0037	-0.0034	-0.0205
	[0.005]	[0.005]	[0.025]
Primary Education	0.0573	0.0915	-0.3848
	[0.094]	[0.098]	[0.345]
# Sex Partners	0.2116***	0.2349***	-0.1357
	[0.050]	[0.052]	[0.220]
Polygamous	0.4251***	0.4105***	0.5997
	[0.094]	[0.097]	[0.384]
Region=Mchinji	0.2486**	0.2291*	-0.2454
	[0.120]	[0.124]	[0.507]
Region=Balaka	0.0924	0.1044	-0.3900
	[0.119]	[0.123]	[0.485]
HIV Positive	0.8646*		
	[0.505]		
Got Result	-0.0254	0.4089*	1.4739**
	[0.876]	[0.211]	[0.639]
HIV*Got Result	0.3116		
	[0.447]		
1st Stage Error (Got Result)	-0.6944***	-0.6921***	-1.9811**
	[0.236]	[0.237]	[0.813]
1st Stage Error (Got Result*HIV)	0.4317		
	[0.897]		
Mean of dependent variable	1.4	1.2	3.5
Observations	807	763	44

Note: Regressions include error terms from the first stage regressions.In the first specification there are two first stage regressions hence two error terms. Robust standard errors in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2.8: Marginal effects of finding out HIV Status for HIV positive and negative women

	HIV Negative	HIV Positive
Likelihood=0	-0.520	-0.144
	[0.207]**	[.071]**
Likelihood=1	-0.018	0.022
	[0.026]	[0.012]**
Likelihood=2	0.002	0.025
	[0.013]	[0.013]*
Likelihood=3	0.065	0.020
	[0.055]	[0.010]**
Likelihood=4	0.056	0.013
	[0.038]1	[0.006]*
Likelihood=5	0.154	0.037
	[0.082]*	[0.018]**
Likelihood=6	0.029	0.007
	[0.030]	[0.004]*
Likelihood=7	0.032	0.006
	[0.030]	[0.003]*
Likelihood=8	0.033	0.008
	[0.034]	[0.004]*
Likelihood=9	n/a	0.003
		[0.002]
Likelihood=10	0.168	0.003
	[0.079]**	[0.002]

Notes: The marginal effect of finding out one's HIV status is computed at the mean of the independent variables There were no observations in the 9 category for HIV positive individuals Robust standard errors in brackets.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2.9: Subjective likelihood of having HIV ordered probit regression results (fewer categories)

	(1) Full Sample	(2) HIV Negative	(3) HIV Positive
Age	-0.0031	-0.0029	-0.0200
	[0.005]	[0.005]	[0.026]
Primary Education	0.0680	0.0938	-0.3172
	[0.095]	[0.098]	[0.359]
# Sex Partners	0.2054***	0.2321***	-0.2156
	[0.051]	[0.053]	[0.224]
Polygamous	0.4244***	0.4079***	0.5822
	[0.094]	[0.097]	[0.399]
Region=Mchinji	0.2403**	0.2197*	-0.2425
	[0.122]	[0.125]	[0.533]
Region=Balaka	0.0978	0.1111	-0.3854
	[0.120]	[0.124]	[0.494]
HIV Positive	0.8345*	n/a	n/a
	[0.474]		
Got Result	0.0647	0.3909*	1.5071**
	[0.804]	[0.213]	[0.669]
HIV*Got Result	0.1835	n/a	n/a
	[0.438]		
1st Stage Error (Got Result)	-0.6851***	-0.6733***	-2.0395**
	[0.237]	[0.238]	[0.830]
1st Stage Error (Got Result*HIV)	0.3315	n/a	n/a
	[0.827]		
Mean of dependent variable	1.3	1.2	2.9
Observations	807	763	44

Note: Regressions include error terms from the first stage regressions.
In the first specification there are two first stage regressions hence two error terms.
Robust standard errors in brackets.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2.10: Marginal effects of finding out HIV Status for HIV positive and negative women

	HIV Negative	HIV Positive
Likelihood=0	-0.530	-0.139
	[0.214]**	[.073]*
Likelihood=1	-0.018	0.022
	[0.027]	[0.013]
Likelihood=2	0.002	0.025
	[0.014]	[.014]*
Likelihood=3	0.066	0.018
	[0.056]	[0.010]**
Likelihood=4	0.058	0.012
	[0.039]	[0.007]*
Likelihood=5	0.157	0.038
	[0.085]*	[0.019]**
Likelihood=6 and up	0.265	0.024
	[0.010]***	[.0120]*

Robust standard errors in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$ The marginal effect of finding out one's HIV status is computed at the mean of the independent variables.There were no observations in the 9 category for HIV positive individuals.

Table 2.11: 2SLS Regression results for the subjective likelihood of being HIV positive

	[1] Full sample	[2] HIV Negative	[3] HIV Positive
Got Result	0.6386*	0.6264*	4.6407*
	[0.338]	[0.338]	[2.406]
Got Result*HIV Positive	0.8444		
	[1.912]		
Age	-0.0056	-0.0043	-0.0613
	[0.009]	[0.008]	[0.076]
Primary Education	0.0575	0.1341	-1.3176
	[0.171]	[0.170]	[1.165]
No. Sex Partners	0.3349***	0.3718***	-0.3213
	[0.103]	[0.104]	[0.649]
Polygamous	0.8272***	0.7841***	1.5239
	[0.189]	[0.188]	[1.374]
Region=Mchinji	0.4570**	0.4194*	-0.7232
	[0.222]	[0.219]	[1.891]
Region=Balaka	0.0677	0.107	-1.299
	[0.215]	[0.213]	[1.656]
Hiv Positive	1.2406		
	[1.339]		
Constant	-0.066	-0.1974	3.9041
	[0.398]	[0.390]	[2.826]
Observations	807	763	44
Mean of dependent variable	1.4	1.2	3.5
R-squared	0.079	0.038	0.162

Robust standard errors in brackets

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2.12: Ordered probit regression results: subjective likelihood you will die in the next 1, 5, 10 years

	[1]	[2]	[3]	[4]	[5]	[6]
		HIV Negative			HIV Positive	
	Die1	Die5	Die10	Die1	Die5	Die10
Age	0.0051	0.0119***	0.0136***	-0.0058	-0.0064	0.0028
	[0.005]	[0.004]	[0.005]	[0.018]	[0.017]	[0.021]
Primary Education	-0.2533***	-0.2524***	-0.1339	-0.1908	0.1944	0.4580
	[0.090]	[0.093]	[0.089]	[0.276]	[0.284]	[0.312]
Married	-0.4168**	-0.3895**	-0.4784***	-0.1867	-0.3022	-0.3037
	[0.167]	[0.169]	[0.177]	[0.335]	[0.323]	[0.375]
Region=Mchinji	0.5568***	0.7277***	0.7736***	0.8418	0.7358	0.4137
	[0.103]	[0.106]	[0.104]	[0.559]	[0.570]	[0.555]
Region=Balaka	0.6979***	0.7264***	0.7745***	0.8618**	0.8319**	1.2772***
	[0.108]	[0.110]	[0.107]	[0.421]	[0.421]	[0.437]
Got Test Result	-0.0919	-0.1893	-0.3003*	0.0159	0.1547	-0.0485
	[0.183]	[0.172]	[0.170]	[0.532]	[0.488]	[0.535]
Error	0.0344	0.1068	0.2334	0.1804	0.1561	0.3114
	[0.196]	[0.196]	[0.193]	[0.663]	[0.635]	[0.715]
Mean of dep. variable	2.06	4.02	5.95	2.78	5.31	6.52
Observations	782	777	762	56	55	49

Note: Respondents were asked on a scale of zero to ten the likelihood they would die within 1,5, and 10 years respectively. Robust standard errors in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2.13: Marginal effects of finding out HIV Status for HIV positive and negative women

	[1]	[2]	[3]	[4]	[5]	[6]
	HIV Negative			HIV Positive		
	die1	die5	die10	die1	die5	die10
Likelihood=0	0.027	0.012	0.008	-0.003	-0.005	0.001
	[.052]	[.011]	[.005]*	[.100]	[.056]	[.011]
Likelihood=1	0.010	0.019	0.004	-0.001	n/a	n/a
	[0.021]	[0.017]	[0.002]	[0.042]		
Likelihood=2	-0.003	0.026	0.016	-0.002	-0.018	n/a
	[0.006]	[0.023]	[0.009]*	[0.073]	[0.056]	
Likelihood=3	-0.007	0.017	0.028	0.000	-0.023	0.004
	[0.013]	[0.016]	[0.015]*	[0.017]	[0.072]	[0.046]
Likelihood=4	-0.005	0.000	0.026	0.001	-0.012	0.004
	[0.010]	[0.002]	[0.015]*	[0.048]	[0.038]	[0.045]
Likelihood=5	-0.017	-0.020	0.036	0.004	0.005	0.008
	[0.034]	[0.017]	[0.023]	[0.130]	[0.020]	[0.086]
Likelihood=6	-0.002	-0.016	-0.001	n/a	0.006	0.002
	[0.003]	[0.014]	[0.002]		[0.018]	[0.026]
Likelihood=7	-0.001	-0.019	-0.018	n/a	0.009	-0.004
	[0.002]	[0.018]	[0.009]**		[0.030]	[0.041]
Likelihood=8	-0.001	-0.010	-0.032	n/a	0.008	-0.003
	[0.002]	[0.010]	[0.018]*		[0.026]	[0.036]
Likelihood=9	0.000	-0.004	-0.021	0.001	n/a	-0.004
	[0.001]	[0.004]	[0.012]*	[0.017]		[0.047]
Likelihood=10	-0.001	-0.006	-0.046	n/a	0.029	-0.008
	[0.002]	[0.006]	[0.029]		[0.090]	[0.089]

The marginal effect of finding out one's HIV status is computed at the mean of the independent variables. Some likelihood categories had no observations in the HIV positive regressions. Robust standard errors in brackets.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2.14: Frequency table of the likelihood categories for the mortality questions

	die1		die5		die10	
Category	Freq.	Percent	Freq.	Percent	Freq.	Percent
0	186	23.46	32	4.06	14	1.82
1	198	24.97	63	7.99	6	0.78
2	144	18.16	111	14.09	31	4.04
3	87	10.97	142	18.02	63	8.2
4	48	6.05	99	12.56	68	8.85
5	108	13.62	168	21.32	186	24.22
6	8	1.01	63	7.99	87	11.33
7	4	0.5	60	7.61	110	14.32
8	4	0.5	23	2.92	94	12.24
9	2	0.25	9	1.14	42	5.47
10	4	0.5	18	2.28	67	8.72

Table 2.15: Ordered probit regression results: likelihood you will die in the next 1, 5, 10 years (grouped categories)

	[1]	[2]	[3]	[4]	[5]	[6]
		HIV Negative			HIV Positive	
	die1	die5	die10	die1	die5	die10
Age	0.0049	0.0135***	0.0139***	-0.0058	-0.0095	-0.0014
	[0.005]	[0.005]	[0.005]	[0.018]	[0.017]	[0.022]
Primary Education	-0.2185**	-0.2927***	-0.1249	-0.0291	0.2713	0.7270
	[0.104]	[0.099]	[0.108]	[0.342]	[0.332]	[0.444]
Married	-0.2870	-0.3886**	-0.3734*	-0.1522	-0.4362	-0.5197
	[0.181]	[0.179]	[0.213]	[0.441]	[0.380]	[0.581]
Region=Mchinji	0.8298***	0.7580***	0.7872***	0.9137	1.1279*	0.1624
	[0.135]	[0.112]	[0.125]	[0.622]	[0.583]	[0.649]
Region=Balaka	1.0815***	0.7680***	0.8418***	1.0248*	1.3307***	1.0467**
	[0.134]	[0.119]	[0.127]	[0.547]	[0.471]	[0.508]
Got Test Result	-0.3058	-0.2092	-0.5165**	0.0804	-0.4315	-0.1951
	[0.229]	[0.199]	[0.201]	[0.610]	[0.557]	[0.624]
Error	0.2300	0.1335	0.4433**	-0.6196	0.8266	0.4515
	[0.251]	[0.226]	[0.225]	[0.834]	[0.758]	[0.847]
Observations	782	777	762	56	55	49

Note: Likelihood categories were grouped to eliminate categories with few observations. I create group 1, which includes responses from 0-2, Group 2, which includes responses from 3-5, and Group 3, which includes responses from 6 and up. Robust standard errors in brackets.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 2.16: Marginal effects of finding out HIV Status on subjective mortality for HIV positive and negative women, grouped categories

	HIV Negative			HIV Positive		
	die1	die5	die10	die1	die5	die10
Group 1 (Likelihood=0, 1, or 2)	0.111	0.064	0.045***	-0.032	0.044	-0.195
	[.085]	[.058]	[.016]	[.241]	[.058]	[.624]
Group 2 (Likelihood=3, 4, or 5)	-0.096	-0.003	0.155**	0.030	0.103	0.004
	[0.072]	[0.004]	[0.061]	[0.223]	[0.141]	[.012]
Group 3 (Likelihood=6 and up)	-0.014	-0.061	-0.201*	0.002	-0.147	0.062
	[0.009]	[0.037]	[0.075]	[0.012]	[0.193]	[.200]

The marginal effect of finding out one's HIV status is computed at the mean of the independent variables.

Table 2.17: Worry ordered probit regression results for HIV negative women

	(1)
Age	0.0551
	[0.038]
Age Squared	-0.0010*
	[0.001]
No. Sex Partners	0.3150***
	[0.049]
Polygamous	0.3654***
	[0.094]
Region=Mchinji	0.0253
	[0.110]
Region=Balaka	0.0957
	[0.112]
Got Test Result	0.3373*
	[0.201]
Observations	767

Women were asked how worried they were about contracting HIV and were given the following response set: none, low, med, high.
Robust standard errors in brackets.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

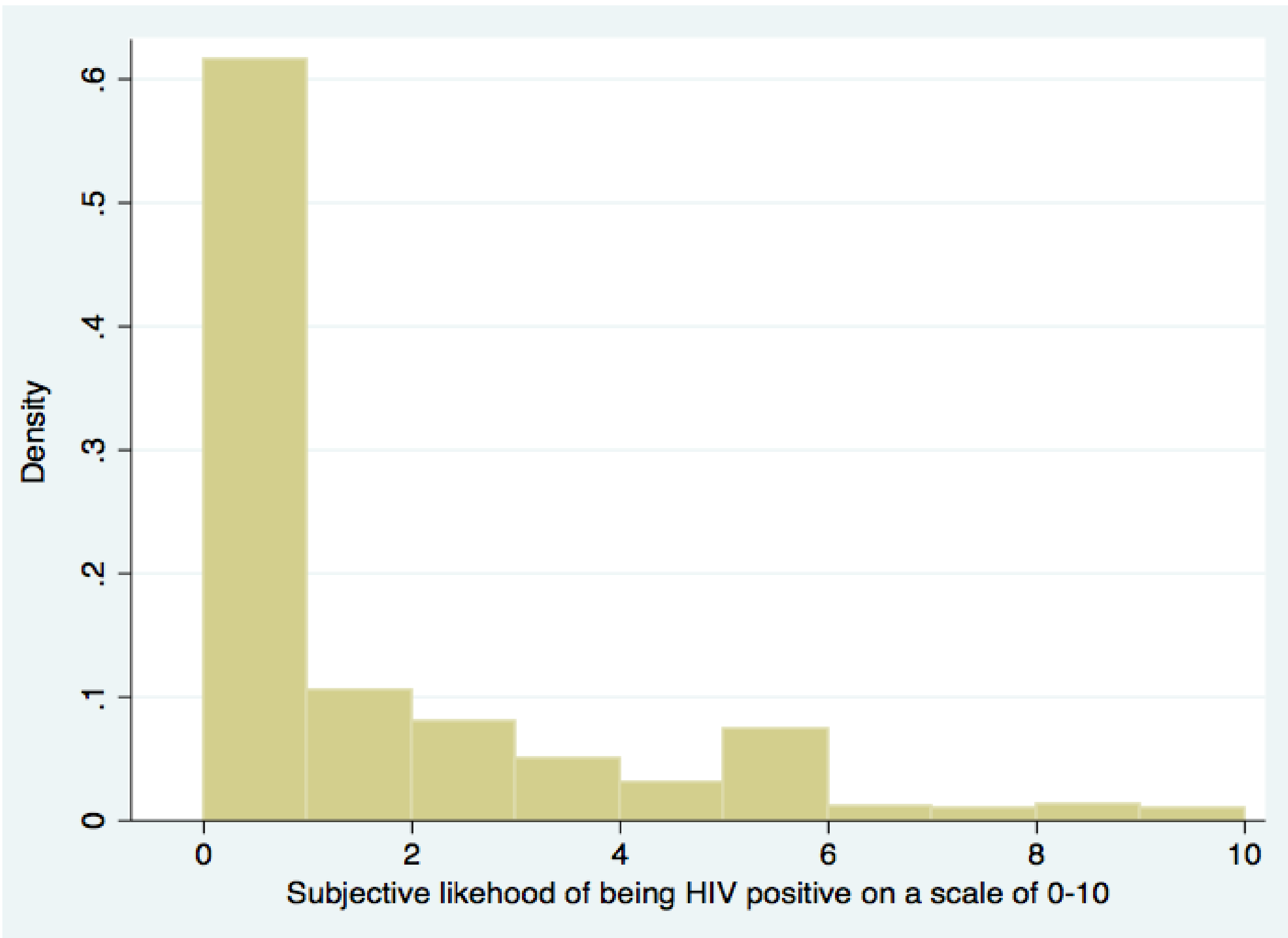

Figure 2.1: Histogram of Beliefs Among HIV Negative Women in 2006

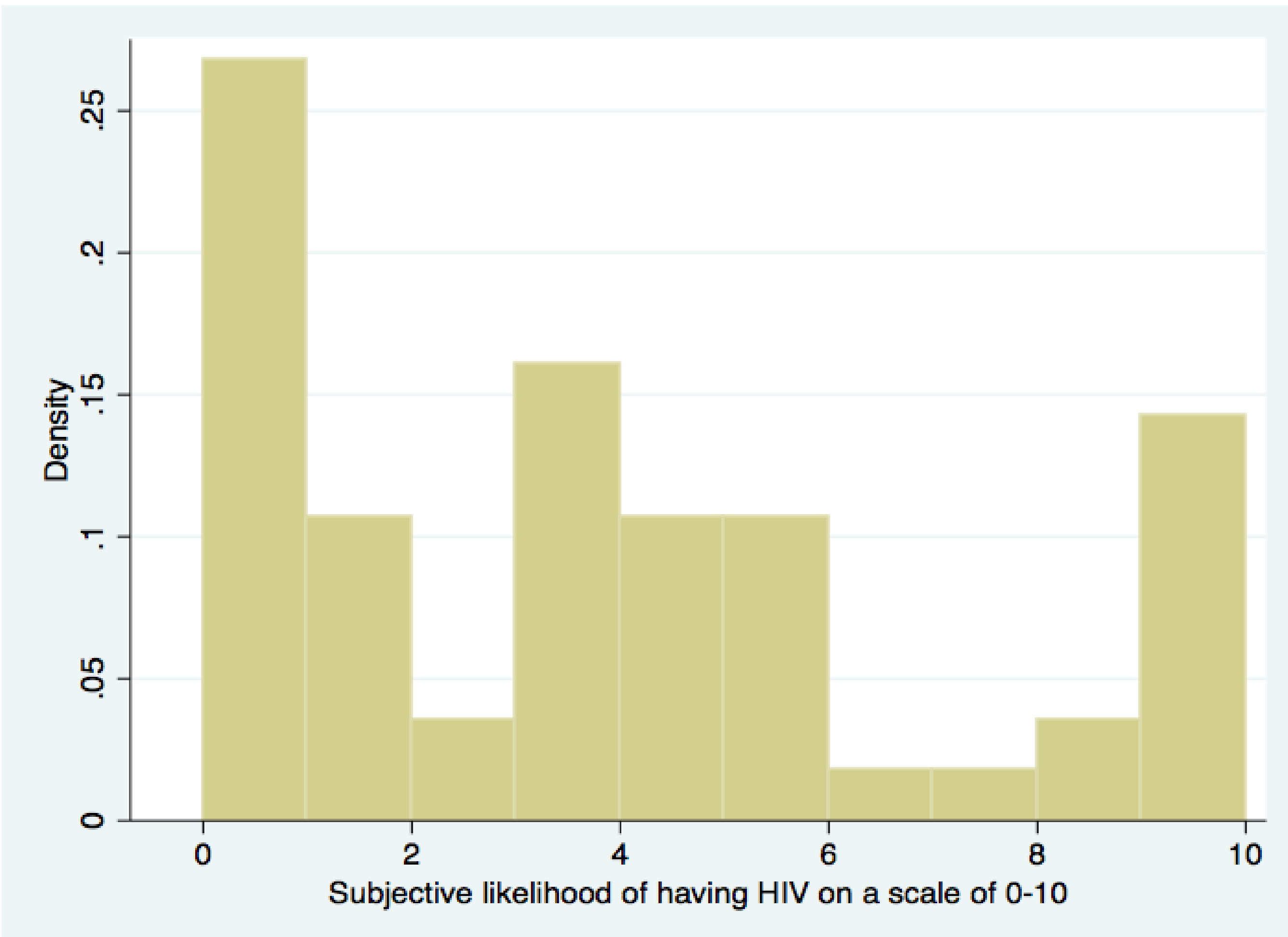

Figure 2.2: Histogram of Beliefs Among HIV Positive Women in 2006

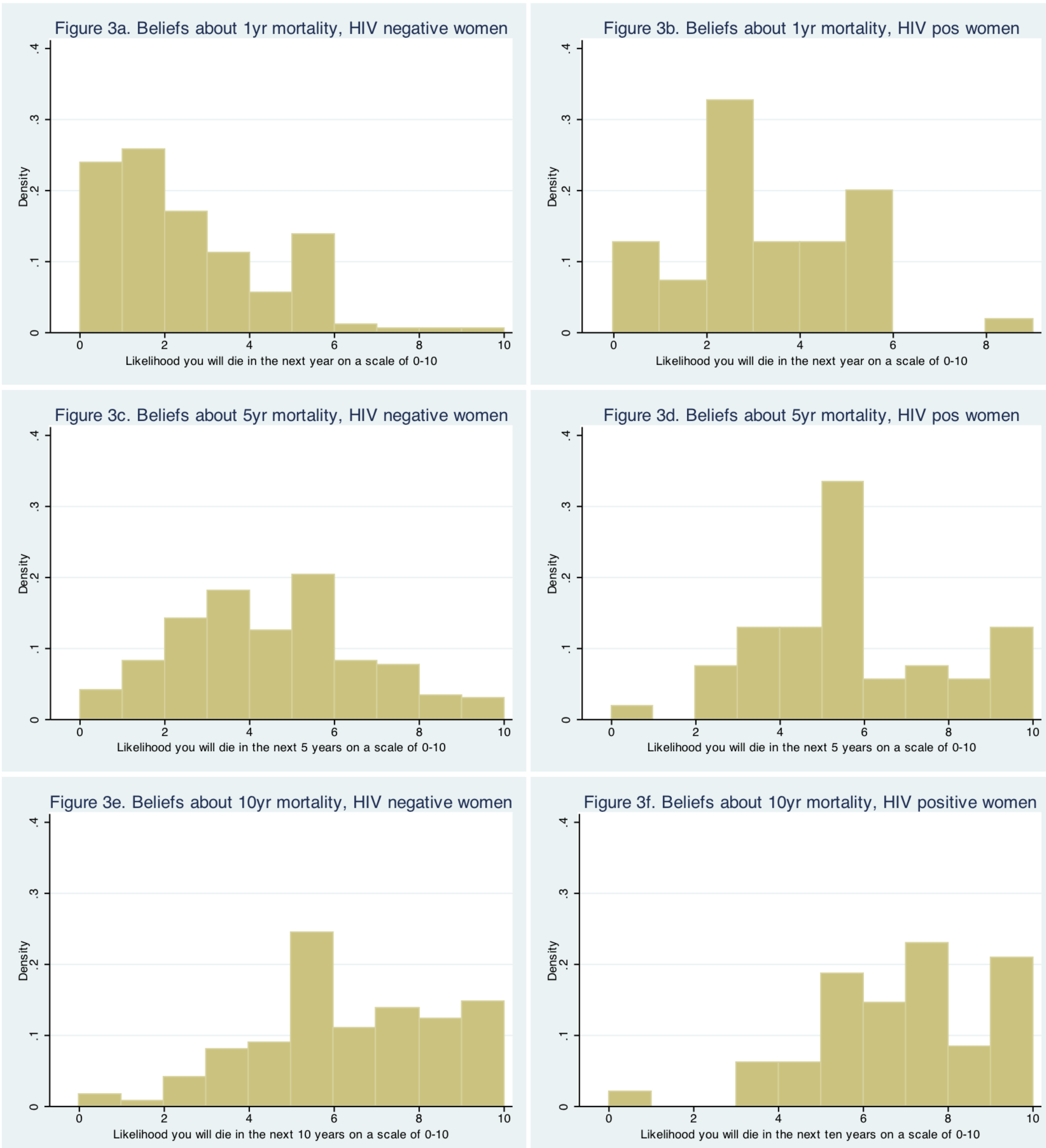

Figure 2.3: Histogram of Beliefs about Mortality Among HIV Negative and Positive Women

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Chapter 3

Knowledge of HIV-Negative Status and Household Decision-making: Experimental Evidence from Malawi

3.1 Introduction

With 14% of individuals currently infected with HIV and 65% of deaths among the 15-59 year old population attributed to AIDS every year, HIV has had a tremendous impact on Malawi's population (Akbulut-Yuksel and Turan (2010)). Despite the high prevalence of HIV in Malawi, HIV testing has been very limited until recently.[1] Previous studies have examined the impact of HIV testing on risky behavior (Gong (2011); Thornton (2008); Delavande and Kohler (2012)), but there could be other consequences of testing on household decision-making and more generally on household structure. In this paper, we investigate the effect of individuals learning their HIV negative status on marital stability. We then consider changes in decision-making within households in response to each spouse learning their HIV negative status.

[1] Until 2003, less than 1% of adults in Malawi had received HIV testing and counseling (Yoder and Matinga (2004))

Malawi is characterized by high marriage and divorce rates, and there is evidence that a woman who suspects that her husband is infected with HIV uses divorce as a means of preventing HIV infection (Reniers (2008)). On the other hand, there may be benefits to marriage that outweigh the risk of contracting HIV, such as risk sharing and the production of public goods (children). In the theoretical considerations section below we examine in greater detail the potential effects of learning one's HIV status on the divorce decision-making process, as well as the indirect effect on household resource allocations. We show that men and women can respond differently to the revelation of their HIV negative status if they value the production of public goods differently.

On the empirical side, we identify the causal effect of learning one's HIV negative status on marital stability and household resource allocations. In our estimation, we use panel data from the Malawi Diffusion and Ideational Change Project (MDICP) between 2004 and 2006. Data collection began in 1998 with a sample of ever-married women and their co-resident spouses. Before the sample was offered testing in 2004, very few had already been tested, but many believed they knew their status based on their behavior and that of their partner.

Test results in 2004 were not available until four to six weeks after testing, so individuals had to make a decision to go to a small mobile clinic to receive their results and post-test counseling. Because of the potential social and financial costs to attending the clinic, those who chose to learn their results have different preferences for learning their status than those who did not. The 2004 MDICP study was designed provide information that would permit controlling for the possible endogeneity of preferences for receiving results: randomized incentives of varying amounts were offered during pre-test counseling, and the location of the mobile clinics was randomized (Thornton (2008)).

Exploiting the randomization of financial incentives as an instrumental variable for getting results, we find that there is no effect on marital stability when a woman learns her HIV status. However, the marriage is less likely to stay intact if the husband discovers he is HIV negative. These results suggest that, relative to his wife, the husband values his outside options more or has a lower valuation of the current marriage. Amongst households that stay intact, our fertility results indicate that having additional children is a benefit that women value more highly than men. We show positive actual fertility and desired fertility effects of the wife learning that she is HIV negative, and the opposite effect when the husband learns he is HIV negative. We also discover that women decrease their share of resource expenditures, but there is no effect on male expenditure shares. Women appear to be reallocating personal consumption in favor of expenditures on children.

There is evidence that parents are updating their mortality expectations after learning their HIV negative status, and that this has consequences for child investments. We find a significant increase in the share of expenditures that are spent on children's schooling and a decrease in the share spent on children's medical expenditures. These results are consistent with the idea that parents are increasing investments in their children's human capital now that they can enjoy the returns to these investments over a longer time horizon. While it is well documented that HIV epidemic has contributed to an underinvestment in human capital, our study is the first to show that learning one's negative status can mitigate this effect. In other words, HIV testing can be an effective policy tool for increasing the incentives to invest in children's human capital. This paper fits into a broad literature on the impact of HIV on household outcomes. Young (2004) finds a negative relationship between fertility and the HIV epidemic in South Africa, but his analysis relies on cohort-level variation in HIV infection rates. Juhn, Kalemli-Ozcan, and Turan (2013) use Demographic and Health Surveys in 13 African countries to examine the relationship between an individual woman's fertility and her HIV status. The authors find a negative relationship between own HIV status and fertility. The drawback of these papers is that they link current HIV status to retrospective fertility outcomes so they cannot determine the causal relationship between learning one's HIV status and fertility.

Using the MDICP data, Yeatman (2009) looks at the effect of finding out one's HIV status on the desire for children in Malawi. She finds that individuals who are surprised that they are HIV positive (negative) desire fewer (more) children. While she separates the effects of HIV status and knowledge of that status, she does not control for the endogeneity of the decision to get the HIV test results. When considering the policy implications of HIV testing, the policy-relevant effect would be the effect of learning one's HIV status. Shapira (2013) estimates a life cycle model of fertility using MDICP data and finds a reduction in fertility amongst HIV positive women in response to testing.

Papers that have used the randomization of incentives in the MDICP survey have focused on risky behavior or beliefs about HIV status as the outcomes of interest. Thornton (2008) examines risk-reducing behavior in response to a positive or negative HIV diagnosis. She finds that individuals who learn they are HIV positive are more likely to purchase condoms than HIV positive individuals who do not receive their test results. There is no difference in condom purchases between HIV negative individuals who learn their test results and HIV negative individuals who do not learn their test results. Thornton (2008) considers whether consumption and savings patterns change in response to HIV testing, since learning one's HIV status can alter an individual's belief about his or her life expectancy. She does not find significant changes in savings or agricultural investments among individuals who find out their HIV status. However, she does not look at children's medical and schooling expenditures as outcomes.

In order for HIV testing to have an effect on long-term decision-making, it must alter an individual's beliefs about HIV status and mortality. Delavande and Kohler (2012) find that individuals who learn that they are HIV positive are more likely to report a higher likelihood of being HIV positive two years after testing. They also find that individuals who learn their HIV negative status report a higher likelihood of being HIV positive two years later compared to negative individuals who did not learn their status. The authors argue that individuals may be overestimating their risk of contracting HIV in the two years following testing, as opposed to not believing the test results. The remainder of the paper is structured as follows. The randomization of financial incentives to receive HIV test results and data are described in Section 2. Section 3 lays out the identification strategy and estimating equations. Results are presented in Section 4, and Section 5 concludes.

3.2 Theoretical Considerations

In this section we consider some potential factors in the decision-making process regarding marriage, fertility, and household resource allocations. Prior to learning her status, a woman has beliefs about her current status; after discovering her status, she has both knowledge of her current status and an updated expected probability of infection in the future. If her spouse learns his HIV negative status, this information could also be used to update her risk of infection. This assumes that spouses disclose their result to one other. In fact, it is not obvious that test results were shared between spouses.[2]

After learning her HIV negative status, the woman may revise the relative benefits and costs associated with maintaining the current marriage versus divorce. Some benefits of marriage include risk sharing (Mazzocco (2004)) and the consumption of public goods (Blundell, Chiappori, and Meghir (2005); Browning, Chiappori, and Weiss (2011)). When there is uncertainty regarding one's HIV status, a husband and wife may form a health risk sharing agreement where they care for one another in the event one of them is HIV positive.[3] If the uncertainty surrounding one's HIV status is eliminated, risk-sharing agreements may be harder to uphold. For example, if the woman discovers she is HIV negative, there will be less of an incentive to remain in the marriage because the insurance value of marriage has decreased.

Additionally, if there is uncertainty about her spouse's status, a woman who learns her HIV negative status may want to divorce her partner in order to minimize the risk of con-

[2] Discussion with survey administrators suggests that spouses did not share their results immediately even if they went to the clinic on the same day. The mobile clinics were tents, and some meters away there were others waiting to get their results. The VCT counselors did not find that people who had learned they were positive showed any indication of this as they left the mobile tent. Further, Anglewicz and Kohler (2009) find that spouses do not necessarily share information with one another.

[3] Note that in 2004, Antiretroviral treatment (ART) was not available in rural areas, which meant that people would believe that sooner or later the infected person would need care.

tracting HIV (Reniers (2008)).[4]

While learning one's negative status may decrease the value of risk sharing between a husband and wife, this negative effect on marital stability could be counteracted by an increased value of public goods within the marriage, namely children. Economic models of intergenerational transfers suggest that parents invest in their children for old age support or altruistic motives (Ehrlich and Lui (1991); Kalemli-Ozcan, Ryder, and Weil (2000)). An individual who learns his or her HIV negative status now has a higher own life expectancy, which increases the value of future transfers from children. Parents may want to invest more in their children's human capital now that the returns to these investments will flow over a longer period. Because now there are higher returns to investing in children, someone who learns they are HIV negative may also want to increase the quantity of children rather than just the quality of the existing stock of children. On the other hand, the benefit of minimizing unprotected sex may outweigh the marginal utility of an additional child.

A woman who learns she is HIV negative also learns that there was no mother-to-child HIV transmission, and may want to invest more in these children for altruistic motives. Her children now have a longer life expectancy and current period health status, which increases the child's expected benefit of investing in their education and decreases necessary health costs. The link between a father's HIV status and his children's status is less clear since it's possible that his wife entered the marriage HIV positive and transmitted the virus to their children.

It is ultimately an empirical question as to whether the costs outweigh the benefits of marriage after learning one's HIV negative status. It is also possible for husbands and wives to evaluate the marriage differently in response to learning their HIV negative status. Men may be more willing to divorce if their remarriage prospects are better than women, or if they value household consumption of public goods less than women.

In addition to marital dissolution, there may be changes to the allocation of household

[4]This assumes that that an individual can match with a lower risk partner in the secondary market. Its possible that learning ones negative HIV status can serve as a signal of being high quality.

resources in response to learning one's HIV status. If learning one's HIV negative status decreases the value of marriage, the spouse who does not learn his or her HIV negative status may have to compensate the other to stay in the marriage by reducing his or her share of household consumption. Conversely, if learning one's HIV negative status increases the value of public goods, then the spouse who learns their HIV negative status may decrease their share of household consumption in favor of increased public good consumption.

3.3 Data

The Malawi Diffusion and Ideational Change Project (MDICP) is a panel data set with surveys in 1998, 2001, 2004, 2006, and 2008. Three districts in Malawi were selected to participate, one in the northern region (Rumphi), one in the central region (Mchinji), and one in the southern region (Balaka).

The 2004 wave was the first survey round in which individuals were offered HIV testing: 91% agreed. Our primary estimation sample consists of married woman and their spouses who were surveyed in both the 2004 and 2006 survey waves. Table 3.1 reports the characteristics of women in 2004 based on whether the woman was present in the 2006 survey. Because HIV testing was new and there were concerns that respondents would be concerned about their blood being taken, the MDICP used saliva tests rather than rapid blood tests. The specimens were analyzed in a laboratory, causing a substantial delay between the test and the availability of results.

In a field experiment, Thornton (2008) randomized two factors that influence the decision to return to a testing center. First, respondents were offered a voucher between zero and three dollars, which was redeemable upon showing up at a voluntary counseling and testing (VCT) center to find out their test results. The average value of the voucher was one dollar, which is equivalent to about a day's wage. Second, the testing centers were randomly placed within the villages. Individuals who returned to a VCT center were told their status and received counseling about HIV prevention methods.

What were an individual's beliefs about his or her HIV status prior to HIV testing? The 2004 wave included a question regarding an individual's self-assessed likelihood of being HIV positive, where the individual could choose from 4 risk categories ranging from "No likelihood" to "High likelihood." She could also answer "Don't Know." Tables 3.2 and 3.3 report the HIV prevalence by gender and beliefs about own HIV status in 2004 and 2006, respectively. For women, there is a positive relationship between HIV prevalence and self-assessed likelihood of being HIV positive. This suggests that women are able to assess their relative risk fairly accurately. On the other hand, there is not a clear relationship between men's beliefs about their status and actual HIV status.

HIV status could have no effect on individual's decision-making in the short term if they do not believe that their life expectancy or quality of life will be affected by the disease. In the 2006 wave, women were asked to compare the mortality rates of four hypothetical women: a woman of the same age as the individual who is healthy and does not have HIV, a women who is infected with HIV, a women who is sick with AIDS, and a women who is sick with AIDS and is treated with antiretrovirals (ART). Responses are reported in Table 3.4. Mortality rates are increasing over the time horizon and with the degree of illness of the hypothetical woman. For example, a woman who is uninfected with HIV has a 20% mortality rate over a one year period, while a woman who is infected with HIV has a 45% mortality rate over the same period. A woman who is sick with AIDS has a 70% mortality rate. On average, women believe there is an 86% chance that a women infected with HIV would not survive ten years from now, compared to a 60% chance if a women is not infected with HIV.

Since we are interested in the effect of both the husband and wife's learning their HIV negative status, we limit our sample to married women whose husband was also tested. Table A.1 compares the characteristics of women whose spouse was tested to women whose spouse was not tested. In the 2004 sample, both the husband and wife were HIV positive in 2.4%

of all monogamous couples. The husband was HIV positive and the wife negative in 4.9% of couples, and the husband was negative and the wife positive in 3.4% of couples. HIV prevalence across the sample is 8%. For the sero-discordant couples, there is potential for both HIV risk-reduction through divorce and remaining at risk by staying in the marriage.

Reniers (2008) reports that divorce rates in Malawi are between 30-50% within the first 15 years of marriage. Table 3.5 shows the overall marriage transitions in the data between 2004 and 2006. In our data, it also appears that short term divorce rates vary across regions. Between 2004 and 2006, 8% of marriages in Balaka dissolve with 5.6% through divorce; in Rumphi, we have only one case of divorce out of 405 couples; finally, in Mchinji, 1.3% of couples divorce while one marriage ends in widowhood. Because Balaka is the only region with significant variation in marital status, some of our marriage regressions will be limited to this region. Table 3.6 illustrates the HIV rates by marriage transition. We observe that women who transition from marriage to divorce over a two year period have a substantially higher HIV rate in 2004 than women who stay married. There could be two explanations: first, that the spouse is trying to prevent infection; second, the husband could be divorcing her because she is the risky type and not a good partner.[5]

We construct expenditure shares in order to examine how household resource allocations change in response to learning one's negative HIV status. Individuals report household expenditures over the past three months across various expenditure categories. Categories include: personal non-medical expenditures, personal medical expenditures, expenditures on children's clothing, expenditures on children's schooling, children's medical expenditures, and farm related expenditures. Individuals were not asked about their spouse's household expenditures, so our measure of household expenditures is an imperfect measure of total household expenditures. A subset of our primary estimation sample includes individuals whose spouse also reports household expenditures. For these couples, we can include the spouse's reported personal expenditures in order to construct a more complete measure

[5]Most individuals in the MDICP say it is not acceptable to divorce a spouse because they have HIV.

of total household expenditures. For example, we add a husband's self-reported personal expenditures to his wife's household expenditure reports.

Table 3.7 presents summary statistics of the expenditure shares for the different estimation samples and measures of expenditure shares. Respondents in Panel A tested HIV negative in 2004 but their spouse may or may not have been tested. The samples in Panel B consist of respondents and their spouses who tested HIV negative. On average, men and women report similar expenditure shares across the different categories. In other words, the men and the women's household expenditure reports seem to be consistent with one another. This is reassuring since there is an overlap of households across the men and women's samples. The only exception is children's clothing expenditures, where men report a higher expenditure share than women. The discrepancy could arise if only one parent purchases children's clothing: only one parent would have an accurate estimate of children's clothing expenditures.

Table 3.7 also reports summary statistics for households where we observe both the husband and wife's reported household expenditures. For this sample, our measure of total household expenditures includes expenditures on the respondent's spouse. According to the men's expenditure reports, a husband and wife have similar shares of household expenditures. If personal expenditure shares were an indicator of an individual's relative bargaining power in the household, it would appear that bargaining power is fairly balanced between a husband and wife. On the other hand, a women's expenditure share is lower relative to her spouse's share according to women's expenditure reports.

We next turn to fertility. An ideal fertility measure would reflect the number of children who were conceived after results were received. We count the number of children present at the time of the 2006 household survey by counting children on the household roster.[6] Results were available in November and December of 2004 so the first children who could be conceived after obtaining test results would be born in late 2005. Since we do not have

[6]This is a lower-bound estimate of the number of children ever born due to mortality between birth and the time of the 2006 survey.

birth month, a woman is considered to have a new child if the child was born in 2006 or if the woman reported being pregnant at the time of the 2006 survey.[7] We restrict our sample to women under age 40 who we expect to be of child-bearing age in our fertility regressions. Around 13% of women had a child in this sample, resulting in 96 new children.[8] Observed fertility is the composition of two effects: the demand for children and the demand for risky sex. A woman who learns she is negative may want more children, but decreasing the amount of unprotected sex could offset this effect. To separate these two potentially opposing effects, we examine both actual fertility and a women's desired fertility after individuals learn their negative status.

3.4 Identification Strategy

For marital status, our unit of analysis is the marital outcomes in 2006 of couples who are married in 2004. The estimating equation for marriage is:

$$Marry_i = \alpha + \beta_1 WifeResult_i + \beta_2 ManResult_i + \mu X_i + \varepsilon_i \tag{3.1}$$

where $WifeResult$ is equal to one if the wife received her result and similarly for the man. A vector of controls, X, including age, age-squared and region fixed effects is included. Our sample is limited to couples in which both individuals are HIV negative due to the small number of HIV positive individuals in the sample.[9] The regression is similar for actual and desired fertility but we add controls for the number of children in 2004 and the wife's level of education. For individuals who are HIV negative, the effect of learning your status is β_1 for women and β_2 for men. Alternative specifications only include the husband's or

[7] In another study, it was shown that some women do not want to tell others they are pregnant until the pregnancy begins to show, so our data will understate pregnancies in 2006.

[8] There is some evidence that there are some inconsistencies in the reported number of children across the survey waves, so this is why we rely on the observed number of children in the household in 2006 instead of a womans reported number of children.

[9] There are only 52 HIV positive individuals in the full sample, so we do not have enough statistical power to identify effects of being HIV positive or learning ones HIV positive status. See online appendix for details.

the wife's result variable. The alternate specifications are discussed in greater detail in the results section.

Thornton (2008) finds that individuals who engage in risky sexual behavior and who are less likely to believe they are HIV positive are more likely to return to a clinic to find out their HIV status; this could bias the estimated effect of learning one's HIV status on marital stability and household decision-making. For example, individuals who engage in risky behavior may be more likely to divorce, which would bias the coefficient on learning one's HIV negative status downward. Conversely, having a lower subjective probability of being HIV positive would bias the estimated effect of learning one's HIV negative status towards zero because these individuals already have low priors about the likelihood of being HIV positive. In other words, learning one's status would not be new information for this group of individuals. To account for these biases, we exploit Thornton's randomization of the distance to the nearest VCT center and the incentives received by the individual to return to the VCT center as instrumental variables for the decision to obtain test results. For specifications where only one spouse learns their HIV negative status, the first stage regression is:

$$GotResult_i = \alpha + \beta_1 Any_i + \beta_2 Amt_i + \beta_3 Amt_i^2 + \mu X_i + \varepsilon_i \tag{3.2}$$

where Any refers to whether the individual received any incentive and X is the same vector of covariates. For our main analysis at the couple level, we include both the man and wife's financial incentives:

$$\begin{aligned} GotResult_i = \alpha &+ \beta_1 WifeAny_i + \beta_2 WifeAmt_i + \beta_3 WifeAmt_i^2 \\ &+ \beta_4 ManAny_i + \beta_5 ManAmt_i + \beta_6 ManAmt_i^2 + \beta_7 TotalAmt_i^2 + \mu X_i + \varepsilon_i \end{aligned} \tag{3.3}$$

The identifying assumption is that the incentives do not affect the outcomes of interest except through their effect on the probability of receiving results.

3.5 Results

3.5.1 Marriage Regressions

OLS results for HIV-negative couples from equation (1) are presented in Table 3.10. Column 1 uses a dummy variable for whether the woman reports being married in 2006 as the dependent variable. The effect of choosing to get results is negative for the female and positive for the spouse, suggesting that the selection mechanism of who chooses to receive results differs between men and women. Because this measure of marriage doesn't capture whether a woman changes spouses, in Column 4, we use whether a woman divorces or changes spouses in 2006 as the outcome of interest; "No Change" is equal to one if the individual is still married to the same person and equal to zero if she either becomes divorced by 2006, widowed by 2006, or marries someone else. Coefficients are similar across both regressions. Women who learn that they are HIV negative are less likely to be married to the same person in 2006; the opposite is true if the husband learns his HIV-negative status.

The selection of individuals who choose to get their results could bias the OLS coefficients. For this reason, we use the randomized incentives as an instrument for getting results. We use both the wife and husband's individual incentives as instruments. The first stage from Equation 3 is presented in Table 3.8. The instruments predict the two endogenous variables well and the F-statistics are large ($F > 10$) for both variables. As expected, the size of the financial incentive has a positive effect on the decision to return to a testing center. There is some evidence that financial incentives affect the decision-making of the spouse who did not receive the incentive. While the husband's financial incentives does not have a significant effect on his wife's decision to return for her test results (Column 1), his wife's financial incentive increases the likelihood that the husband obtains his test results (Column 2). Table **??** reports the first stage regressions where the spouse's incentives are excluded (Equation 2). Point estimates of the financial incentives are similar to the estimates in Table 3.8.

We show the IV results for both being married in 2006 and not changing spouses in 2006 in Table 3.10. There is a striking difference between the IV and OLS coefficients. In particular, the sign of the estimated coefficients change from positive to negative for men, and negative to positive for women. In the IV regression, if a husband learns his status, the wife is 2.5 percentage points less likely to be married in 2006. Similarly, in column (5), we see that the marriage is 7 percentage points less likely to survive until 2006 when the husband learns his HIV negative status. Finally, because much of the variation in marriage outcomes (namely, divorce) is in Balaka, we consider only observations from Balaka in columns (3) and (6). Coefficients are larger but insignificant, most likely because of a small sample size. However, the same patterns hold.

We investigate the selection of who chooses to receive results by comparing characteristics of those who got results and those who did not get results in 2004. The selection mechanism does act differently across sexes. Women who get results are on average 1.5 years younger, less likely to have a primary education (by 8 percentage points), and are slightly (1.5 percentage points) more likely to report using a condom with their spouse. Men that choose to learn their HIV negative status are 3 years older on average, somewhat less likely to have a primary education (4 percentage points), and 1 percentage point less likely to report using a condom with their spouse. Surprisingly, the two groups do not differ on HIV expectations, number of prior marriages, or sexual behavior.

Our hypothesis for the negatively biased OLS coefficient for women and positively biased OLS coefficient for men is that the women's result is driven primarily through the large differences in primary school education and that the men's result stems from differences in unobservable characteristics between younger and older men. In fact, women who do not have a primary school education are more likely to divorce which is consistent with the negative OLS coefficient. Also, older men are much less likely to divorce; the fact that men who get results are much older means that comparing those who get results to those who do not get results without controlling for this selection will bias the coefficient upwards.[10]

There might be some concern that the two receiving results variables are highly correlated if the couple attends together. Therefore, Table 3.11 presents the same IV regressions but with only the female coefficients and then only the male coefficients. Similar patterns present themselves in this regression: if the wife learns her HIV status, there is no effect on marriage outcomes. However, the husband learning his status has a negative effect on the marriage and the probability of the woman being married in 2006.

It appears that husbands who learn their HIV negative status value the options outside of marriage more highly than women who learn their HIV negative status. Conversely, women may value the benefits of their current marriage more highly than men. For example, women may want to invest in more children or invest in her existing children. Since, in our data, only the male's status determines marital dissolution, we next turn to expenditures within the intact household to see if bargaining power changes under the threat of marital dissolution.

3.5.2 Expenditure Shares Excluding Spouse's Expenditures

We present expenditure share results in Table 3.12, where our measure of total household expenditures does not include expenditures of the respondent's spouse. The estimation sample consists of all individuals who tested HIV negative in 2004. Women and men are estimated separately in Panels A and B, and then together (Panel C). Standard errors are clustered at the household level in Panel C to control for within household correlation. There some notable differences in the signs of the estimated coefficients between the male and female samples. For women, learning one's HIV negative status is associated with a ten-percentage point reduction in personal (non-medical expenditures), but there is no decrease in personal expenditures among HIV negative men who find out their status. The decrease in women's expenditure shares does not seem to be consistent with the argument that learning one's

[10]Controlling for primary school and male age in the regression does not completely erase the difference between the OLS and IV coefficients; this is either because (a) these variables are not very good measures of the underlying unobservable characteristics associated with age and education; or (b) there are other unobservable characteristics which explain the differences.

HIV status increases one's relative bargaining power in the household. On the other hand, women may be reallocating their consumption to child specific goods in response to learning her HIV negative status. We find a positive but statistically insignificant effect of learning one's HIV negative status on children's clothing expenditures for women, and a negative effect for men.

Interestingly, finding out one's HIV negative status reduces children's medical expenditures by approximately three percentage points, and the estimated effect is similar across the male and female samples. These results suggest that individuals who learn their HIV negative status revise their beliefs downwards about their children's HIV status. Because of this, parents spend less in care related to HIV treatment if they believe that their children are less likely to be HIV positive. It is somewhat surprising that the magnitude of the effect of learning one's HIV status is similar for men and women because there is a more direct relationship between the mother and child's HIV status than the father and child's HIV status.

If parents revise their beliefs about their children's life expectancy and their own life expectancy in response to learning their own HIV negative status, then the value of investing in children's human capital should increase. Consistent with this, we find that there is a significant positive effect of learning one's negative HIV status on children's schooling expenditure shares. The positive and significant coefficient in the pooled sample (Panel C) appears to be driven by the male sample; the coefficient is positive and significant in the male only sample (Panel B) and positive and insignificant in the female only sample (Panel A). Although we find evidence of increased investments in children, we do not find any evidence of increased expenditures on agriculture. Point estimates for agricultural expenditure shares are positive but insignificant across all samples. The lack of an effect of HIV testing on economic activity is also found in Thornton (2012), who examines outcomes such as labor supply, consumption, and savings.

We next examine whether a respondent's spouse learning his or her HIV status affects the respondent's reported expenditure shares. Regression results are presented in Table 3.13 when we restrict the estimation sample to individuals whose spouse also tested HIV negative in 2004. Women and men are estimated separately in Panels A and B, and then together in Panel C. In Panel A, there is a significant negative effect of the husband learning he is HIV negative on the wife's reported farm expenditures and positive effect on the wife's reported children's clothing expenditures. It is unclear whether these results indicate that the wife has also learned her husband's HIV status. The effect on household expenditure could therefore be due to changes in an individual's belief's about his or her spouse's status rather than knowledge of the spouse's actual HIV status.

Turning to the husband's reported expenditure shares, there is a significant positive effect of the wife learning she is HIV negative on the children's medical expenses. In the pooled sample (Panel C), learning one's HIV negative status has a significant positive effect on children's clothing shares and medical shares, and negative effect on children's schooling shares.

Point estimates of the effect of learning one's own HIV negative status vary from the estimates derived from the main estimation sample (Table 3.12), which calls into question the external validity of the estimated coefficients for a spouse learning his or her HIV negative status. For example, the point estimate of the effect of a woman learning her HIV negative status on her personal expenditures shares (Panel A) is now smaller and statistically insignificant from zero. Additionally, the effect of learning her HIV status on children's clothing expenditure shares changes from positive to negative. The estimated coefficients for the male only sample (Panel B) do not change signs when restricting the estimation sample to individuals whose spouse was also tested HIV negative, but the point estimates for the schooling expenditure coefficients are smaller compared to the main specification (Table 3.12).

It is important to note that the difference in point estimates between the sample where the respondents tested HIV negative (Table 3.12) and the sample where both the respondents and their spouses tested HIV negative (Table 3.13) are not directly comparable because the regressions do not include the same covariates. To compare the estimated effect of learning one's HIV negative status across the two samples, we drop the indicator variable for whether the respondent's spouse learns his or her HIV status. Results are reported in Table 3.14. The estimated coefficients for child related expenditure shares continue to be smaller in magnitude compared to the estimates derived from the main estimation sample. Ultimately, any comparisons of coefficients across the difference samples are merely suggestive because the differences in the coefficients are not statistically significant.

3.5.3 Expenditure Shares Including Spouse's Expenditures

Table 3.15 reports regression results where we are able to include expenditures on a respondent's spouse in our measure of total household expenditures, which requires both a husband and wife to answer the household expenditure module. The estimated effect of learning one's HIV status follows the same pattern as the partial expenditure share estimates. The effect of a woman learning her HIV negative status continues to be negative but is now statistically insignificant from zero. For both men and women, learning one's HIV negative status has a negative effect on children's medical expenditures and positive effect on schooling expenditures.

Table 3.16 presents expenditure share results for individuals whose spouse was HIV tested in 2004 and answered the household expenditure module. The results follow the same patterns as the expenditure share results that exclude the spouse's expenditures.

To summarize, expenditure share results indicate an increased investment in children's human capital as well as a decrease in child medical expenditures in response to learning one's HIV negative status. This is consistent with parents having a longer life expectancy for their children and investing in them accordingly. The distribution of resources seems to shift away from women's personal expenditures, possibly because they value expenditures on children more highly than men after learning their HIV negative status. We further investigate gender differences in the gains from marriage through the quantity of children in the next section.

3.5.4 Fertility

Fertility results are presented in Table 3.17. All regressions consider couples who were married in 2004. The first two columns consider both the woman's and man's HIV status. The OLS and IV estimates are of the same sign but the OLS are smaller. This suggests that there was less selection bias than in the marriage regressions. We find significant effects of learning your HIV negative status, and that these effects differ across men and women. There is a 32.8 percentage point increase in the probability of having a child if the wife learns her HIV negative status. Conversely, couples have a 27.4 percentage point decrease in the probability of having a child if the husband learns his HIV negative status.

Considering the results of the husband and wife separately in columns (4) and (6), respectively, we see that these patterns remain consistent. Learning her status increases the likelihood that a woman has another child by almost 19 percentage points. For men, the probability of a child decreases by 20 percentage points. These results could be explained by either a change in desired fertility or a change in the willingness to engage in unprotected sex. In particular, it is unclear whether a man learning his negative status reduces fertility due to changes in family planning or wanting to minimize his potential exposure to HIV. To separate these two effects, we next turn to desired fertility results.

3.5.5 Desired Fertility

To isolate the effect of knowledge of HIV status on family planning, we regress a woman's reported ideal number of children in 2006 on the same regressors as before. Women were asked what their ideal number of children was in 2001, so we include this variable as an additional control. Column 1 of Table 3.18 reports the OLS regression results. The point estimates are similar in magnitude and sign as the IV regression results, which are reported in Column 2. The marginal effect of learning that she is HIV negative is a desire for 0.22 more children for a woman. For men, there is no significant effect. These results suggest that the observed increase in fertility due to a women learning her HIV negative status is driven by an increased desire for more children.

The results from the observed and desired fertility also suggest that men and women respond differently to learning one's HIV status along this margin. While both men and women invest more in their existing children's human capital after learning their HIV negative status, it is only the women who want to increase the quantity of children. This difference could also explain why men may be more willing to divorce after learning their HIV negative status than women: women have more to gain from keeping the marriage intact (having more children) than men.

3.6 Conclusion

Previous research has not found significant changes in economic activity in response to learning one's HIV negative status, but our findings suggest that individuals may respond to this information in other ways. We find evidence that HIV testing has positive implications for children in the household. In particular, parents invest more in their children's schooling when they learn their HIV negative status. While the HIV epidemic has contributed to an underinvestment in human capital (Akbulut-Yuksel and Turan 2012), our results indicate that HIV testing can be used as a policy tool to increase human capital investments in children.

We also observe responses to HIV testing on household structure. With respect to marriage, we find a higher likelihood that the marriage dissolves when the husband learns his negative status. There is no evidence of increased marital dissolution when the wife learns her HIV status. This differential effect could be due to two reasons. First, a woman's utility outside of the current marriage may be lower compared to men's utility outside marriage.

Second, women may derive more utility from the current marriage than men, possibly because they have a higher taste for public goods. Consistent with this, we find that women have an increased desire for more children after learning their HIV negative status, while men do not.

Unfortunately, the relatively small scale of the MDICP prevents us from being able to make any inferences about HIV positive individuals. Larger scale experiments are needed to be able to examine the effect of learning one's HIV positive status on household outcomes. Furthermore, researchers should consider household decision-making as a joint process that depends on a husband and wife's preferences, beliefs about their own HIV status, and the status of their spouses. While we control for both a husband and wife learning their own HIV status, we cannot identify the effect of learning your spouse's status. Because it is unclear whether test results are shared between spouses, future experiments should be designed to compare the effect of joint HIV testing and counseling among couples versus individual testing and counseling.

Table 3.1: Comparison of Women in 2004 and 2006 waves by panel status

	2004				2006			
	All		Panel		All		Panel	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Consented to HIV test	1487	0.90	1139	0.91	1563	0.93	1139	0.94
Got test result	1343	0.69	1040	0.73	1457	0.97	1071	0.98
HIV positive	1323	0.08	1026	0.06	1438	0.07	1053	0.07
Married	1482	0.86	1136	0.87	1446	0.87	1071	0.88
Widowed	1482	0.04	1136	0.04	1446	0.05	1071	0.04
Divorced	1482	0.04	1136	0.04	1446	0.06	1071	0.06
Age	1209	35.0	953	35.4	1474	34.3	1139	37.0
Rumphi	1132	0.33	1132	0.33	1556	0.32	1132	0.33
Mchinji	1132	0.30	1132	0.30	1556	0.35	1132	0.30
Balaka	1132	0.37	1132	0.37	1556	0.33	1132	0.37
Multiple wives					1260	0.32	942	0.32

Table 3.2: HIV status by self-assessed likelihood to be HIV positive in 2004

	Women		Men	
	Obs	Mean	Obs	Mean
no likelihood	719	0.06	720	0.06
low	208	0.09	121	0.07
medium	123	0.07	54	0.04
high	107	0.14	38	0.03
don't know	275	0.12	230	0.12

Table 3.3: HIV status by self-assessed likelihood to be HIV positive in 2006 (on a scale of 0 to 10)

	Women		Men	
	Obs	Mean	Obs	Mean
likelihood =0	572	0.03	527	0.02
likelihood = {1,2}	178	0.04	120	0.06
likelihood = {3,4}	87	0.17	36	0.08
likelihood = {5,6}	78	0.06	26	0.19
likelihood = {7,8}	20	0.15	9	0.22
likelihood = {9,10}	20	0.40	13	0.23

Table 3.4: Beliefs about Mortality Likelihood of Hypothetical Women on a Scale of Zero to Ten

	Woman who is healthy and no HIV	Woman who is infected with HIV	Woman who is sick with AIDS	Woman who is sick with AIDS and treated with ARV
Individual will die within one year	2.0 (1.7)	4.5 (1.8)	7.0 (2.0)	4.5 (1.9)
Individual will die within five years	4.1 (2.0)	7.0 (2.0)	9.1 (1.3)	6.9 (1.9)
Individual will die within ten years	6.0 (2.1)	8.6 (1.6)	9.8 (0.5)	8.7 (1.6)

*Standard deviations in brackets

Table 3.5: Marriage Transition matrix

		2006	
		Not Married	Married
2004	Not Married	73	65
	Married	56	874

Table 3.6: 2004 HIV status by Marriage transition

		2006	
		Not Married	Married
2004	Not Married	0.10	0.05
	Married	0.29	0.04

Table 3.7: Summary Statistics of Expenditure Shares

Panel A: Respondent was HIV tested

	Partial Shares						Total Shares					
	Men			Women			Men			Women		
	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
Personal expenditures	484	0.22	0.24	806	0.23	0.25	353	0.17	0.20	480	0.16	0.19
medical expenditures	484	0.04	0.12	806	0.06	0.14	353	0.03	0.10	480	0.03	0.08
farm expenditures	484	0.18	0.24	806	0.17	0.26	352	0.19	0.25	480	0.18	0.26
children's clothing	484	0.29	0.25	806	0.24	0.25	353	0.23	0.21	480	0.17	0.20
children's school	484	0.10	0.18	806	0.11	0.21	353	0.09	0.15	480	0.09	0.18
children's medical	484	0.06	0.11	806	0.08	0.17	353	0.05	0.10	480	0.05	0.11
spouse's expenditures							353	0.16	0.21	480	0.25	0.29

Panel B: Respondent and spouse were HIV tested

	Partial Shares						Total Shares					
	Men			Women			Men			Women		
	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD	Obs	Mean	SD
Personal expenditures	377	0.20	0.23	413	0.22	0.24	311	0.17	0.21	352	0.15	0.19
medical expenditures	377	0.04	0.12	413	0.04	0.13	311	0.04	0.07	352	0.03	0.09
farm expenditures	377	0.20	0.25	413	0.18	0.27	311	0.20	0.25	352	0.20	0.28
children's clothing	377	0.29	0.26	413	0.24	0.26	311	0.23	0.22	352	0.16	0.20
children's school	377	0.11	0.19	413	0.13	0.23	311	0.09	0.15	352	0.10	0.19
children's medical	377	0.07	0.12	413	0.07	0.16	311	0.06	0.11	352	0.05	0.11
spouse's expenditures							311	0.15	0.20	352	0.24	0.29

Table 3.8: First stage regressions for decision to learn HIV negative status where spouse's incentives are included as controls

	(1) Wife Results	(2) Man Results	(3) Wife Results	(4) Man Results
Wife any	0.228***	0.081	0.400***	0.243**
	(0.070)	(0.067)	(0.126)	(0.124)
Man any	0.027	0.292***	-0.021	0.147
	(0.062)	(0.069)	(0.105)	(0.130)
Wife incentive	0.0027***	0.0015*	0.0023**	0.0022*
	(0.0007)	(0.0008)	(0.001)	(0.0012)
Man incentive	0.0008	0.0018*	0.0013	0.0030**
	(0.0008)	(0.0008)	(0.0010)	(0.0012)
Wife incentive^2	-0.000005***	-0.000003	-0.000005	-0.000007
	(0.0000005)	(0.000005)	(0.000004)	(0.000006)
Man incentive^2	-0.000006	-0.000002	-0.000006	0.000007
	(0.000004)	0.000002	(0.000004)	(0.000005)
Region	All	All	Balaka	Balaka
R-squared	0.2462	0.2557	0.3278	0.2580
F-statistic	22.25	25.80	8.84	9.17
N	620	620	199	199

Notes: Regressions include controls for age and age-squared as well as region fixed effects. F-statistics are presented for the joint significance of the instruments. Robust standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.9: First stage regressions for decision to learn HIV negative status where spouse's incentives are not included as controls

	Wife Result	Man Result
Any incentive	0.233***	0.283***
	(0.0708)	(0.0707)
Incentive	0.0025***	0.0017**
	(0.0007)	(0.0008)
Incentive^2	-0.000006***	-0.000004*
	(0.000002)	(0.000002)
Region	All	All
R-squared	0.2401	0.2342
F-statistic	36.49	38.30
N	620	620

Notes: Regressions include controls for age and age-squared as well as region fixed effects. F-statistics are presented for the joint significance of the instruments. Robust standard errors are presented in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.10: Effect of learning one's HIV negative status on Marriage Outcomes, both spouses' status

	(1)	(2)	(3)	(4)	(5)	(6)
		Married in 2006			No Change Between 2004 and 2006	
	OLS	IV	IV	OLS	IV	IV
Wife result	-0.0134	0.018	0.0868	-0.0197	0.0396	0.1639
	(0.0101)	(0.015)	(0.0951)	(0.0167)	(0.0404)	(0.1559)
Man result	0.0232*	-0.0256*	-0.1031	0.0247	-0.0722**	-0.171
	(0.0142)	(0.0156)	(0.1007)	(0.0201)	(0.0323)	(0.129)
Regions	All	All	Balaka	All	All	Balaka
N	620	620	199	620	620	199

Notes: Regressions include controls for age and age-squared as well as region fixed effects. Robust standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.11: Effect of learning one's HIV negative status on marriage outcomes, spouses' status entered separately

Panel A: Outcome = Married in 2006				
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Wife result	-0.0037	0.0055		
	(0.0082)	(0.0095)		
Man result			0.0182	-0.0155*
			(0.0125)	(0.0095)

Panel B: Outcome = No Change between 2004 and 2006				
	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV
Wife result	-0.0094	0.0080		
	(0.0171)	(0.0371)		
Man result			0.0175	-0.0601**
			(0.0194)	(0.0273)

Notes: N=620. Regressions include controls for age and age-squared as well as region fixed effects. Robust standard errors are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3.12: Second Stage IV Expenditure Share Results, Unmatched Respondents

	(1) Own Expenses	(2) Farm Expenses	(3) Children's Clothes	(4) School Expenses	(5) Children's Medical
Panel A: Women's Expenditure Reports					
Got Result	-0.1028**	0.0618	0.0395	0.0399	-0.0301
	(0.048)	(0.051)	(0.046)	(0.038)	(0.031)
N	727	727	683	683	683
Panel B: Men's Expenditure Reports					
Got Result	0.0404	0.0133	-0.0855	0.0747**	-0.0331
	(0.049)	(0.056)	(0.057)	(0.037)	(0.026)
N	484	484	451	451	451
Panel C: Both Men and Women's Expenditure Reports					
Got Result	-0.0283	0.0370	-0.0153	0.0599**	-0.0353*
	(0.033)	(0.036)	(0.034)	(0.026)	(0.019)
N	1,288	1,288	1,201	1,201	1,201

Robust standard errors in parentheses. Respondents were not asked about their spouse's expenditures so expenditure shares are out of total household expenditures excluding the spouse's expenditures. All regressions include controls for age, age squared, educational attainment, regional dummies, number of boys and girls under the age of 15, and the total number of hh members. Panel A reports regression results for the effect of a woman finding out she is HIV negative on her reports of household expenditure shares. Panel B reports regression results for the effect of a man finding out he is HIV negative on his reports of expenditure shares. Panel C includes both men and women's reports. Controls in Panel C also include a male dummy and couple fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 3.13: Second Stage IV Expenditure Share Results, Matched Respondents

Panel A: Women's Expenditure Reports					
	(1) Own Expenses	(2) Farm Expenses	(3) Children's Clothes	(4) School Expenses	(5) Children's Medical
Got Result	-0.0356	0.0782	-0.0345	0.0311	-0.0386
	(0.063)	(0.077)	(0.074)	(0.062)	(0.043)
Spouse	-0.0294	-0.1322*	0.2186***	-0.0587	-0.0069
Got Result	(0.062)	(0.077)	(0.072)	(0.064)	(0.042)
N	413	413	388	388	388

Panel B: Men's Expenditure Reports					
	(1) Own Expenses	(2) Farm Expenses	(3) Children's Clothes	(4) School Expenses	(5) Children's Medical
Got Result	0.0916	0.0459	-0.0935	0.0527	-0.0596
	(0.063)	(0.072)	(0.075)	(0.053)	(0.037)
Spouse	0.0029	-0.0783	-0.0035	-0.0876	0.0785***
Got Result	(0.065)	(0.067)	(0.075)	(0.058)	(0.030)
N	377	377	359	359	359

Panel C: Both Men and Women's Expenditure Reports					
	(1) Own Expenses	(2) Farm Expenses	(3) Children's Clothes	(4) School Expenses	(5) Children's Medical
Got Result	0.0235	0.0283	-0.0505	0.0534	-0.0559**
	(0.042)	(0.049)	(0.047)	(0.039)	(0.025)
Spouse	-0.0121	-0.0715	0.0890*	-0.0701*	0.0424**
Got Result	(0.042)	(0.047)	(0.046)	(0.040)	(0.022)
N	829	829	785	785	785

Robust standard errors in brackets. Respondents were not asked about their spouse's expenditures so expenditure shares are out of total household expenditures excluding the spouse's expenditures. All regressions include controls for age, age squared, educational attainment, regional dummies, number of boys and girls under the age of 15, and the total number of hh members. Panel A reports regression results for the effects of a woman finding out she is HIV negative and her spouse finding out he is HIV negative on her reports of household expenditure shares. Panel B reports regression results for the effects of a man finding out he is HIV negative and his spouse finding out she is HIV negative on his reports of expenditure shares. Panel C includes both men and women's reports. Controls in Panel C also include a male dummy and couple fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 3.14: Second Stage IV Expenditure Share Results, Excluding Control for Whether the Spouse Learned Status

Panel A: Women's Expenditure Reports					
	(1) Own Expenses	(2) Farm Expenses	(3) Children's Clothes	(4) School Expenses	(5) Children's Medical
Got Result	-0.0566	0.0378	0.0302	0.0157	-0.0423
	(0.056)	(0.065)	(0.062)	(0.059)	(0.037)
N	413	413	388	388	388
R-Squared	0.071	0.043	0.035	0.123	0.050

Panel B: Men's Expenditure Reports					
	(1) Own Expenses	(2) Farm Expenses	(3) Children's Clothes	(4) School Expenses	(5) Children's Medical
Got Result	0.0900	0.0289	-0.0889	0.0405	-0.0475
	(0.057)	(0.068)	(0.069)	(0.047)	(0.034)
N	377	377	359	359	359
R-Squared	0.040	0.057	0.049	0.127	-0.022

Robust standard errors in brackets. Respondents were not asked about their spouse's expenditures so expenditure shares are out of total household expenditures excluding the spouse's expenditures. All regressions include controls for age, age squared, educational attainment, regional dummies, number of boys and girls under the age of 15, and the total number of household members. The analytic samples are restricted to couples where both the husband and wife tested HIV negative in 2004. *** p<0.01, ** p<0.05, * p<0.1

Table 3.15: Second Stage IV Expenditure Share Results Including Spouse's Expenditures

Panel A: Women's Expenditure Reports						
	(1) Own Expenses	(2) Spouse Expenses	(3) Farm Expenses	(4) Children's Clothes	(5) School Expenses	(6) Children's Medical
Got Result	-0.0487	-0.0175	0.0292	0.0295	0.0621*	-0.0410*
	(0.040)	(0.061)	(0.050)	(0.045)	(0.037)	(0.025)
N	480	480	480	451	451	451

Panel B: Men's Expenditure Reports						
	(1) Own Expenses	(2) Spouse Expenses	(3) Farm Expenses	(4) Children's Clothes	(5) School Expenses	(6) Children's Medical
Got Result	0.0574	0.0046	0.0116	-0.0531	0.0577*	-0.0303
	(0.043)	(0.046)	(0.055)	(0.055)	(0.033)	(0.028)
N	353	353	353	338	338	338

Panel C: Both Men and Women's Expenditure Reports						
	(1) Own Expenses	(2) Spouse Expenses	(3) Farm Expenses	(4) Children's Clothes	(5) School Expenses	(6) Children's Medical
Got Result	0.0042	-0.0182	0.0227	-0.0115	0.0637**	-0.0354*
	(0.029)	(0.039)	(0.037)	(0.035)	(0.025)	(0.019)
N	833	833	833	789	789	789

Robust standard errors in brackets. All regressions include controls for age, age squared, educational attainment, regional dummies, number of boys and girls under the age of 15, and the total number of household members. Full household expenditures are calculated by merging the respondent's reported expenditures with the spouse's reported personal expenditures. Panel A reports regression results for the effect of a woman finding out she is HIV negative on household expenditure shares. Panel B reports regression results for the effect of a man finding out he is HIV negative on household expenditure shares. Panel C includes both men and women's reports. Controls in Panel C also include a male dummy and couple fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 3.16: Second Stage IV Expenditure Share Results Including Spouse's Expenditures, Matched Respondents

	(1) Own Expenses	(2) Spouse Expenses	(3) Farm Expenses	(4) Children's Clothes	(5) School Expenses	(6) Children's Medical
Panel A: Women's Expenditure Reports						
Got Result	-0.0041	0.0019	0.0298	0.0141	0.0249	-0.0399
	(0.051)	(0.075)	(0.072)	(0.058)	(0.045)	(0.037)
Spouse Result	-0.0785	0.0361	-0.0918	0.1210**	0.0323	-0.0413
	(0.051)	(0.077)	(0.072)	(0.058)	(0.049)	(0.039)
N	352	352	352	329	329	329
Panel B: Men's Expenditure Reports						
	(1) Own Expenses	(2) Spouse Expenses	(3) Farm Expenses	(4) Children's Clothes	(5) School Expenses	(6) Children's Medical
Got Result	0.0531	-0.0188	0.0505	-0.0630	0.0425	-0.0384
	(0.053)	(0.061)	(0.067)	(0.067)	(0.039)	(0.036)
Spouse Result	0.0312	-0.0341	-0.0612	-0.0409	-0.0487	0.0761**
	(0.052)	(0.067)	(0.065)	(0.072)	(0.043)	(0.030)
N	311	311	311	299	299	299
Panel C: Both Men and Women's Expenditure Reports						
	(1) Own Expenses	(2) Spouse Expenses	(3) Farm Expenses	(4) Children's Clothes	(5) School Expenses	(6) Children's Medical
Got Result	0.0263	-0.0208	0.0130	-0.0123	0.0461	-0.0433
	(0.036)	(0.050)	(0.049)	(0.045)	(0.031)	(0.027)
Spouse Result	-0.0271	0.0001	-0.0465	0.0329	-0.0160	0.0271
	(0.036)	(0.051)	(0.047)	(0.044)	(0.032)	(0.025)
N	689	689	689	653	653	653

Robust standard errors in brackets. All regressions include controls for age, age squared, educational attainment, regional dummies, number of boys and girls under the age of 15, and the total number of household members. Full household expenditures are calculated by merging the respondent's reported expenditures with the spouse's reported personal expenditures. Panel A reports regression results for the effect of a woman finding out she is HIV negative on household expenditure shares. Panel B reports regression results for the effect of a man finding out he is HIV negative on household expenditure shares. Panel C includes both men and women's reports. Controls in Panel C also include a male dummy and couple fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 3.17: Second stage results: Fertility

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Wife result	0.097**	0.328***			0.084***	0.189***
	(0.039)	(0.106)			(0.037)	(0.088)
Man result	-0.031	-0.274***	-0.031	-0.203***		
	(0.042)	(0.106)	(0.042)	(0.097)		
N	383	383	383	383	383	383

Notes: Regressions include controls for age and age-squared as well as region fixed effects. Robust standard errors are presented in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3.18: Second stage results: Desired fertility

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Wife result	0.042	0.226*			0.042	0.178
	(0.063)	(0.135)			(0.057)	(0.113)
Man result	-0.001	-0.072	0.014	0.006		
	(0.059)	(0.130)	(0.053)	(0.117)		
N	336	336	336	336	336	336

Notes: Regressions include controls for age and age-squared as well as region fixed effects. Robust standard errors are presented in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

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