Three Essays in Development and Health Economics

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Abstract

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This dissertation is on three essays on issues in development and health economics. In these essays, I try to examine how different health issues affect economic outcomes and vice versa. I examine individual and household responses to different economic and health issues in Bangladesh and Tanzania. In the first two chapters, I examine how different shocks affect family's fertility decisions and decision to make investments on their children in Tanzania. In the third chapter, I examine how information regarding dangers of pesticide affects the likelihood of pesticide exposure for farmers in Bangladesh.

In the first chapter, I examine how parental illness affects child labor and schooling outcomes using panel data from Tanzania. Prior literature provides limited empirical evidence on the impact of parental illness on child labor and schooling outcomes. I examine if parental illness

causes households to reallocate children's time from school to work. I find that a father's illness hinders child schooling by decreasing attendance and hours spent in school. These effects on schooling are substantially greater for severe illnesses. There is also evidence that a father's illness has long-term impact on child education, as it decreases their likelihood of completing primary school and leads to fewer total years of schooling. However, a father's illness has no effect on child labor. In contrast, a mother's illness does not affect child education, but does cause a small increase in children's work. Surprisingly, parental illness does not have a differential impact by children's gender. Additionally, illness of other household members, such as grandparents, adult siblings, and child siblings, has no effect on children's schooling. Thus, overall, there is no evidence that parental illness or illness of other household members affects children's schooling through increased child labor. Instead, the results suggest that only illness of fathers, who are typically the primary income earners in Tanzanian households, reduces household income and severely decreases the family's ability to afford child education.

In the second chapter, which is a joint work with Claus Portner, we examine the relationship between household income shocks and fertility decisions. Using panel data from Tanzania, we estimate the impact of agricultural shocks on contraception use, pregnancy, and the likelihood of childbirth. To account for unobserved household characteristics that potentially affect both shocks and fertility decisions we employ a fixed effects model. Households significantly increase their contraception use in response to income shocks from crop loss. Furthermore, pregnancies and childbirth are significantly delayed for households experiencing a crop shock. We argue that these changes in behavior are the result of deliberate decisions of the households rather than income shocks' effects on other factors that in influence fertility, such as women's health status, the absence or migration of spouse, and dissolution of partnerships.

In the third chapter, which is a joint work with Hendrik Wolff, we examine how different information sources influence precautionary behavior when using pesticide and likelihood of pesticide exposure. Modern agriculture heavily depends on the use of pesticides and has successfully increased productivity, but also led to increasing concerns regarding farmers' health. Mishandling of pesticides continues to pose a serious health problem for farmers especially in developing countries. This chapter describes supply side and demand side regulations for pesticide handling, health outcomes and adoption of health technologies using a detailed household level dataset from Bangladesh. The dataset is unique as it spans the chain from: 'where do farmers obtain information from', 'which precautionary tools (i.e. masks, gloves) are used' and 'what are subsequent health outcomes after spraying'. Previous studies hypothesized that pesticide sellers in developing countries misguide farmers regarding pesticide use. On the other hand, government field extension workers reduce pesticide exposure by training farmers in Integrated Pest Management (IPM) techniques. In our dataset we cannot confirm these hypotheses. In contrast, we find that those famers that use information from pesticide sellers increase the adoption of precautionary tools. These same farmers also enjoy subsequently improved health outcomes. Further, our results show that the agricultural extension program does not significantly impact technology adoption or health. We find instead evidence of social learning as peer farmers, especially those trained in handling pesticides, have a substantial influence. We conclude with policy recommendations.

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DEDICATION

To my father, Aminul Alam

Chapter 1

Parental Health Shocks, Child Labor and Educational Outcomes: Evidence from Tanzania

1. Introduction

Health shocks have devastating effects on poor households. Certain diseases, such as HIV/AIDS and malaria, have severe impacts with high levels of morbidity and mortality (Yamano and Jayne, 2004). Such major illnesses can substantially increase medical expenditure and decrease household income and consumption for poor households in developing countries (Gertler and Gruber, 2002; Wagstaff, 2007; Genoni, 2012).[1] Consequently, households adopt different coping mechanisms, such as borrowing, dissaving, and selling of assets, to mitigate the effects of such shocks (Wagstaff and Lindelow, 2010). Comparative studies suggest that major illnesses are as frequent, costly, and unpredictable as other income shocks such as unexpected crop loss, a decline in crop prices, or unemployment (Gertler and Gruber, 2002; Kochar, 1995; Wagstaff and Lindelow, 2010). Given the detrimental effects of illnesses and the long-term positive effects of schooling on adult earnings, it is important to understand how illnesses of adults, especially parents, influence child labor and schooling outcomes in a household.

This paper explores the link between parental illness and child schooling. Parental illness can hinder schooling through two potential channels. First, parents' illness may decrease their own productivity at work or cause the parents to miss work entirely. For a credit-constrained household, the net income lost from missed work and increased medical expenditure may reduce the household's ability to afford child education. Second, when a parent is ill, the household may need

[1] There is some disagreement in the literature about the effect of adult illness: Gertler & Gruber (2002) find a decrease in both household income and consumption following adult illness, but Genoni (2012) argues that only income is affected. On the other hand, Wagstaff (2007) finds that food consumption decreases and medical expenditure increases following adult illness.

cheap labor to substitute for the parent's missed work at the farm or in the household. Thus, even if the parents are able to afford child education following an illness, they may need their children to leave school to substitute for parents' work and meet the household's labor demands.

Employing longitudinal data from Tanzania, we examine whether parental illness affects child labor and schooling outcomes, and explore the channel through which the impact on schooling occurs. Using detailed time use data, we examine whether parental illness causes households to reallocate children's time from school to work, and whether there are differential impacts of illnesses of fathers as compared to mothers. Using individual fixed effects, we control for all time-invariant unobserved heterogeneity that may bias the results.

We find that only father's illness hinders children's education by decreasing their attendance and hours spent in school. The effects are substantially greater for severe cases of illness. We also find strong suggestive evidence that father's illness has long-term effects on children's education, as it decreases their likelihood of completing primary school and ultimately causes them to finish fewer years of school. However, illness of fathers does not affect child labor. In contrast, illness of mothers has no effect on child schooling outcomes and only causes a small increase in child labor. Similarly, illness of other household members, such as grandparents, infants, child siblings, and adult siblings, has no effect on educational outcomes. Overall, we find no evidence that illness of parents and of other household members affects children's schooling through increased child labor. Instead, the results suggest that the effect on schooling primarily occurs through the income channel. As fathers are typically the primary income earners in households in Tanzania, only their illnesses substantially decrease household income and, consequently, their ability to afford child education.

These results are surprising in contrast to the literature on parental deaths. While some studies argue that both maternal and paternal deaths decrease schooling, others find that it is primarily maternal deaths that affect schooling.[2] While the precise reason for the difference in the findings in the literature is unclear, the latter finding is consistent with another branch of literature, which shows that children work as a substitute for mothers. When mothers spend more time on market work, children, especially girls, spend less time in school and more hours working to substitute for mothers' domestic duties (Hazarika and Sarangi, 2005; Katz, 1995; Skoufias, 1993). However, in our study, as we find that mother's illness only causes a small increase in child labor (just 2 hours in prior week), it consequently does not displace time spent in school.

We also find that parental illness does not have a differential effect by child gender on schooling. This is in contrast to findings in other countries that show that boys receive preferential treatment compared to girls, primarily due to intrahousehold resource allocation that favors boys (Deolalikar and Rose, 1998; Rose, 2000; Strauss and Thomas, 1995). Similarly, Pitt and Rosenzweig (1990) find that illness of infants is more likely to decrease schooling for a female sibling than a male sibling, as girls typically care for the infants in their families. However, we find no such biases, as boys and girls have a similar mean attendance rate in our study area, which suggests there is no gender bias in child schooling in this region.[3]

On the relationship between parental illness and child schooling, there has been only limited empirical evidence in the prior literature. The few studies on this topic finds evidence that adult illness decreases schooling (Hannum et al., 2009; Sun and Yao, 2010) or increases likelihood of child labor (Dillon, 2008; and Bazen and Salmon, 2010).[4] However, as these papers are based

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[2] While Beegle, Weerdt and Dercon (2006), Gertler et al. (2003) and Case, Paxson and Abledinger (2004) argue that the death of either parent hinders schooling, Ainsworth, Beegle and Koda (2005), Case and Ardington (2006) and Evans and Miguel (2007) find that maternal deaths have a much greater effect on schooling than paternal deaths.

[3] Also, Thomas (1994) finds a gender bias by parents. He finds that fathers typically invest more resources in their sons, while mothers invest more in their daughters. Other studies simply show that mothers typically invest more in children compared to fathers, especially with regard to children's health (Case and Paxson, 2001; Case et al., 2000).

[4] Additionally, Bratti and Mendola (2014) find the effect of parental illness on schooling of older children and young adults (ages 15-24). As in most developing countries most children does not continue till secondary education, and labor work is considered to be child labor only until age 15, other literature and our study focuses on children in the primary-school age range, i.e. ages 7-15. In addition, As other studies also show that health technology, such as introduction of antiretroviral treatment for adult AIDS patients, can increase child labor and decrease schooling (d'Adda et al., 2009; Zivin et al., 2009).

on cross-sectional data, and do not use instruments or panel data with fixed effects, they are unable to establish a causal relationship. Additionally, these papers have some data limitations: (i) they do not have time-use data, which is needed to find the changes in child labor hours following parental illness; (ii) moreover, lack of data on each individual household member's illness (father, mother, child, or other household member) does not allow them to identify the effect of any specific individual's illness on schooling (Hannum et al., 2009; Sun and Yao, 2010)[5]; (iii) and lastly, the data from the Sun and Yao study may suffer from recall error, as individuals have to remember the timing of illness over the prior 15 years.[6]

Our paper, in contrast, uses a 4-wave panel survey that includes a comprehensive time use survey for each household member and detailed information on health shocks. More specifically, this paper is important for three reasons. First, using detailed longitudinal data on schooling and illness, we are able to (a) address concerns on unobserved heterogeneity that bias cross-sectional estimates; and also (b) separately examine the impact of illness of each household member, especially of father and mother, on child schooling. Second, this work adds to the child labor literature (Edmonds, 2005) and is the first paper that uses detailed time-use data to examine the effect of health shocks on child labor. Employing time-use data in a panel setting allows us to examine the reallocation of children's time from school to work following parental illness, and thus examine a potential channel through which shocks may affect schooling.[7] Third, this paper also contributes to the literature on consumption smoothing and coping mechanisms adopted by households facing shocks (Kochar, 1999; Morduch, 1995; Townsend, 1994; Rosenzweig and Wolpin, 1993). If households are credit-constrained or lack buffer stock, they have to use other

[5] Their survey question asks whether any household member was ill but does not identify which household member was ill

[6] Sun and Yao asked individuals to recall the dates of illnesses over the prior 15 years and then matched the reported illness and schooling data. However, individuals may not be able to correctly report the timing of illness over the prior 15 years. Thus, their study may be susceptible to reporting errors.

[7] Several studies examine the tradeoff between child labor and schooling: Ravallion and Wodon (2000), Beegle, Dehajia and Gatti (2009) and Janvry, et al. (2006). Additionally, Emerson & Souza (2011) find the effect of child labor on future labor market outcomes.

strategies to mitigate the effect of shocks on consumption. Our results indicate that households decrease child schooling to smooth their consumption following parental illness.[8]

The paper proceeds as follows. In Section 2 we discuss the data and describe the area where the survey data used for this study was compiled. The empirical methodology is presented in Section 3 and the results in Section 4. Finally, this study concludes with a discussion of policy implications in Section 5.

2. Overview of Data and the Kagera region

This study uses the Kagera Health and Development Survey (KHDS), a longitudinal survey conducted from 1991–1994 in the Kagera region in Tanzania. The Kagera region is in the Northwestern corner of Tanzania, west of Lake Victoria, and borders Burundi, Rwanda, and Uganda. It is a rural area primarily engaged in agriculture, with limited use of wage labor. In Kagera and other parts of rural Tanzania, there is a gendered division of labor within households. Typically, men are responsible for cash crop farming, the primary source of income for households, as well as other income-generating activities, such as self-employment and wage labor. Women are in charge of household-related chores and the production of food crops in small garden plots (food crops are consumed by the household and typically do not generate income) (Tibaijuka, 1994; Lymio-Macha and Mdoe, 2002; Leavens and Anderson, 2011). While women's primary focus is on food crops, they also spend time on cash crop production to varying degrees. Despite the significant labor contributions of women, men control nearly all household income (Tibaijuka, 1994; Leavens and Anderson, 2011).

[8] This finding is similar to studies that show income shocks, such as financial crises, natural hazards, crop losses, and unemployment, cause households to increase child labor and decrease school attendance to mitigate the effect of such shocks on consumption. The following papers find that income shocks decrease school attendance: Duryea, Lam and Levison (2007); Fallon and Lucas (2002); Funkhouser, (1999); Jacoby and Skoufias (1997); Jensen (2000); Thomas et al. (2004). Furthermore, Duryea et al. (2007) and Beegle et al. (2006) find that child labor increases following income shocks.

The World Bank and the University of Dar es Salaam conducted the KHDS in four rounds from September 1991 to January 1994. The KHDS surveyed over 800 households, drawn from 51 communities (49 villages) in six districts of Kagera. The sampling was randomized based on the 1988 Tanzanian Census.[9] Households were interviewed on a rolling basis throughout the year, with an average interval of six to seven months between each survey round. The KHDS contains detailed information on all household members, such as illness suffered, education, hours worked, assets owned, and a number of other socioeconomic characteristics. Overall, 90.4% of all households remained in the survey for all four rounds. Probit estimations show that adult illness does not predict the incidence of households leaving the survey. When households dropped out of the survey, the surveyors randomly included additional households into the survey as replacements. In addition to the original four rounds, a fifth survey round was conducted in 2004. This fifth round is particularly useful for this study, as it allows us to follow up on the children 13 years after the first round and to examine the effect of parental illness on their final educational attainment.

For the remainder of the paper, only the male household head is referred to as the father, and the wife of the household head or a female head is referred to as the mother. This is because a fraction of the children (8%) are orphans. Thus, the household heads are not their biological parents but are actually the orphans’ grandparents or uncles/aunts, and they play the role of parents to the orphans. To keep our terminology simple, we continue to call those parents ‘father’ or ‘mother’.

2.1 Education and Child Labor in Tanzania

This paper focuses on children aged 7–15. This is because the minimum age for starting school is 7 (children are expected to start primary school when they are between 7 and 8 years of age), and it takes 7 years for children to complete primary school. The minimum age for legal

[9] For further details on the sample selection, please refer to World Bank (2004).

employment is also 15, and thus, children, who are older than 15 and also work, are not considered to be doing child labor. The survey contains detailed data on education and time-use of each household member aged 7 and above. Household members were asked the number of hours they worked, broken down by specific tasks, in the seven days prior to the interview. This allows us to determine the number of hours they spend weekly on household work and market work, along with the total hours of work.[10] Additionally, KHDS compiles data on child's education, such as, if they were ever enrolled in school, their attendance and hours spent in school in the last week, and the highest grade completed in each of all five survey rounds.

The school year starts in January for primary schools in Tanzania. School expenses include the cost of attendance, textbooks, and uniforms, and these expenses increase with each higher grade level. The average schooling cost for a child in this sample was 1,200 Tanzanian shillings. During the period of the study, the median household savings in Kagera was approximately 3,000 Tanzanian shillings, and the median monthly per-capita income was approximately 2,700 Tanzanian shillings. These income and savings statistics suggests that schooling represents a significant cost to households: 1,200 Tanzanian shillings is more than or equal to the savings of 34% of all households. A study on Tanzania by Burke (1998) shows that 46% of parents report that they are unable to afford educational costs for their 13 to 15 year-old children.

2.2 Illness

As we examine the effect of health shocks, it is important to note the major illnesses present in the region at the time of the survey. HIV/AIDS and malaria were prevalent in parts of Kagera. In the regional capital Bukoba in the Northeast, the adult HIV/AIDS rate was as high as 24%

[10] This study defines the following tasks as household work: preparing meals, cleaning the house, doing laundry, shopping for food, collecting firewood, collecting water, and caring for the ill. Market work is comprised of the following tasks: outside employment, work in the farm and garden (i.e. cash crop and food crop production), processing crops for sale, caring for poultry and livestock, collecting or transforming household livestock and animal products for sale (milk, eggs, etc.), attending to household business, and seeking additional paid work.

during the time of the survey (World Bank, 2004). However, in the southern and western regions of Kagera, the HIV/AIDS rates were nearly at zero. Moreover, 4% of all individuals in this study sample were diagnosed with malaria, while an additional 6% had malaria-type symptoms but did not visit a doctor. While KHDS does not have data on the types of illnesses suffered, it does contain detailed data on the incidence of illness during 4 weeks prior to the respective survey rounds.

KHDS asked all household members about any illnesses they had suffered in the 4 weeks prior to the interview, though these illnesses could have begun much earlier. Furthermore, the survey also asks "For how many days were you unable to conduct your usual activities because of this illness?" As there can be substantial variation in the severity of illness, this study only considers an individual to be ill if a person reports illness and also reports they were unable to conduct their usual tasks for at least a day because of the illness.[11] This measure of illness allows us to identify individuals whose physical functioning is affected, which then affects their efficiency or ability to work. This measure provides a similar objective measure as the Activities of Daily Living (ADL) used in a few other studies (Gertler and Gruber, 2002; Genoni, 2012), which ask individuals to rate if they are able to conduct a usual daily activity, such as the ability to stand up from a sitting position, to eat or bathe without help, or to walk uphill without assistance.[12] In addition to questions on illness, all women aged 14–50 were also asked if they were pregnant at the time of the interview.

[11] There are variations in "daily activity" among individuals, for example across gender and age. Thus, individuals doing more physical labor may be more likely to be considered ill according to this definition of illness, because illnesses are more likely to have an effect on their daily activity. While individual fixed effects would address some concerns over these kinds of systematic measurement errors, this paper conducts robustness check by defining individuals as ill if a person only reports illness and the definition does not take into consideration whether the illness affected their daily activity. The estimates on the effect on schooling and child labor remain robust using this measure of illness.

[12] We also conduct robustness checks by using other definitions of illness that are based on limited daily activity. For example, household members were asked (i) whether the illness caused them to be confined to bed at any time; and (ii) whether the illness restricted them from doing their work. We find the results to be robust for both these definitions of illness.

2.3 Summary Statistics

Table 1.1 presents the descriptive statistics. While 91% of all children report working at least one hour in the prior week, only 70% of children have started schooling. The children who started schooling spend approximately 27 hours in school each week, with an attendance rate of 87%. There is no significant gender difference in the percentage of children who have started schooling (70% of boys and 69% of girls). Likewise, the attendance rate for boys and girls is equal in magnitude (87% for both boys and girls).

For illness, on average in each survey round, 42% of the children have at least one ill parent. 21% have an ill father, and 29% have an ill mother. Table 1.1 also lists the illness rates of other members of the household.[13] Additionally, 7% of mothers were pregnant during the time of the interview. The survey provides detailed data on age, number of household members, crop loss shocks faced by the household in the prior six months, and the value of household asset holdings, which include land, business equipment, and durable goods. Lastly, over 5% of households faced adult deaths between survey rounds.

Table 1.2 presents the descriptive statistics on hours worked, divided into three categories: (i) total hours worked; (ii) hours spent on household work; and (iii) hours spent on market work. On average, children work slightly over 18 hours each week, with 12.6 hours spent on household work and 6 hours on market work. Children who attend school also work for a similar number of hours. On average, boys work (17.3 hours) slightly fewer hours than girls (19.5 hours). This is because girls spend more time doing household chores. However, there is a much greater gender difference in work among adults: women work 36.9 hours and men work 31.3 hours each week.[14]

[13] Although 29% of all adults report suffering from illness, only 12% report visiting a health facility. The definition of a health facility includes health centers, hospitals and dispensaries, which are typically operated by NGOs, government and private organizations. These facilities are not uniformly accessible; while there are multiple health facilities in some communities, a few have no health facilities at all. For the latter case, people have to travel further to access a health facility.

[14] The *average* hours worked may appear to be low because there is a strong seasonality in farm work.

Women contribute almost equally to household (18.8 hours) and market work (18.1 hours). In contrast, men work far more hours on market work, 26 hours, compared to only 6 hours on household work.

3. Empirical Methodology and Specification

This paper uses a linear model with individual (child) fixed effects to find the effect of health shocks on child labor and schooling outcomes. A linear model is preferred over a non-linear model, because: (i) it allows easier interpretation of the coefficients; (ii) it allows for the consistent use of the same estimation technique for binary (attendance) and non-binary dependent variables (hours spent in school and child labor hours), and thus allows us to compare the coefficients of explanatory variables across estimations with different dependent variables. We also conduct robustness check using fixed-effects logit model for school attendance, and find the estimates to be robust using this technique.

The individual fixed effects allows us to control for time-invariant characteristics associated with the individual (child), such as: religion, gender, child birth order effects, parental characteristics and preferences, general health status of both the child and the parent, gender differences between children, and any other unobserved time-invariant child and parent heterogeneity. The fixed effects also address the problem of systematic measurement errors in the explanatory variables. Thus, this estimation procedure will address concerns on unobserved heterogeneity that could have biased the results. The following specification is used for the estimations:

$$Y_{i,j,t} = \beta_0 + \sum_k \beta_{1,k} Illness_{k\,j,t} + \beta_2 Illness_{i\,j,t} + \beta_3 X_{i,j,t} + \delta_i + \gamma_{j,t} + \varepsilon_{i,t} \qquad (1)$$

where subscripts i, j, and t denote individual, household, and survey rounds, respectively. Y represents the dependent variable for the estimation equation, which is attendance, hours spent in school, and hours spent at work. $Illness_k$ is a set of dummy variables indicating the illness of the k^{th} person in the household, where k represents the following individuals: father, mother, grandparents, adult siblings, child siblings, and any other household member. $\beta_{1,k}$, the coefficient of $Illness_k$, is our coefficient of interest. $Illness_i$ is a dichotomous variable representing the illness of the child. X represents a set of control variables, which include: the value of household assets and dummy variables for: crop loss, pregnancy status of mother and other women in household, adult death, and orphanhood status of the child. γ_j represents survey round fixed effects; as attendance or child labor hours may have seasonal variations, this specification also controls for the month of interview. δ_i represents the individual fixed effects. Standard errors are clustered at the household level.

4. Results and Discussion

4.1 Effects on School Attendance

Table 1.3 demonstrates the impact of parental illness on school attendance of children who have already started schooling. School attendance is represented by an indicator variable that is equal to 1 if the child attends school for at least an hour in the prior week and 0 otherwise.[15] Column (1) uses the ordinary least squares (OLS) technique to find the effect on school attendance. The OLS estimate shows that while a child's own illness significantly decreases attendance, parental illness does not have a significant effect. However, individual or household level unobserved heterogeneity, which the OLS is unable to control for, may confound the effects of parental illness. Thus, we address such concerns using an individual fixed effects model in column (2). With fixed effects, we find that father's illness leads to a 4.5 percentage point decrease in school attendance, and the effect is statistically significant. In contrast, mother's illness does not

[15] Children currently on vacation are not included in the estimation.

have a significant effect, while adult death and a child's own illness significantly decrease attendance. Columns (1) and (2) also control for value of assets owned per capita, crop loss, pregnancy status of mother and other women in the household, number of household members, month of interview and survey round dummies. To explore the effect of the illness of other household members, we add a set of controls for illness in column (3) for each of the following groups: grandparents, children younger than 5, children aged 5–18, adult siblings, and any other household members. These variables do not have a significant effect and, moreover, the coefficient of parent's illness remains robust to the inclusion of these variables.

In columns (4) and (5), we conduct a number of robustness checks. Although this sample (in Table 1.3) only considers children who have started schooling, it is possible that some children may have dropped out of school before the start of the survey, and consequently those observations may bias the estimates. To eliminate the possibility of such bias, column (4) excludes children who did not attend school in any of the survey rounds. The coefficients remain similar and father's illness decreases attendance by 6.3 percentage points.

While the individual fixed effects controls for time-invariant characteristics, there may be time-varying village/community-level shocks that will not be captured by the fixed effects or the survey round dummies.[16] To capture these community-level shocks, survey round dummies interacted with each community are added to the specification in column (5). There are 51 communities followed over 4 survey rounds, thus a set of over 200 time dummies are added to the specification to capture time-varying unobserved heterogeneity at the community level. As shown in column (5), the coefficient of parent's illness remains robust to the inclusion of community-time dummies.

[16] 49 villages divided into 51 communities, where, in particular, 2 villages are divided into 4 communities in the survey.

Columns (6) and (7) examine the impact of parental illness on another variable of interest: hours spent in school. Similar to the results on school attendance, mother's illness has no effect, while father's illness significantly decreases schooling hours by 2.4 hours each week. Once again, we include the illness of other household members, but they do not have a significant effect (Column 7); though the coefficients of parental illness remain robust to their inclusion.

The effect of parent's illness on schooling may vary depending on the severity of illness. This question is examined in Table 1.4. The severity of illness is measured by the number of days individuals were unable to conduct their usual activities because of illness. This definition is used because the more severe the illness, greater is the number of days individuals would be unable to conduct their usual tasks. The duration of irregular daily activity is divided into 4 ranges (dummies): 1–10 days; 11–20 days; 21–30 days; and 31 days or more.[17] Column (1) shows that a father's illness of 31 days or more substantially decreases the likelihood of attendance by 20 percentage points. In contrast, illness of a lesser severity decreases attendance by 6 percentage points or less, and is statistically significant for the 1–10 days case. Similarly, father's illness of 31 days or more significantly decreases schooling hours by 5.1 hours each week. Illnesses of lesser severity have much smaller effects on schooling hours. However, severe illnesses of mothers do not have a greater effect on child schooling. These results suggest that while severe illness of fathers has a considerably greater effect on school attendance, comparatively milder illnesses also do have some, but smaller, effect.

4.2 Effects on Child Labor

[17] These ranges are chosen as the reports of the number of days were grouped around 10-day marks in the data. Of the children with fathers having illness, 74% of ill fathers have illness for 1–10 days; 13% are ill for 11–20 days; 6% are ill for 21–30 days; and 7% are ill for 31 days or more. Of the children with mothers having illness, 70% of ill mother have illness for 1–10 days; 17% are ill for 11–20 days; 7% are ill for 21–30 days; 6% are ill for 31 days or more.

Next, we examine the effect on child labor to find evidence of any reallocation of time from school to work following illnesses. As only father's illness affects schooling, we are particularly interested in examining if this effect arises via an increase in child labor. In Table 1.5, columns (1) and (2) examine the effect on labor hours for all children in the sample, regardless of whether they were ever enrolled in school. Column (1) shows that a father's illness increases child labor by 0.3 hours on average in the prior week, but the effect is not statistically significant. In contrast, mother's illness significantly increases children's work by 1.9 hours (approximately 10 percent of the mean hours of child work). Illness of children younger than 5 years also significantly increases work by 2.4 hours (Column 2). However, illness of the other household members does not significantly impact child labor.

Columns (3) to (5) examine the impact on hours worked for the subset of children who have started schooling (the children analyzed in Table 1.3). Column (3) shows that mother's illness has a similar effect as in the overall sample by significantly increasing work by 2 hours; the coefficient of father's illness is negative (-0.45 hours) but insignificant. Columns (4) and (5) disaggregate hours worked by type into household and market work. The disaggregation reveals that the increased labor hours following mother's illness is mostly driven by an increase in household work. In contrast, fathers' illness causes only a negligible and statistically insignificant reallocation of children's labor from household to market work.

4.3 Identification of the Channel of Effect

To summarize the results of the previous sections, while father's illness hinders schooling, there is no evidence that it causes a reallocation of children's time from school to work. Thus, we find no evidence that the effect on attendance is via increased child labor. Instead, it is likely that father's illness may affect attendance via another channel: a decrease in household income and consequently, the ability to afford education. Therefore, we explore whether father's illness has a differential impact on household income, consumption, and savings, compared to illness of other household members (Table 1.6). The survey asks each household their total consumption expenditure and income in the prior six months. Furthermore, in each survey round, households are asked the value of their savings/cash-holdings and livestock owned. Therefore, using the illness data, we find the impact of individual illnesses on income, consumption, and savings in the following six months. It is important to note that if the household recovers quickly following adult illness, then we would be unable to capture its effect on these variables; hence, these estimates would provide an underestimate of the actual effects.

We find that father's illness decreases per-capita household income, but the effect is not statistically significant. However, father's illness substantially decreases agricultural profits and consumption expenditure in the household, and the effects are statistically significant (columns 2 and 3). Illness of other household members has no such effect. To examine whether the decrease in household income affects a family's liquid assets, we examine the effect on their livestock holdings and savings. We find that the total value of their livestock holdings decreases following father's illness, which suggests that households maybe selling their livestock to cope with this health shock (column 4). Similarly, their savings also decreases following father's illness (column 5). Illness of other household members does not have a statistically significant impact on savings or value of livestock owned.[18] These results suggest that it is primarily father's illness that decreases household income, and consequently, the household's ability to afford child education.

Given the cultural setting in Tanzania, it is not surprising that only father's illness affects a household's ability to afford education, as fathers are in charge of most income-generating

[18] Households with the top 2% of household income and agricultural profits are dropped for this estimation because these high outlier values bias the above estimates. However, the estimates on per-capita household income, consumption expenditure and value of livestock owned remains robust even with the entire sample. However, estimates on value of per-capita agricultural profits and savings do not remain robust in the entire sample. But these estimates remain robust for other cut-off points of outliers, where top 1%, 5%, or 10% are dropped. This suggests that only the households with top 1% of income biases the estimates on agricultural profits and savings for the entire sample.

activities for the household. However, mothers also spend some time on income-generating activities, such as cash crop production.[19] Therefore, it is important to understand the labor allocation decision within a household following father's illness to determine whether a mother works more to compensate for the fewer hours of work performed by father following his illness. Table 1.7 examines this issue. We find that mothers do not work more, neither in terms of time spent on market work nor in total hours, following father's illness (columns 1 and 2). However, mother's illness decreases their own work by 6.6 hours in the prior week. Similarly, columns (3) and (4) show that fathers do not work more following mother's illness; but fathers considerably decreases their own work by 6 hours, as 5.7 hours is reduced from market work (a 22% decrease from the mean level). These results show that while fathers substantially decrease their time spent on income generating activities following own illness, mothers do not work more hours to substitute for fathers' market work. These results possibly suggest that mothers are unable to substitute for certain skills that fathers provide in market work.

It is also possible that other adults in the household work more to compensate for the hours that parents are unable to work due to illness. However, we find no evidence that other adults work additional hours following illnesses of the parents (columns 5 and 6). These results suggest that other household members (children, mother, and other adults) are not able to work more on income-generating activities to compensate for the impact of father's illness on household income.

4.4 Heterogeneity by Gender and Age of Children

We also explore if parental illness has differential effects by gender of parents and children (Table 1.8). The estimates show that parent's illness does not have a differential effect (i.e. statistically insignificant) by child gender on attendance and child labor. This is not surprising in

[19] While women spend 18 hours each week on market work, this includes a significant time spent on food crop production, which does not generate income.

the context of Tanzania, as the mean level of child labor and attendance of boys and girls are not significantly different in magnitude. This is in contrast to the literature on gender differences in other countries, which finds that girls work more and receive less schooling compared to boys. Consequently, when there is a greater demand for household labor, girls are preferred for work over boys, and girls' labor hours come at the expense of their schooling (Pitt and Rosenzweig, 1990). In this paper, as there is no gender differential in attendance at the mean level, and given that fathers' illness affects schooling primarily because of their difficulty in affording education (instead of increased demand for child labor), it is not surprising that we find no differential effect by gender on children's schooling.

We also explore if the effect of parent's illness varies with the age of children. As there is not enough statistical power in the interaction term of children's age and parent's illness, children's age is divided into four groups: 7–9, 10–11, 12–13, and 14–15. Table 1.9 shows that mother's illness does not have a differential impact on child labor or attendance for different age groups. Similarly, the effect of father's illness on school attendance does not vary with the age of the children. However, we find that when the father is ill, the oldest group of children, aged 14–15, is significantly likely to work increased hours compared to the youngest group. The oldest group of children is differentially affected, possibly because they have the most physical strength to be able to work more hours compared to younger children. Even though children aged 14–15 work more following father's illness, their school attendance is not differentially affected. This result provides further evidence that father's illness does not affect attendance via increased child labor.

4.5 Long-term Effects on Education

It is important to note that school attendance only informs us about the short-term schooling status of children. Since children may reenroll after temporarily leaving school, it is important to learn the potential longer-term effects on education. Thus, this paper examines the impact of parental illness on: (i) the years of schooling children have completed between 1994 and 2004 and (ii) whether they finish primary school by 2004. As primary education is 7 years long, children enrolled in school in 1994 are expected to finish their primary education by 2004. As there is no within-individual variation, we are unable to use individual fixed effects for these estimations. Columns (1) and (2) in Table 1.10 presents the OLS estimates, which show that both father's and mother's illness cause a significant decrease in further years of schooling. However, neither parent's illness has any effect on the likelihood of children finishing primary school.

As discussed earlier, OLS estimations are unable to control unobserved heterogeneity that may affect both the likelihood of parental illness and children's future education. To control for unobserved household time-invariant characteristics, household fixed effects are introduced into the specification. As only children aged 7–15 (primary school-going age for children) are included in our sample, siblings in a particular household may enter and exit this sample at different periods based on their ages. Hence, as the number of periods a sibling stays in the sample varies depending on their age, siblings can have had varied exposure to the illness of a parent.[20] This varied exposure to illnesses of household members allows us to employ household fixed effects. On the other hand, the variation in the dependent variable arises from different education levels of siblings within a household. Columns (3) and (4) present the results with household fixed effects. We find that father's illness causes a 1.5 years decrease in years of schooling. This effect is substantially greater than the effect found in the OLS estimate (0.3 years). Father's illness also decreases the likelihood of finishing primary school by 20 percentage points. However, consistent with previous results, mother's illness does not have a statistically significant effect on these long-term educational outcomes when the household fixed effects are employed.

[20] For example, within one household, there may be two children, aged 6 and 7. The household's 7-year-old child will be in this sample for all four rounds, whereas the 6-year-old child will be in this sample for three rounds or less. Hence, we get two children within the same household who are in the sample for different number of periods.

Although the above specification does not allow the use of individual fixed effects, it controls for several important individual characteristics, such as gender, age, orphanhood status, and the number of periods the children were in the sample. An important limitation of this analysis is that this estimation is unable to control for future shocks that occurred between 1994 and 2004 survey rounds. An example of a future shock can be a recurring illness for the parent. Such future shocks may be correlated with past parental illness, and hence bias the estimates if they are not controlled for in the estimation. Therefore, Table 1.10 only provides suggestive evidence for the effect of parental illness on final education level. It is also important to note that the retention rate of respondents from the initial 1994 survey round to the final 2004 survey round is 82%. Hence, attrition may bias these estimates on long-term educational outcomes.

4.6 Robustness Checks

In Table 1.11, we investigate potential endogeneity concerns: whether prior assets owned or income shocks cause parental illness. If health shocks are exogenous, we would expect that assets owned or income shocks to be orthogonal to illness. The following estimations test if assets owned and income shocks, measured in the form of crop loss, are determinants of parental illness. Column (1) shows that assets owned prior to the health shocks have no significant effect on parental illness. Similarly, crop loss before the prior survey round has no effect on illness as well (column 2). Lastly, we examine the effect specifically on father's illness (column 3) and mother's illness (column 4) and find that neither prior crop loss nor assets owned are significant determinants of illness. This suggests that illness is not endogenously determined by a household's wealth status or income shocks. We also conduct other sensitivity analysis and find that coefficients of parental illness remain robust to the exclusion of important control variables, such as assets owned, crop loss, and illness of other household members.[21]

5. Conclusion

Employing longitudinal data from the Kagera region in Tanzania, this paper examines the role of illness of parents and of other household members on child labor and schooling outcomes. We find that father's illness substantially decreases children's attendance and hours spent in school. The effects are substantially greater for severe illnesses. The paper also finds suggestive evidence that father's illness affects children's long-term schooling outcomes by reducing the likelihood of finishing primary school and causes them to finish fewer total years of school. In contrast, mother's illness and illness of other household members has no effect on schooling. While mother's illness causes a small increase in child labor (primarily household work), father's illness has no such effect.

These results show that although father's illness hinders child education, there is no evidence that it causes a reallocation of children's time from school to work. Therefore father's illness does not affect attendance through increased child labor. Instead, the results suggest that since fathers are typically the primary income earners in households, their illness decreases household earnings and savings, and reduces their ability to afford child education. In contrast, illness of other household members does not have a substantial impact on household earnings. We also find no evidence that the mothers increase their market work to compensate for the fewer hours worked by the father when he is ill. This may suggest that mothers are unable to substitute for certain skills of fathers when they are ill.

[21] We further analyze the effect of heterogeneity by wealth level and female-headed households (i.e., single mothers). However, we find no significant effect of illness of single mothers, or differences in effects at different wealth levels. Illness of female household head also has no effect on child education because female heads do not work substantially more in market work than mothers in male headed households. Thus, their illness does not affect market income. These results are available on request.

Thus, policies are needed that insure children against the risk of not enrolling in school. Government may consider providing financial assistance to schoolchildren who can provide medical evidence from health care providers to confirm the existence of parental illness.[22] Vouchers providing financial support for books and uniforms could also be considered for children with parental illness. Schools may also consider allowing affected households substantial delays in the payment of schooling fees and expenses until after the household member recovers from illness. For agricultural households, who may prefer to pay immediately following a harvest season, being allowed to pre-pay schooling expenses may insure such households and their children against any unanticipated future shocks.

[22] A concern is that not all households have easy access to health facilities.

Table 1.1: Summary Statistics

Variable	Mean	Std. Dev.
Children who started primary schooling	70%	
- Boys	70%	
- Girls	69%	
Attendance rate for children who started schooling	87%	
- Boys	87%	
- Girls	87%	
Hours spent in school by children	26.7	(14.1)
Years of current schooling, if started schooling	2.45	(2.0)
Final years of schooling in 2004	6.95	(2.0)
Proportion having finished primary school in 2004	84%	
Percentage of children working	91%	
Average illness rates in each survey round:		
- Any Parent ill	42%	
- Father ill	21%	
- Mother ill	29%	
- Adult sibling ill	14%	
- Grand parents ill	3%	
- Other household members ill	7%	
- Children under 7 ill	39.9%	
- Child's own illess	39%	
Parents sick at least once in all four survey rounds	80%	
- Father sick at least once	46%	
- Mother sick at least once	62%	
Mother pregnant	6.9%	
Other household member pregnant	2.7%	
Percentage of households having adult death	5.9%	
Age	11.1	2.6
Number of household members	7.8	(3.7)
Percentage of crop loss	34%	(0.5)
Per capita asset owned x 1000 (in Tanzanian shillings)	165.6	(2016.1)
Number of observations	5397	

This table provides the mean over all four rounds of survey unless otherwise noted. $1 = 526 Tanz. Shillings in 1994.

Table 1.2: Summary Statistics of Hours Worked

Hours worked by:	Total hours	Household work	Market work
Children aged 7-15	18.4	12.6	5.9
	(15.1)	(11.1)	(7.8)
- Boys	17.3	9.5	7.8
	(14.3)	(8.9)	(10.0)
- Girls	19.5	12.9	6.7
	(15.9)	(15.9)	(8.7)
Children who started schooling	18.5	13.1	5.4
	(13.1)	(10.0)	(6.5)
Adult males	31.3	5.4	26.0
	(23.6)	(8.4)	(21.5)
Adult females	36.9	18.8	18.1
	(22.8)	(13.6)	(15.3)

This table provides average number of hours worked in the prior week over four survey rounds. Standard errors are provided in parenthesis. Household work is defined as the following tasks: time spent preparing meals, cleaning the house, doing laundry, shopping for food, collecting firewood, collecting water, and caring for the ill. Market work is defined as the following tasks: outside employment, work in the farm and garden, processing crops for sale, taking care of the poultry/livestock, collecting or transforming household livestock/animal products for sale (milk, eggs, etc.), household business, and time spent seeking additional paid work

Table 1.3: Effect of Parental Illness on School Attendance and Hours Spent in School

Dependant variable	School Attendance					Schooling Hours	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Specification	OLS	FE	FE	FE	FE	FE	FE
Father ill	-0.032	-0.045**	-0.058**	-0.063***	-0.055***	-2.420***	-2.338***
	(0.022)	(0.021)	(0.024)	(0.024)	(0.018)	(0.872)	(0.887)
Mother ill	0.008	0.019	0.009	0.009	0.027	1.103	0.974
	(0.017)	(0.016)	(0.017)	(0.018)	(0.017)	(0.736)	(0.751)
Ill Child	-0.038**	-0.036*	-0.042**	-0.044**	-0.044**	-2.539***	-2.485***
	(0.018)	(0.020)	(0.020)	(0.021)	(0.019)	(0.761)	(0.774)
Grand parents ill			-0.004	0.003	0.012		0.959
			(0.027)	(0.029)	(0.031)		(1.806)
Child aged 5 or below ill			0.003	0.003	0.010		0.378
			(0.022)	(0.023)	(0.020)		(0.961)
Other Children aged 6-18 ill			0.015	0.018	-0.008		-0.798
			(0.017)	(0.017)	(0.015)		(0.667)
Adult siblings ill			-0.034	-0.035	-0.021		-0.540
			(0.023)	(0.024)	(0.022)		(0.961)
Adult death	-0.152***	-0.129***	-0.125***	-0.130***	-0.142***	-3.670**	-3.820**
	(0.047)	(0.042)	(0.042)	(0.045)	(0.043)	(1.726)	(1.725)
Assets owned	0.012**	0.005	0.004	0.002	0.000	0.138	0.092
	(0.005)	(0.012)	(0.011)	(0.012)	(0.010)	(0.427)	(0.398)
Community-Time Dummy	No	No	No	No	Yes	Yes	Yes
Number of observations	2,590	2,590	2,590	2,465	2,465	2,465	2,465

Note: Linear Model. Standard errors are in parentheses and are computed after correcting for correlation and heteroskedasticity within household clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. All estimations control for number of household members, orphanhood status, pregnancy status of mother and other women, month of interview, and the round of survey.

Table 1.4: Effect of Severity of Illness on Child's School Attendance using Individual Fixed Effects

Dependent variable:	Attendance	Schooling Hours
Duration of Father's Illness:		
- 1 - 10 days	-0.057**	-2.987***
	(0.028)	(1.140)
- 11 - 20 days	-0.046	0.154
	(0.044)	(2.069)
- 21 - 30 days	-0.019	0.056
	(0.058)	(2.613)
- 30 + days	-0.206**	-5.730*
	(0.083)	(3.107)
Duration of Mother's Illness:		
- 1 - 10 days	-0.001	1.056
	(0.021)	(0.832)
- 11 - 20 days	0.014	1.507
	(0.031)	(1.117)
- 21 - 30 days	0.007	1.605
	(0.058)	(2.706)
- 30 + days	0.043	0.887
	(0.038)	(1.816)
Ill Child	-0.047**	-2.696***
	(0.021)	(0.835)
Grand parents ill	-0.003	0.220
	(0.027)	(1.634)
Adult Death	-0.130***	-3.593**
	(0.044)	(1.645)
Number of observations	2465	2465

Note: Linear Model with individual (child) fixed effects. Standard errors are in parentheses and are computed after correcting for correlation and heteroskedasticity within household clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. All estimations control for illness of adult siblings, child siblings, and other household members, crop loss, per-capita assets owned, number of household members, orphanhood status, pregnancy status of mother and other women, month of interview, and the round of survey.

Table 1.5: Effect of Parental Illness on Child Labor Hours using Individual Fixed Effects

	All Children		Only Children who are in school		
Dependent Variable:	Total Hours	Total Hours	Total Hours	Household Work	Market Work
	(1)	(2)	(3)	(4)	(5)
Father ill	0.303	0.205	-0.448	-0.731	0.283
	(0.774)	(0.756)	(0.980)	(0.696)	(0.587)
Mother ill	1.85***	1.6**	1.94**	1.27**	0.666
	(0.648)	(0.639)	(0.824)	(0.534)	(0.545)
Ill Child	-2.328***	-2.384***	-1.622**	-1.440***	-0.182
	(0.577)	(0.558)	(0.699)	(0.492)	(0.406)
Grand parents ill		0.916	1.310	1.319	-0.009
		(1.964)	(1.988)	(1.618)	(1.347)
Child aged 5 or below ill		2.399***	0.912	0.373	0.538
		(0.832)	(1.036)	(0.750)	(0.580)
Other Children aged 6-18 ill		-0.499	-0.136	0.011	-0.146
		(0.508)	(0.702)	(0.529)	(0.409)
Adult siblings ill		-0.446	-1.807**	-1.189*	-0.618
		(0.801)	(0.873)	(0.676)	(0.539)
Assets owned per capita	0.054	0.053	-0.250	-0.105	-0.144
	(0.369)	(0.376)	(0.381)	(0.294)	(0.232)
Crop loss	0.740	0.629	1.247	0.892	0.355
	(0.742)	(0.743)	(1.081)	(0.709)	(0.654)
Adult Death	-2.113*	-2.106*	0.335	-0.827	1.162
	(1.159)	(1.190)	(1.798)	(1.054)	(1.198)
Number of observations	5,305	5,305	2,465	2,465	2,465

Note: Linear Model with individual (child) fixed effects. Standard errors are in parentheses and are computed after correcting for correlation and heteroskedasticity within household clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. All estimations control for number of household members, orphanhood status, pregnancy status of mother and other women, month of interview, and the round of survey.

Table 1.6: Impact of Illness of Household Members on Income, Consumption, and Savings

Dependent Variable:	Per-capita Household Income	Per-capita Agricultural Profits	Per-capita Consumption Expenditure	Per-capita value of Livestock Owned	Per-capita value of Household Savings
	(1)	(2)	(3)	(4)	(5)
Father ill	-11,490	-1,187**	-3,075***	-187*	-972*
	(10245.2)	(591.3)	(1001.0)	(103.4)	(558.3)
Mother ill	-6,540.5	481.7	1,062.0	2.9	-332.1
	(7846.8)	(563.0)	(828.7)	(74.1)	(429.4)
Ill Child	113.9	495.3	1,002.8	113.7	-790*
	(1334.5)	(499.1)	(821.3)	(159.7)	(448.4)
Grand parents ill	119.5	1,801.5	3,435.9	337.5	1,200.1
	(3381.4)	(1683.2)	(2130.5)	(327.9)	-(2062.9)
Child aged 5 or below ill	22,357.2	-806.7	-1,196.2	36.9	261.5
	(23669.7)	(684.2)	(1094.2)	(104.9)	(718.2)
Adult siblings ill	1,081.2	201.3	7.6	4.6	6.2
	(2570.0)	(903.3)	(1453.0)	(128.1)	(553.7)
Prior assets owned	-1,620.3	-193.3	-493.7	-40.8	-844.1
	(1626.0)	(405.4)	(536.8)	(59.2)	(769.0)
Crop loss	-8,388.2	-838.7	-33.0	69.3	2,174.0
	(8628.4)	(579.1)	(989.5)	(124.2)	(2098.8)
Number of observations	1502	1502	1502	1502	1502

Note: Linear Model with individual (child) fixed effects. Standard errors are in parentheses and are computed after correcting for correlation and heteroskedasticity within household clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. All estimations control for illness of other household members, number of household members, month of interview, and the round of survey.

Table 1.7: Effect of Household Member's Illness on Hours Worked by Parents and Other Adults

	Mother's work		Father's work		Other adult's work	
Dependent variable:	Total hours	Market work	Total hours	Market work	Total hours	Market work
	(1)	(2)	(3)	(4)	(5)	(6)
Father ill	-0.027	-0.601			1.984	0.591
	(1.356)	(0.941)			(1.733)	(1.163)
Mother ill			0.248	-0.330	1.844	0.151
			(1.292)	(1.185)	(1.422)	(1.109)
Own illness	-6.577***	-3.299***	-5.919***	-5.657***	-3.248*	-2.197
	(1.184)	(0.833)	(1.281)	(1.168)	(1.811)	(1.451)
Grand parents ill	0.015	0.972	-2.628	0.021	3.727	1.819
	(3.228)	(2.403)	(3.978)	(3.969)	(2.908)	(2.492)
Child aged 5 or below ill	-0.122	0.090	-0.163	0.118	-0.104	-0.847
	(1.506)	(1.050)	(1.459)	(1.358)	(1.821)	(1.482)
Other Children aged 6-18 ill	1.053	-0.052	0.491	0.184	0.959	1.337
	(1.204)	(0.806)	(1.264)	(1.187)	(1.341)	(1.058)
Adult siblings ill	1.767	-0.360	2.147	1.489	-1.793	-1.218
	(1.676)	(1.239)	(1.813)	(1.718)	(1.661)	(1.300)
Number of observations	2,051	2,051	1,603	1,603	1,957	1,957

Note: Linear Model with individual (child) fixed effects. Standard errors are in parentheses and are computed after correcting for correlation and heteroskedasticity within household clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. All estimations control for illness of other household members, crop loss, per-capita assets owned, number of household members, orphanhood status, pregnancy status of mother and other women, month of interview, and the round of survey.

Table 1.8: Effect of Parental Illness on Child Labor and Attendance by Gender

Dependent variable:	Attendance	Hours worked
	(1)	(2)
Father ill x Girls	0.001	0.459
	(0.043)	(1.611)
Mother ill x Girls	-0.005	0.463
	(0.031)	(1.442)
Father ill	-0.052*	-0.646
	(0.027)	(1.159)
Mother ill	0.020	1.737*
	(0.022)	(1.001)
Ill Child	-0.042*	-1.626**
	(0.021)	(0.697)
Adult Death	-0.134***	0.358
	(0.046)	(1.794)
Number of observations	2,465	2,465

Note: Linear Model with individual (child) fixed effects. Standard errors are in parentheses and are computed after correcting for correlation and heteroskedasticity within district clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. All estimations control for illness of grandparents, adult siblings, child siblings, and other household members, crop loss, per-capita assets owned, number of household members, orphanhood status, pregnancy status of mother and other women, month of interview, and the round of survey.

Table 1.9: Differential Effects of Parental Illness on Child Labor and Attendance by Different Age Group

Dependent variable:	Attendance	Hours worked
	(1)	(2)
Father ill x Age 10-11	-0.001	2.689
	(0.063)	(2.379)
x Age 12-13	0.002	2.018
	(0.068)	(2.089)
x Age 14-15	-0.015	5.839***
	(0.077)	(2.254)
Mother ill x Age 10-11	-0.030	-0.495
	(0.056)	(2.165)
x Age 12-13	-0.006	-0.442
	(0.055)	(1.909)
x Age 14-15	-0.051	-2.029
	(0.060)	(2.053)
Father ill	-0.042	-3.409*
	(0.062)	(1.865)
Mother ill	0.040	2.752
	(0.051)	(1.766)
Number of observations	2,465	2,465

Note: Linear Model with individual (child) fixed effects. Standard errors are in parentheses and are computed after correcting for correlation and heteroskedasticity within district clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. All estimations control for illness of grandparents, adult siblings, child siblings, and other household members, crop loss, age-group dummy, per-capita assets owned, number of household members, orphanhood status, pregnancy status of mother and other women, month of interview, and the round of survey.

Table 1.10: Effect of Parental Illness on Years of Further Education and Likelihood of Finishing Primary School

Dependent variable:	Years of Education	Likelihood of Finishing Primary School	Years of Education	Likelihood of Finishing Primary School
Specification	OLS	OLS	HH-FE	HH-FE
Father's illness	-0.311**	-0.041	-1.506***	-0.198**
	(0.151)	(0.027)	(0.558)	(0.100)
Mother's illness	-0.494***	-0.026	-0.789	-0.085
	(0.159)	(0.029)	(0.513)	(0.115)
Number of observations	843	843	843	843

Note: Linear Probability Model. Standard errors are in parentheses and are computed after correcting for correlation and heteroskedasticity within household clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. All estimations control for illness of grandparents, adult siblings, child siblings, and other household members, crop loss, per-capita assets owned, number of household members, orphanhood status, pregnancy status of mother and other women, month of interview, and the round of survey.

Table 1.11: Robustness Check Examining the Effect of Prior Assets and Crop Shocks on Parental Illness

Dependent variable:	Parental illness	Parental illness	Father's Illness	Mother's Illness
Assets before parental illness	0.003	0.002	0.013	-0.009
	(0.012)	(0.012)	(0.017)	(0.017)
Crop loss prior to parental illness		-0.018	-0.049	0.010
		(0.026)	(0.035)	(0.035)
Number of observations	3,540	3,520	1,596	1,924

Note: Linear Probability Model. Standard errors are in parentheses. Standard errors are computed after correcting for correlation and heteroskedasticity within household clusters. All estimations control for number of household members, month of interview, and the round of survey.

Chapter 2

Income Shocks, Contraceptive Use, and Timing of Fertility

1. Introduction

Analyzing how households cope with income shocks has been an active research area for many years. One area that has not received much attention is to what extent household decisions on fertility are affected by shocks. Furthermore, standard economic models of fertility focus mainly on the effect of household and individual characteristics on fertility outcomes. Although these models have been useful for understanding the broad outlines of fertility decisions they tend to ignore the dynamic aspect of fertility decisions. There is evidence that shocks affect short term fertility, but it is not clear whether changes in fertility are the result of intentional planning or an unintended consequence of the effect of income shocks on other outcomes (Lindstrom and Berhanu 1999; Pörtner 2008; Evans, Hu, and Zhao 2010).

Understanding the relation between shocks and fertility decisions is important for three reasons. First, children are expensive both in terms of direct and opportunity cost. A child birth diverts resources from other uses and investments because of the direct cost of maintaining the child and because less of the mother's time is available for productive work. This potentially hampers the household's recovery after a shock. Because many developing countries experience a large number of income shocks, understanding the factors that help or hinder households' recovery after a shock is important. Second, children born immediately after a shock fare worse than other children. In the short and medium term they have worse health as measured by height-for-age (Pörtner 2010). Long term effects include worse self-reported health, lower schooling, and less wealth (Maccini and Yang 2009). Finally, it will improve our understanding of how households regulate their fertility. Couples may try to control fertility through increased use of traditional contraceptive methods if modern contraceptives are not available. Traditional contraceptive methods are less effective than modern contraceptives, and if parents show intent to control fertility this has policy implication for the availability and targeting of family planning services.

This paper examines the direct effect of income shocks on family planning. It shows that an exogenous income shock, measured here by accidental crop loss, leads to a greater use of contraception. Income shock significantly increases the likelihood of using contraceptives. We also find that the likelihood of pregnancies and child births decreases in households facing income shocks and this reduction is the result of contraception use rather than a biological response or separation of spouses.

The paper makes three contributions to the literature. It contributes to the consumption smoothing literature as households affected by income shock use family planning as a mechanism to smooth their consumption. In the short run bearing a child means removing scarce resources away from other useful purposes to the birth and maintenance of the child. Farmers can therefore smoothen their consumption by delaying child birth during times of income shock.

Secondly, this paper also contributes to the family planning and fertility literature. This is the first paper to show that households respond to income shocks through family planning, which, in turn, affects fertility. Earlier studies have shown that fertility rate decreases in response to major economic shocks (Pörtner 2008; Lindstrom and Berhanu 1999; Evans, Hu, and Zhao 2010). Our study provides evidence that the reduced fertility occurs through a planned decision process rather than as an unplanned consequence.

Thirdly, the paper contributes to the buffer stock literature (Deaton 1992) by examining the role of asset holdings as a coping mechanism to shocks. We find that households with greater assets are able to offset the shock, with no increase in their contraception use in response to shocks. Hence, greater assets act as a buffer for households and does not necessitate change in family planning for those households.

2. Prior Literature

Most of the prior literature on the impact of economic and other shocks on fertility have used historic data on what are now developed countries. Data from Rouen, France, over the period 1681-1787, show that increases in wheat price led to a dramatic fertility decline for the urban poor, while fertility of urban wealthy was unaffected in response to those shocks (Galloway 1987).

Similarly, English data from 1542 to 1800 show that mortality shocks led to short term fertility declines, with the largest decline typically the year following the shock (Bailey and Chambers 1998). This data also indicated that an increase in real wage leads to an increase in short term fertility. Eckstein, Mira and Wolpin (1999) found that increases in wage rate and decline in child mortality explains a significant part of the long term fertility decline in Sweden during the period 1736 to 1946. In another study on Sweden, Schultz (1985) uses aggregate county level data to show that an increase in the value of women’s time relative to men’s time led to a decrease in fertility in Sweden during the period 1860-1910. He finds that an increase in prices of butter increased women’s relative wage compared to men, thus leading to a decline in fertility. Eckstein, Schultz and Wolpin (1985) also uses Swedish data to find that a positive crop shock, positive weather shock and positive wage shock increases fertility through higher population growth for the following five to ten years period. However, the increase in birth rate is found to be only a change in the timing of birth and has no cumulative effect on long term fertility rate. They also find that an increase infant death rate is followed by a short term increase in birth rate. They also find that an increase in non-infant death rate first reduces fertility (child bearing population in marriage are reduced), but is followed by a rise in fertility with the peak occurring in about five years. In a developing country setting, [more recent evidence - need German/Russian studies here] Lindstrom and Berhanu (1999) also provides evidence that famine and domestic/regional military attacks in Ethiopia leads to a short-term decrease in the likelihood of conception.

Although there are many studies that show the impact on contraception use, such as, contraception use increases in response to schooling (Ainsworth et al., 1996; Chen and Guilkey, 2003; Feyisetan and Ainsworth, 1996), focused information campaigns (Chen and Guilkey, 2003), participation in savings or credit group (Steele et al., 2001), etc., there has only been one study (Hernandez-Correa, 2010) that attempts to show the impact of shocks on contraception use. He uses a cross-sectional data to find that households suffering from adverse events are more likely to use contraception compared to ones not suffering from that event.[1] However, the paper does not claim or provide evidence that the adverse events are exogenous or transitory in nature. The effect of the adverse event is not clearly identified and there is potential endogeneity bias as the paper only compares these two groups without any household or individual level

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[1] Adverse events include economic and environmental aspect, such as: rise in input cost, rise in cost of goods, difficulty finding buyers, difficulty finding inputs, foods, late rains, early rains, droughts, pest problems, etc. Households may be able to anticipate many of these problems and therefore they can adjust their behavior accordingly which can lead to endogeneity. However, the author does not claim that these adverse events are actually exogenous or transitory in nature, so the author may possibly recognize this as an endogenous variable.

fixed effects, and therefore the difference in contraception use can result from some other endogenous characteristics present within the group. The cross-sectional data, rather than a panel also limits his study as they cannot find the before and after effects of shocks on contraception use.

3. Methodological Framework

The basic question in this paper is: do income shocks affect timing of fertility? There are at least three reasons why a household may want to delay fertility in the event of a shock. First, children are costly in the short run. Having more children may eventually contribute to the household's production in the long run and help it overcome shocks (Pörtner 2008), but the short term impact on availability of resources for other household members is almost certainly negative. Secondly, at least some of the mother's time will be diverted from other activities towards care of the new child. If households respond to a shock by increasing hours worked as suggested by Kochar (1999), then diverting time away from work will be even more costly. It is, however, also possible that the shock will temporarily lower the cost of time for women, which would make it more attractive to have a birth now. Finally, the household may realize that children born following a shock have worse health outcomes and are more likely to malnourished and therefore decide to postpone having the next child.

Observing a decline in fertility following a shock is, however, not direct evidence of a conscience decision to limit fertility. One possible response to a shock is to have one or more households members migrate in search of better economic opportunities. If either the husband or wife are gone for extended periods of time this will have a negative effect on the probability of conception.

Furthermore, reduction in the likelihood of intercourse may result from psychological depression caused by the shock. We would also observe a decline in fertility if people delay marriage or if there is an increase in the dissolution of marriage. Finally, severe income shock can lead to health problems and starvation for household members. This could increase the incidence of secondary sterility through a reduction in age of menopause or famine induced amenorrhea. Shocks could also lead to malnutrition of mothers, which may lead to more stillborn births and fewer infants surviving after birth.

To focus on the effect of income shocks this model abstracts from other types of uncertainty such as child mortality.[2]

4. Data and Estimation Strategy

The data comes from the Kagera Health and Development Survey (KHDS) conducted by the World Bank and the University of Dar es Salaam in the Kagera region of Tanzania. The survey was conducted in four rounds from 1991 through 1994 and surveyed over 800 households, drawn from 51 communities (49 villages) in the six districts of Kagera. The Kagera region is on the western shore of Lake Victoria and borders Uganda, Rwanda and Burundi. The population (1.3 million in 1988, about 2 million in 2004) is overwhelmingly rural and primarily engaged in producing bananas and coffee in the north and rain-fed annual crops (maize,

[2] See Sah (1991) and Pörtner (2001) for examples of fertility models that incorporate child mortality.

sorghum, cotton) in the south (Beegle et al. 2006). Tree-crops and cassava, a commonly grown crop, have fairly continuous cultivation over the year.

The average interval between each of the survey rounds was between six and seven months. The sample selection was based on a variable probability sampling procedure (a two-stage, randomized stratified procedure) based on expected mortality.

In the first stage, based on the 1988 Tanzanian census, the census clusters were randomly selected after stratifying them based on mortality rates and agro-climatic zones. Households were then stratified into "high-risk" and "low-risk" groups in the second stage, based on illness and death of households in the 12 months before the enumeration process. Finally, households were randomly sampled from the groups.[3]

The data contain detailed information on individual and household level demographic and socioeconomic characteristics, which makes it suitable for this study. The survey asked detailed questions about fertility and birth control of all married women, regardless of age, and unmarried women 14 years and older. Our main sample consists of all married or partnered women 18-45 years of age who are observed in all four survey rounds.[4]

Specific questions include total number of prior births; whether the respondent is currently pregnant; whether she has given birth since the last survey round; whether she is currently using contraception, and if so the type. Contraception is split into traditional or modern. Traditional contraceptives include abstinence and rhythm method, while modern contraceptives

[3] For further details on the sample selection, please see World Bank (2004).

[4] This sample is expanded when examining whether dissolution of households are important. The age restriction means that if a woman is 17 in the initial survey she will not be included even if we observe her in all four survey rounds

include condom, diaphragm, pill, IUD, injection, female and male sterilization. If a woman is currently pregnant we code her as not using contraceptive. As female and male sterilizations are typically permanent procedures, once an individual is sterilized we remove them from our sample because their fertility decision is longer a choice variable. There are a small subset of women who report using both modern and traditional methods of contraception. These women are included in both categories.

To capture wealth status of the household we use total reported assets of the household. This include self-reported values of land, livestock, business assets, durable goods, and savings. Assets are measured per capita in 10,000 Tanzanian Shilling (TZS).

The survey also asked about any accidental crop loss experienced since the last survey. The survey specifically asks whether the households lost any crop due to insects, rodents, re, rotting, or other calamities. We use a dummy for accidental crop loss greater than 200 TZS as our main measure of income shock. The results presented hold equally well if we use a linear specification of crop loss instead of a dummy variable.

As with most data collected in developing countries there are a number of issues related to the quality of the data. Two problems are especially important here, misreporting of age and the other is misreporting of education level. For age some women report the same age over all survey rounds despite the first and last survey round being up to 21 months apart while other's reported age goes up by 1 year between each survey round despite the surveys only being 6 to 7 months apart. Furthermore, there is substantial heaping of reported ages around numbers ending in 0 and 5 in the first wave. This pattern is still evident when using all waves although slightly less so, but this may simply be because women remember their previous response and add 6 to 7 months with each survey. Because the time span of the surveys is too short to confidently identify effects of age using the change in age between surveys we instead create a variable that captures the age of the woman at the first survey round she is capture in. If her reported age vary more than possible given the number of survey rounds she is interviewed in we instead use her median reported age rounded down. Of 435 women observed in at least two consecutive survey rounds 82, or approximately 19 percent, reported ages inconsistent with the timing and length of time between surveys. To take account of heaping we create 5-year age groups centered around the ages ending in 0 and 5.

The second problem is misreporting of education levels. Given the age of the women in the sample, they should report the same level of education across all survey rounds but 105 out of 435 do not. We address this issue two way. First, for women with different reported education levels we assign the modal education level if possible. If there is no modal observation, we instead use the median years of education. Second, we divide education levels into three groups, no education, some primary (1-6 years of education), and graduated primary school or above (7 or more years of education). Even with this more encompassing definition of education there are 73 women who report different enough levels of education to create uncertainty as to which category they belong in.

Table 2.1: Wave 1 Descriptive Statistics for Women

	Mean	St Dev
Age 18-22	0.23	0.42
Age 23-27	0.17	0.38
Age 28-32	0.23	0.42
Age 33-37	0.21	0.41
Age 38-45	0.16	0.37
No education	0.29	0.45
1 - 6 years of education	0.26	0.44
7 plus years of education	0.45	0.50
Assets per capita in wave 1 (10,000 TZS)[a]	7.67	12.75
Number of women	247	

[a] Assets capture self-reported values of land, livestock, business assets, durable goods, and savings.

Table 2.1 show descriptive statistics for the women in the sample capture at wave 1. Women are equally distributed between the 5 age groups. Only married/partnered women are in the sample which explains the relatively equal distribution despite population growth in the area. A notable characteristics is the very high level of reported education for a poor rural area. Only about 30 percent of the women report no education, about 25 percent some primary, and 45 percent primary or above. This is most likely the result of the 1974 Universal Primary Education Movement which resulted in large increases in the accessibility to primary education and enrollment rates, although there are reports that the quality was very low. In addition, the crisis

Tanzania experienced in the 80s further lowered the quality and enrollments declined again.[5] Hence, it is unclear to what extent the reported education levels reflect women's actual human capital. Finally, the average level of assets in wave 1 was just shy of TZS 80,000.[6] There is, however, wide dispersion in asset levels with the minimum reported wave 1 asset level around TZS 510 and the maximum almost TZS 19,000,000. The 25 percentile asset level is around

Table 2.2: Descriptive statistics for Crop loss and Outcomes

	Wave				Total
	1	2	3	4	
Dummy crop loss (1-7 months) ¸ TZS 200	0.71	0.26	0.02	0.03	0.25
	(0.45)	(0.44)	(0.13)	(0.18)	(0.44)
Contraceptive use	0.15	0.09	0.09	0.10	0.11
	(0.36)	(0.29)	(0.29)	(0.30)	(0.31)
Contraceptive use – Traditional[a]	0.11	0.06	0.07	0.04	0.07
	(0.32)	(0.24)	(0.25)	(0.21)	(0.26)
Contraceptive use – Modern[b]	0.04	0.02	0.02	0.05	0.03
	(0.20)	(0.14)	(0.14)	(0.22)	(0.18)
Currently pregnant	0.17	0.23	0.15	0.14	0.17
	(0.37)	(0.42)	(0.36)	(0.35)	(0.38)
Gave birth since last survey	0.19	0.16	0.22	0.12	0.17
	(0.40)	(0.37)	(0.41)	(0.32)	(0.38)

[a] Traditional contraceptives include abstinence and rhythm method.

[b] Modern contraceptives include condom, diaphragm, pill, IUD, injection, female and male sterilization.

[5] See Galabawa (2001) and Wedgwood (2005) for detailed discussion of the development of education in Tanzania over time.

[6] In 1991 the official exchange rate was TZS 200 to the dollar, while the parallel market it was TZS 440 to the dollar

TZS 19,000, median is approximately TZS 35,000, and 75 percentile is just slightly higher than the mean at TZS 86,000. In other words, the area is characterized by very low assets level for the majority with a few relatively wealthy households.

Table 2.2 shows the main explanatory variable of interest and the 5 outcomes that we examine. The main explanatory variable is a dummy for whether the household experienced an accidental loss of crops greater than TZS 200 in the period up to the date of the survey. That period is approximately 6 to 7 months for the last three surveys but covers the previous 12 months for the first survey. There are substantial variation in the number of households that experience a crop loss between the 4 surveys. In the 12 months prior to the first survey just over 70 percent of households lost crops, while just over 25 percent lost crops between the 1st and 2nd survey. That falls even further for the 3rd and 4th surveys, with less than 5 percent reporting crop loss of more than TZS 200 for both.

The outcomes variables are all measured the same way in all 4 surveys and are all dummy variables. The extent to which a woman is aiming to avoid getting pregnant is captured by whether she is currently using contraceptives at the time of the survey, which is further divided into whether she is currently using traditional contraceptives or modern contraceptives as described above. Contraceptives use is very low; at the time of the first survey 15 percent of women report using any type of contraceptive, split between 11 percent that use traditional contraceptives and 4 percent that use modern contraceptives. In subsequent surveys the contraceptive use rate hovers around 10 percent with between 4 and 7 percent using traditional contraceptives and 2 to 5 percent using modern contraceptives.

An important concern when estimating the effects of shocks on contraceptive use and fertility is that there may be unobserved factors that affect both likelihood of shocks and outcomes. A household with lower (unobserved) ability may, for example, be more likely to both experience a shock and simultaneously be less likely to be able to afford or have knowledge about contraceptives. This would bias OLS estimates of shocks' effect on contraceptive use down-wards relatively to the true effect. To address the problem of unobserved heterogeneity and endogeneity we use an individual level fixed effects model. This allows us to control for all time-invariant mother characteristics when estimating the impact of crop loss on contraceptive use and fertility outcomes.

We begin by estimating the fixed effects version of the following equation:

$$\begin{aligned} Y_{i,t} &= \beta_1 Croploss_{i,t} + \beta_2 Croploss_{i,t} \times Asset_{i,1} \\ &+ \boldsymbol{survey}_{i,t}{}' \boldsymbol{\alpha} + \mu_i + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where $Y_{i,t}$ is contraception, pregnancy, or child birth, $\boldsymbol{survey}_{i,t}$ is a vector of survey wave dummies, and μ_i is time-invariant individual specific characteristics. We use dichotomous outcomes for contraception use, pregnancy and child birth in all the following estimations. In other words, the estimated equations are fixed effects linear probability models.

5. Results

Table 2.3 presents the effect of crop loss on contraceptive use using the basic fixed effects specification. Column 1 shows results for crop loss in the last 7 months without interactions, while column 2 shows results when crop loss in the last 7 months is interacted with assets in wave 1. In both cases the effect of a crop lost in the 7 months prior is to statistically significantly increase the probability that a woman uses contraceptives. Furthermore, the effects are substantial considering that average contraceptive use rates are between 10 and 15 percent. Experiencing a crop loss increases the probability of using any type of contraceptives by more than 7 percent-age points. There is some evidence that the effect of crop loss on contraceptive use is stronger among households with fewer assets, although the effect of the interaction between initial assets and crop loss in not statistically significant. With the interaction between crop loss and initial assets the effect of crop loss at the mean level of assets is essentially the same as before at 7 percentage points, while a woman in a household without assets would have an increased probability of using contraceptive of more than 9 percentage points.

Table 2.4 examines the effects of shocks on traditional and modern contraceptive use separately. Not surprisingly given the low level of modern contraceptives use most of the effect of shocks are concentrated in the use of traditional contraceptives. Both with and without

Table 2.3: The Effects of Crop Loss on Any Contraceptive Use

	Any contraception use	
Crop loss in last 7 months (200 TZS or above)	0.071**	0.094**
	(0.033)	(0.037)
Crop loss x initial assets (10,000 TZS)		-0.003
		(0.003)
Wave dummies	Yes	Yes
Woman fixed effects	Yes	Yes

Observations	985	985
Number of women	247	247

Note. Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Crop loss is a dummy for a per capita crop loss of 200 TZS or above. Assets are per capita and measured in 10,000 TZS.

interaction with initial assets there is a statistically significant effect of experiencing a crop loss on the current use of traditional contraceptives, with an estimated increase of between 5.4 and 6.6 percentage points. The effect for modern contraceptives is much smaller and not statistically significant.

Table 2.4: The Effects of Crop Loss on Traditional and Modern Contraceptive Use

	Contraceptive Type			
	Traditional		Modern	
Crop loss in last 7 months	0.054**	0.066**	0.003	0.021
	(0.025)	(0.032)	(0.020)	(0.016)
Crop loss x initial assets		-0.002		-0.002
		(0.003)		(0.002)
Wave dummies	Yes	Yes	Yes	Yes
Woman fixed effects	Yes	Yes	Yes	Yes
Observations	985	985	984	984
Number of women	247	247	247	247

Note. Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Crop loss is a dummy for a per capita crop loss of 200 TZS or above. Assets are per capita and measured in 10,000 TZS.

Table 2.5: The Effects of Crop Loss on Pregnancy and Births

	Currently Pregnant		Childbirth since last survey	
Crop loss in last 7 months	-0.097**	-0.100**		
	(0.043)	(0.045)		
Crop loss in last 7 months		0.000		
x initial assets (10,000 TZS)		(0.001)		
Crop loss - 7-14 months			-0.159***	-0.164***
			(0.050)	(0.053)
Crop loss - 7-14 months				0.001
x initial assets (10,000 TZS)				(0.002)
Wave dummies	Yes	Yes	Yes	Yes
Woman fixed effects	Yes	Yes	Yes	Yes
Observations	985	985	741	741
Number of women	247	247	247	247

Note. Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Crop loss is a dummy for a per capita crop loss of 200 TZS or above. Assets are per capita and measured in 10,000 TZS.

Do these changes in contraceptive behavior translate into changes in pregnancy and fertility outcome? Table 2.5 shows the effects of shocks on pregnancy and childbirth in the 7 months since last survey round. The effect on pregnancy is consistent with our previous results on contraceptives. A crop loss leads to a statistically significant decline in the likelihood of pregnancy of around 10 percentage points. There is no evidence of any differences in this effect by initial assets levels. For a child birth to have occurred in the last 7 months prior to the survey a woman would have conceived in the prior survey round. We therefore use whether the household experienced a shock in the period 7 to 14 months when estimating the effect on child birth. Columns 3 and 4 show that shocks 7 to 14 months prior to the survey has a negative and statistically significant effect on childbirth in the last 7 months of approximately 16 percentage points. There is again little evidence of differences in the response to shocks by initial asset levels.

5.1 Decomposing the Effect by Education and Age

In our basic specification, we interact crop loss with assets in the initial survey round to capture any effects of wealth on fertility decisions. This specification, however, leads to two possible problem. First, asset levels are based on reported data that can have measurement errors. There are significant variations in reported household asset levels between periods, and it is possible that part of these variations are a result of reporting errors. Second, there is no information available on assets before the beginning of the survey. We use assets levels reported by the household in survey round one, but clearly those can have been affected by any shocks that occurred beforehand and we include shocks that occurred in the period before the first survey in our analysis. Although there are little evidence that the estimated effects of crop loss differ between the specifications that include assets level and those that do not, it is important to further understand whether there are differences between households in their response to shocks. We therefore replace assets with women's education in our specification. We use education for two reasons. First, education is highly correlated with household wealth in developing countries making it an ideal replacement. Second, unlike household assets, women's education is unlikely to change over time, especially as we look at women aged 18 and above. The main issue with using education is with the rapid expansion and contraction of primary education in the period where most of the women in our sample were of school age it is unclear to what extent the reported education level reflects actual human capital improvements.

Table 2.6 shows the effect of crop loss on contraceptive use for women at different education levels. Only for women with 7 or more years of education is the effect of crop loss onuse of any contraceptives statistically significant with an estimated effect of close to 10 percentage points. Women with no education show an effect of around 8 percentage points while for women with 1 to 6 years of education the effect is only 2 percentage points, but neither of those are statistically significant. Furthermore, the responses to crop loss do not di er statistically significantly from each other. As before most of the effect is concentrated in the use of traditional contraceptives with none of the effects for modern contraceptives statistically significant.

We examine the effect of crop loss on pregnancy and childbirth for women at different education levels in Table 2.7. Consistent with the effects on contraceptive use, women with either none or 7 or more years of education are less likely to be pregnant after experiencing a shock in the prior 7 months, but only the effect for women with 7 or more years of education is statistically significant. There is a more consistent response for child birth with the effect for all three education groups substantial at between 11 and 19 percentage point reductions in the likelihood of a woman having given birth after being exposed to a crop loss in the period 7 to 14 months before. The effects for women with no education and women with 7 or more years of education are both statistically significant while the effect for women with some primary education is not.

Table 2.6: The Effects of Crop Loss on Contraceptives Use by Education Level

	Contraceptive Type		
	Any	Traditional	Modern
Crop loss x no education	0.081	0.042	0.032
	(0.051)	(0.041)	(0.029)
Crop loss x 1-6 years of education	0.020	0.037	-0.034
	(0.052)	(0.040)	(0.032)
Crop loss x 7 plus years of education	0.097**	0.072*	0.009
	(0.043)	(0.039)	(0.018)
Wave dummies	Yes	Yes	Yes
Woman fixed effects	Yes	Yes	Yes
Observations	985	985	984
Number of women	247	247	247

Note. Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Crop loss is a dummy for a per capita crop loss of 200 TZS or above. Assets are per capita and measured in 10,000 TZS.

As education is a proxy for assets, we would expect households with lesser education to use more contraceptive when facing a shock. Additionally, younger women should be more likely to postpone birth as they continue to have childbearing years remaining even following the shock. However, older women are unlikely to postpone birth following a shock as they do

Table 2.7: The Effects of Crop Loss on Pregnancy and Childbirth by Education Level

	Currently Pregnant	Childbirth since last survey
Crop loss x no education	-0.076	
	(0.061)	
Crop loss x 1-6 years of education	-0.009	
	(0.063)	
Crop loss x 7 plus years of education	-0.170***	
	(0.050)	
Crop loss (7-14 months) x no education		-0.165**
		(0.064)
Crop loss (7-14 months) x 1-6 years of education		-0.115
		(0.072)
Crop loss (7-14 months) x 7 plus years of education		-0.185***
		(0.062)
Observations	985	741
Number of women	247	247

Note. Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Crop loss is a dummy for a per capita crop loss of 200 TZS or above. Assets are per capita and measured in 10,000 TZS.

not have many childbearing years left. Column 1 shows that women with none or some primary education are more likely to use contraceptives for the age groups 17-34 compared to women who finish primary school. However, this relationship is reversed for the age group 35-39. It is possibly because this age group is near the end of their childbearing age and hence they cannot afford to postpone their births any longer. Similarly, columns 2 and 3 show the effect on traditional and modern contraceptive use, and we find a similarly strong and positive effect on contraceptive use for the younger and less educated women.

6. Robustness Checks

Shocks may cause households to delay pregnancy not only through increased contraceptive use, but also through its effect on other factors such as, starvation or illness of mothers, migration of partners, or dissolution of marriage. In order to better understand whether the pregnancy and child birth responses we find above are, indeed, the result of conscience decisions and use of contraceptives we examine if shocks affects these other factors.

As Table 2.8 shows there are not statistically significant effect of crop loss on neither BMI or self-reported illness, although for both outcome the effect has the expected sign. Women who have experiences a crop loss in the last 7 months have slightly lower BMI and are slightly more likely to report having been ill.

Table 2.8: The Effects of Crop Loss on Women's Health

	Respondent BMI	
Crop loss in last 7 months	-0.015	-0.011
	(0.016)	(0.016)
Pregnant	0.083***	0.083***
	(0.013)	(0.013)
Crop loss x initial assets (10,000 TZS)		-0.000
		(0.001)
Wave dummies	Yes	Yes
Observations	985	741
Number of women	247	247
	Illness	
Crop loss in last 7 months	0.023	0.025
	(0.047)	(0.051)
Crop loss £ initial assets (10,000 TZS)		-0.000
		(0.002)
Wave dummies	Yes	Yes
Observations	985	741
Number of women	247	247

Note. Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All values of crop lost and assets are per capita and measure in 1,000 TZS. Variables not shown: Age of mother and number of births.

Similarly, Table 2.9 shows that shocks do not lead to a significant increase in migration (column 1) or a significant increase in dissolution of marriages (column 2). As for the health the coefficients on migration and dissolution have the expected sign but neither are statistically significant and in all cases are the effects too small to explain the reductions in pregnancies and births.

Table 2.9: The Effects of Crop Loss on Absence of Partner and Marriage Dissolution

	Absence/migration of partner	Dissolution of of marriage
Crop loss - last 7 months	0.002	0.005
	(0.004)	(0.011)
Crop loss - last 7 months x lagged assets	-0.000	-0.000
	(0.000)	(0.000)
Crop loss - 7-14 months	-0.000	0.002
	(0.001)	(0.002)
Crop loss - 7-14 months £ lagged assets	0.000	-0.000
	(0.000)	(0.000)
Wave dummies	Yes	Yes
Woman fixed effects	Yes	Yes
Observations	985	741
Number of women	247	247

Note. Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All values of crop lost and assets are per capita and measure in 1,000 TZS. Variables not shown: Age of mother and number of births.

In Table 2.10, we examine to what extent shocks cause a delay in pregnancy through the increased use of contraceptive by type of contraceptive. Despite the use of contraceptives obviously being endogenous, this provides evidence that shocks does, indeed, delay pregnancy through increased use of contraceptives. The interaction effect of crop loss 7-14 months ago and traditional contraceptive used following those crop loss has a negative and significant effect on pregnancy. The same is the case for modern contraceptive, which also has a negative and significant effect on the likelihood of currently being pregnant when interacted with crop loss. Interestingly, there is no independent effect of using either traditional or modern contraceptives on the likelihood of being pregnant. Only women with a strong enough incentive because of shocks are successful in preventing a pregnancy through the use of contraceptives. Furthermore, there is essentially no difference in the effectiveness of the two types of contraceptives.

Table 2.10: Contraceptive Use and Pregnancy

	Currently Pregnant	
	Traditional	Modern
Contraceptives (7 months)	0.043	0.029
	(0.052)	(0.061)
Crop loss - 7-14 months	-0.099***	-0.092***
x Contraceptives (7 months)	(0.019)	(0.019)
Crop loss - 7-14 months	-0.018	-0.021
	(0.013)	(0.014)
Number of women	247	247

Note. Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All values of crop lost and assets are per capita and measure in 1,000 TZS. Variables not shown: Age of mother and number of births.

7. Conclusion

This paper examines the relationship between household income shocks and fertility decisions. To account for unobservable household characteristics that potentially affect both shocks and fertility decisions we employ a fixed effects model. We show that households consciously plan the decision of delaying child births through adjustment in household's contraceptive use when coping with income shocks. Our estimates demonstrate that contraceptive use, especially use traditional methods like abstinence and rhythm, significantly increases in response to crop and that both the likelihood of pregnancy and birth decrease.

Although the reduction in pregnancies and births could be driven by other factor we also show that crop loss shocks do not worse women's health enough to drive the reduction in pregnancies and child births. Furthermore, there is no evidence that the reduction is due to physical separation of spouses or partner with no significant change in the likelihood of migration or dissolution of partnership in response to crop loss.

The data unfortunately do allow us to establish whether the postponed births has any impact on long-term fertility outcomes. Results from Pörtner (2008) indicate that only shocks that occur toward the end of a woman's reproductive life is likely to have an impact on final fertility. Hence, there is little reason to believe that the changes in response to crop loss lead to overall changes in fertility. This does not mean that the ability to postpone birth is unimportant. Children born after a shock is likely to fare worse than child born during better times. The mother is also likely to fare better if she does not give birth immediately following an economic shock that may impact her ability to recover and care for the new child. Hence, our results imply that providing better access to contraceptives during times of economic shocks could improve the ability of households to postpone births. This could, in turn, lead to better mother and child health outcomes.

Chapter 3

Do Pesticide Sellers Make Farmers Sick? Health, Information Sources and Adoption of Technology in Bangladesh

1. Introduction

Modern agriculture heavily depends on the use of pesticides and has successfully increased productivity, but also led to increasing concerns regarding the health of farmers (Zilberman et al., 1991, Antle and Pingali, 1994). Mishandling of pesticides continues to pose a serious health problem for farmers especially in developing countries. Annually, 26 million cases of pesticide poisoning result in 220,000 deaths worldwide (Richter, 2002). In the U.S. alone, Pimentel (2005) estimates that the public health cost of pesticide use amounts to $1.1 billion per year. Furthermore, prolonged pesticide exposure can reduce labor productivity and cause serious long-term eye, dermal, cardiopulmonary, neurological, and gastrointestinal problems (Pingali et al., 1994). While pesticides play a major role in enhancing agricultural productivity, these statistics necessitate a better understanding of the determinants of pesticide exposure.[1]

Prior studies (Antle and Pingali, 1994; Crissman et al., 1994; Palis et. al., 2006) find that the main cause of pesticide poisoning is the ignorance about its dangers. In principle, this problem of pesticide exposure can be managed using two approaches, supply side and demand side regulations. On the demand side, subsidized field educational programs try to raise awareness among farmers to increase their use of health technologies during pesticide applications. On the supply side, profit-maximizing pesticide sellers can provide proper instructions and sell health protection products (i.e. masks, gloves). This study contributes to the

[1] Here we use the term *pesticide exposure* as synonym for obtaining a negative health outcome due to pesticide applications.

debate of relative effectiveness of demand versus supply side interventions that influence farmers to adopt health technology.

In practice, demand side interventions have been dominating in development projects. There have been major efforts to raise awareness of the proper handling of pesticides and to encourage the use of Integrated Pest Management (IPM) techniques by local governments partnering with international donor organizations and NGOs (Berg and Jiggins, 2007; Dasgupta et al., 2007b; Rejesus et al., 2009). The government of Bangladesh initiated several projects over the last two decades (worth over $200 million) to train extension workers and farmers on IPM with assistance from donor organizations (Department of Environment, 2007; Ministry of Foreign Affairs, 2012). Despite these efforts, cases of pesticide exposure are on the rise in developing countries (Gunnell and Eddleston, 2003); in our dataset from Bangladesh, one in every two farmers suffers from pesticide exposure.

In Bangladesh, there are three major *information sources* that disseminate pest prevention knowledge: pesticide sellers, government field extension workers and social learning amongst peer farmers. In this paper, we describe the role of each information source and test the relative effectiveness, using unique data on farmers' subjective risk assessment, adoption of precautionary behavior and health outcomes.

First, it has been repeatedly hypothesized that pesticide sellers in developing countries may misguide farmers by convincing them to purchase excessive quantities of often more toxic pesticides that lead to severe health outcomes. This view is particularly prevalent within state agencies and institutions of the United Nations such as the UK Department of International Development (DFID), the World Health Organization (WHO) and the Food and Agriculture

Organization (FAO) (Hainsworth and Eden-Green, 2000; Vapnek et al., 2007; Aitio, et al., 2006). This is in contrast, however, to the idea that pesticide sellers—who also sell seeds and fertilizers—aim to maintain a long run relationships with clients and not to mislead for short-term profits.

Despite numerous studies on health outcomes and regulation of pesticide use, there is only one study that we are aware of, Soares and Porto (2009), which *empirically* investigates the relationship between *information sources* and farmers' health. Consistent with the hypothesis that vendors could misguide farmers, Soares and Porto find that advice from pesticide sellers significantly increased farmers' illness. This controversial role of pesticide sellers warrants further investigation. In this paper, we study the impact of sellers in the context of Bangladesh.

Second, farmers receive information from agricultural field extension workers. The Bangladesh Ministry of Agriculture trains extension workers to disseminate information on handling pesticides, educate farmers on the need to wear protective equipment (such as masks, glasses, boots) while spraying and to promote IPM techniques (Rahman 2003; Ricker-Gilbert et al., 2008; Department of Environment, 2007). The government considers these programs to be a success (Rahman, 2003).[2] In this paper, we study whether the information of these governmental programs actually arrives at the farm level.

Third, farmers discuss pest management strategies with neighboring peers. A growing literature (Foster and Rosenzweig 1995; Munshi 2004; Conley and Udry 2010) demonstrates that farmers learn about new technologies (i.e. new varieties of seeds and fertilizers), from the experience of their peers. Studies on the adoption of *health* technologies have been few and show

[2] Although there has been no study in a developing country, Lichtenberg and Zimmerman (1999) find that US farmers who believe extension services are important have a greater concern for pesticide exposure.

non-uniform results on whether peers increase adoption: On the one hand, Dupas (2012) find that individuals increase adoption of antimalarial bednets because of the influence of peers. In contrast, Kremer and Miguel (2007) find that the negative side-effects to deworming lead households to discourage their social contacts from participating in similar deworming programs in Kenya. Similarly, farmers in Bangladesh also report discomfort of wearing full body protective equipment in hot and humid climate as a reason for not using any protection. In this study we add to this literature and present the first paper to examine if social learning from peers influences the adoption of health technology in agriculture.

We make several contributions to the literature. This paper brings into attention the role played by the three key information sources, peers, pesticide sellers and agricultural extension workers in influencing farmers. This paper presents the first empirical study that examines these primary sources of information to *both*, adoption of health technology and actual health outcomes of farmers. Using the likely most detailed currently available household survey on the information flow of pesticide usage, we find that farmers who report to obtain advice from the supply side—pesticide sellers—increasingly adopt precautionary tools (i.e. masks) and are less likely to become ill. These same farmers also show a heightened concern regarding the long term cancer risk of pesticide exposure. Second, on the demand side, we do not find evidence that the training by the governmental field extension has any measurable influence on illness or precautionary behavior on the *average* farmer. However, a subset of 'educated' farmers are is positively affected by 'training'. Third, in terms of social learning we make an interesting observation: we find that the 'average' peer has a negligible effect on farmer's behavior. However, the learning effect is strong when information is provided by educated 'trained' peers.

While the fraction of 'trained' peers is very small in these communities, trained peers serve as important social multipliers into the farmers' network.

Lastly, this study has important policy implications. First, we demonstrate the significance of the network of pesticide sellers as an information source to farmers. This suggests that sellers could be more actively used as a valuable policy instrument to disseminate information and protective equipment. Second, we suggest that the government of Bangladesh and international donors reevaluate the current policy program of extension services, as their information does not seem to effectively arrive at typical farm level. Finally, we find that the very small fraction of educated trained farmers has a particularly positive effect on peers suggesting that more targeted training programs to social multipliers can be valuable to enhance the information flow.

Our study is based on cross-sectional household data, which theoretically hinders us from drawing inferences on causality if unobserved confounders are present. We overcome these empirical challenges by performing the following tasks: First, we believe to have employed the most comprehensive survey data currently available which allows us to carefully explore heterogeneity over a range of robustness checks. Second, we do not observe endogenous sorting into the first contact with pesticide sellers as almost all farmers (98%) purchase pesticides themselves from the local seller. However, whether a farmer reports to have obtained information from a particular information source can still be endogenous. Third, we condition our estimates on a wide set of the arguably most important characteristics[3] that should be correlated with sorting. Our point estimates remain robust to the inclusion or exclusion of this set

[3] Number of household members, per-capita income, farm size, farm equipment value, household head's body mass index, smoking behavior, educational characteristics and various versions of fixed effects.

of characteristics. If omitted variable bias were a problem, one would expect that endogenous factors are correlated with some of these observables. In sum, we argue that unobserved heterogeneity is not a first order problem in the interpretation of our cross-sectional analysis.

This paper is organized as follows. Section 2 describes the information flow in Bangladesh. In Section 3 we present the survey data and the estimation strategy; summary statistics are presented in Section 4. Section 5 discusses our estimation results and we conclude with policy recommendations in Section 6.

2. Information Flows in Bangladesh

How does information about proper handling of pesticides reach farmers? Manufacturers and wholesale importers of pesticides are required to label pesticide containers with detailed information on the recommended dosage, precautionary measures needed while handling and spraying the pesticide, as well as the symptoms of pesticide poisoning (Pesticide Rules, 1985). Labels are typically written in the native language Bengali. To empirically check whether these regulations are followed, the first author of this article first-hand observed and interviewed a selection of large scale pesticide wholesale stores as well as pesticide sellers in rural areas and confirmed that—among the sampled villages—pesticide containers provide the required information.[4,5]

[4] Photographs taken by the first author displaying pesticide stores and pesticide containers are available upon request. Staff at the International Rice Research Institute (IRRI) and Bangladesh Rural Advancement Committee (BRAC) confirmed with us in interviews that pesticides sold in Bangladesh, even in remote rural communities, typically contain the required detailed labels.

[5] Note that this practice is in stark contrast to the situation in some other developing countries. For example, Wolff (1999) and Wolff and Recke (2000) report that pesticides in Ghana are typically refilled at stores into much smaller

Case studies of Bangladesh indicate that farmers seek advice from pesticide sellers on the selection and usage of pesticides (Robinson, et al., 2007; Department of Environment, 2007).[6] In addition to pesticides, farmers also purchase seeds and fertilizers from these sellers, which indicate that many farmers are in frequent contact with these sellers (Robinson et al., 2007). In sum, these studies suggest that sellers may have incentives to maintain long-run relationships with farmers (and do not intentionally misguide them for short-term gains, as has been hypothesized by Hainsworth and Eden-Green (2000), Vapnek et al. (2007) or Aitio, et al. (2006)). Due to this conflict of interest, though, previous IPM training strategies and awareness programs typically excluded the network of pesticide sellers as a primary stakeholder to disseminate information.

To assist farmers with agriculture and pesticide related issues, the government employs agricultural field extension workers (AFEW). Their role is to advise farmers directly on productivity-enhancing techniques, to adopt IPM, and to discourage pesticide use (Ricker-Gilbert et al. 2008; Department of Environment 2007). AFEWs conduct regular farm visits and organize local training programs. However, as each AFEW is responsible for 1000-1200 farmers, it has been criticized that AFEWs may not be able to reach all farmers effectively in their area (Haque 2012).[7]

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containers, such as Coca Cola bottles, and hence the information on content and appropriate handling is lost throughout the supply chain.

[6] A survey by Dasgupta et al. (2005) in seven districts of Bangladesh finds that 72% of sellers have basic training in handling pesticides.

[7] While the literature on AFEWs is sparse, Robinson, Das and Chancellor (2007) and Haque (2012) find that farmers criticize that AFEWs do not perform in their area, or are unavailable at the time when farmers need help. According to qualitative studies by (2012) farmers complained that AFEWs are not adequately competent to provide technical advice. An IPM pilot project on farmers in central Bangladesh in 1999 achieved *"reductions of pesticide [use] of as much as 80% ...within one season following training in IPM in Bangladesh*" (Department of Environment, 2007) We are not aware of any more quantitative study that analyzes the effectiveness of the AFEW system in Bangladesh.

Clearly, information in Bangladesh also flows via face to face conversations with peer farmers. In particular, Robinson et al. (2007) and Ricker-Gilbert et al. (2008) note that as Bangladesh is very densely populated, farmers often discuss pest management techniques with neighboring farmers making social learning from peers an important source of information.

3. Data

This paper uses the 2003 Bangladesh Pesticide Use Survey (BPUS) conducted by the World Bank. The survey covers eleven agricultural districts, where pesticide intensive crops are produced, and farmers are randomly selected within these districts.[8] BPUS is unique in design as it focuses on identifying the sources that inform farmers regarding many aspects of pesticide handling. In particular, detailed questions are asked with respect to the following five topics: information sources, farmers' perceptions of risk, pesticide usage, precautionary behavior and health symptoms experienced after pesticide applications. To our knowledge, information with this level of detail regarding pesticide usage is not present in other surveys. All farmers apply pesticide themselves. Furthermore, 98 percent of the farmers report that they purchase the pesticides themselves from pesticide sellers. This is an important feature of the dataset because it shows that potential endogenous sorting into the contact with pesticide sellers is only a concern for the 2% of the farmers that do not purchase the pesticides themselves.

Figure 1 displays the pathway through which information sources affect health outcomes. The four main information sources that we identify from the survey are AFEWs, pesticide sellers, peer farmers and labels on pesticide containers. How knowledge about handling

[8] See Dasgupta et al. (2007a) for a detailed description of the survey.

pesticides is transformed into precautionary behavior, however, depends both on the information source as well as on the risk perception of the farmer. According to our survey, precautionary measures can be distinguished into: (i) using health products, i.e. wearing protective equipment while spraying and handling pesticides, (ii) reading labels and instructions on pesticide container, (iii) following instructions and prescribed dosages indicated on the labels, and (iv) not using bare hands when mixing pesticides. Finally, accessibility and affordability of protective equipment and farmer-specific application practices determine health outcomes.

The following sub-sections provide details regarding the data collected on information source, risk perception, precautionary behavior and health outcomes.

Information Source: The survey asks if information regarding pesticides was obtained from the following three key sources[9]:

(A) AFEWs

(B) pesticide sellers

(C) peer farmers[10].

These three sources, (A) to (C), can influence farmers through two channels: a direct channel and/or an advisory channel. A direct channel provides direct person-to-person information to farmers, while an advisory channel consist of trained personnel, possibly acting as an auxiliary source, from whom farmers can seek advice. For policy implications, it is important to identify if the influence on health or behavior is originating from the direct or advisory channel.

[9] Less than 0.5 percent of farmers report to have received information from NGOs. As this percentage is too small for further statistical analysis, we drop these observations from our estimations.

[10] In the survey, this category is labeled ‘other sources’. Because this category mainly consists of neighboring farmers, friends and family members, we refer to this category as ‘peer farmers’.

Direct Channel: Farmers are first asked about the direct channel: “What is the main information source of the following instructions that you may have received…”:

(1) …While spraying pesticides, you should wear precautionary equipment (gloves, hat, mask, full sleeve shirt, full length trousers, and shoes)...”

(2) …You should read labels on the package and follow instructions (if you cannot read, please get help from others who can read)…”

(3) …You should not mix pesticide with bare hands…”

Which sources of information are the most prevalent? Table 3.1 provides a break-down of the fraction of farmers obtaining the above three key instructions from each of the sources (A) to (C). 80.1% of the farmers report that they have been informed that wearing protective equipment is necessary while spraying pesticides (column 1). Among them, ‘peer farmers’ represents the biggest fraction (43.6%), followed by pesticide sellers (26.2%) and AFEWs (10.3%). The subsequent columns in the table represent similar breakdowns for each of the questions (2) to (3) by information source. While the table indicates that peer farmers and pesticide sellers are the most *common* information sources in Bangladesh, in Section 5 we estimate which information source is the effective. Additionally, farmers can be influenced by indirect sources. We analyze this through the *advisory channel*.

Advisory Channel: In terms of training, 97% of the sample did not obtain any formal training on the handling of pesticides.[11] However, the survey asks each farmer whether he or she knows of

[11] Training is typically provided by AFEWs in agricultural field education extension programs on pesticide usage.

any *other* person who can provide such training. We label these persons as 'trained peers' of type AFEWs, type pesticide seller, or type peer farmer. These 'trained peers' represent the advisory channel. We examine if these advisory sources influence farmers in a different way that otherwise will not be captured in our estimation. As shown in section (ii) of Table 3.1, only 24% of farmers have trained peers, and among them, the type AFEW (9.75%) is the most prevalent followed by trained pesticide sellers (7.25%) and trained village peers[12] (7.25%).

Precautionary Behavior: Does knowledge translate into changes in precautionary behavior? Following the knowledge questions (1) to (3) on information sources, the survey meticulously asks follow-up questions about farmers' actual application practices, namely:

(1#) Do you use Personal Protective Equipment (PPEs) during pesticide application?

(1a#) Mask; (1b#) Gloves; (1c#) Boots; (1d#) Hats; (1c#) Glasses;

(2#) Do you read labels on pesticide package?

(2a#) Do you follow instructions and the prescribed dose mentioned on the label?

(2b#) Do you read instruction on flyers that come with purchased pesticide describing safety issues or procedures?

(2c#) Do you seek assistance if you are unable to read the labels?

(3#) Do you use bare hands to mix pesticide?

Table 3.2 displays the percentage of farmers that actually respond to the information received (1) to (3) with precautionary actions (1#) to (3#). We essentially find that most farmers

[12] Whether the trained village peers obtained the original training from AFEWs, pesticide seller or both is unfortunately not tracked in the data.

do not follow through with actual precautionary action. Although 81% of the farmers are aware that wearing protection is required, only 14% actually use PPEs. Similarly, although 91% of farmers are informed that reading labels is important, only 58% of these informed farmers actually read labels, 46% follow the instructions on labels, and 28% follow the prescribed dose. We see a similar pattern for all other precautionary behaviors. This lack of implementation could arise because farmers may not find certain sources of information credible. In our below regression analysis we aim to identify those sources that actually have an influence on farmers' precautionary behavior and ultimately health outcomes.

A second set of follow up questions—for those that do not wear PPEs—asks for the barriers why PPEs are not adopted. Responses are displayed in Table 3.3. The majority of the sampled farmers deemed protections as unnecessary for four of the five PPEs: mask (54%), gloves (52%), hats (56%), and glasses (55%). Lack of availability[13] and discomfort of wearing the PPEs in the hot tropical climate are the second and third most cited reasons why PPEs are not adopted. These results are disconcerting as 94% of the sample uses 'highly toxic' pesticides.

Risk Perception: To quantify the level of subjective 'perceived risk' the survey asks about the 'perceived long-term effects' of pesticide use: "Do you think that pesticide use and/or exposure, overall, has any negative long-term impacts on health, such as cancer?" The answers are on the scale of five categories: 'no effect'(1), 'small effect' (2), 'medium effect' (3), 'large effect' (4), and 'fatal effect' (5). Figure 2 shows that 43% reported that it has no or small effect, while only 1% reported it has fatal effect. Since the survey also details the pesticides used during the past 12

[13] How does the availability of PPEs correlate with farmers characteristics? We find that it is not the lack of financial resources that explains the low adoption rate of PPEs. We regress lack of availability of the PPEs on the individual characteristics of the farmer and find that income is positively correlated with unavailability but statistically insignificant. Instead, we find that lack of education is positively correlated with unavailability of the PPE's. In summary, we find that it is not the lack of financial resources which explains the low adoption rate of PPEs but it is rather a question of education.

months for each farmer, we can compare these answers with the WHO toxicity standard (WHO 2009) of the listed pesticides. We find that 94% of the sample has used at least one ‘highly toxic’ pesticide in the last year, which can cause severe health effects if proper precautionary measures are not taken. This difference in actual versus perceived toxicity risk indicates an important knowledge gap by most farmers.

Health Outcome: In our regression analysis, our main variable of interest is the health outcome of farmers. The survey asks if—within the past year prior to the date of the interview—the farmer got ill from a list of symptoms after spraying pesticides—eye irritation, headache, vomiting, dizziness, diarrhea, fever, convulsions, skin irritation or shortness of breath[14]. If a respondent has felt one or more of the listed symptoms, we code the health outcome dummy as one, and zero otherwise.[15] Under-reporting of the true pesticide exposure occurs if symptoms are not visible immediately or built up over longer term exposures only from repeated spraying.

4. Estimation Strategy and Summary Statistics

In this paper, we examine the effect of information sources on risk perception, precautionary behavior and health outcomes from pesticide exposure. We estimate the effects using the following equation:

$$Y_{ij} = \sum_c \sum_k \beta_{1k} I_k C_c + \beta_2 X_{ij} + \beta_3 A_{ij} + \mu_j + \varepsilon_{ij} \tag{1}$$

[14] Symptoms of toxic pesticides, are typically visible within a few hours (World Resources, 1998-1999; Dasgupta et al., 2007a).

[15] 85 percent of the farmers report that they are ‘very’ or ‘extremely’ sure that pesticide exposure caused those symptoms.

where Y_{ij} represents alternatively an indicator for risk perception, precautionary behavior or the dummy variable for illness of individual i in sub-district j. I_k is a set of dummy variables indicating the k^{th} information source, where $k \in \{(A), (B), (C)\}$ and C_c represents whether the information was obtained via the direct or the advisory channel indexed by c. A_{ij} includes information related variables such as instructions on labels or fliers. Farmers characteristics age, education, body mass index (BMI), farm size, household income, and value of farming equipment are represented by X_{ij}. As smoking is known to aggravate the symptoms of pesticide exposure, such as pulmonary problems (Pingali et al., 1994), we also include a dummy variable for smoking. Lastly, μ_i indexes the sub-district[16] level fixed effects. We cluster standard errors at the district level to allow for spatial correlation across farmers in the same jurisdiction.

Prior to moving on to our estimation results, it is useful to note potential limitations in the interpretation of results. An important caveat in our analysis is that it is based on cross-sectional data, which theoretically hinder us from drawing strict inferences on causality as we are unable to control for unobserved farmer heterogeneity. Hence our estimations may suffer from endogeneity biases. We believe however that this problem is not of first order concern in our dataset. First, we do not observe endogenous sorting into the contact with pesticide sellers as almost all farmers (98%) purchase pesticides themselves. Second, we condition our estimates on a wide set of the arguably most important characteristics that should be correlated with sorting. To this end, Table 3.4 displays summary statistics and p values comparing characteristics of ill farmers to non-ill farmers. Ill farmers tend to be significantly younger and use more pesticide than non-ill farmers. In our following regressions, we hence control for these individual and

[16] The 2003 BPUS survey took place in 31 sub-districts of 11 districts in Bangladesh. Sub-districts are jurisdictions which often have their own legislative procedures. To account for potential differences we control for the sub-district fixed effect and due to spatial correlation we cluster the error term ε_{ij} by district.

household characteristics. In particular, note that the following—arguably most important—variables (that potentially could concern endogenous sorting) do *not* show statistically significant differences: the number of household members, per-capita income, farm size, farm equipment value, household head's BMI, smoking behavior and education.

5. Results and Discussion

The regression results follow the chart in figure 1 from left to right. Do any of the sources (A) – (C) influence the risk perception, precautionary behavior and health outcomes of farmers? Table 3.5 displays the effect of information sources on farmers' perceived long-term health effects of pesticide using ordinary least squares (OLS).[17] In columns (1) to (3), we first aggregate the direct channel and the advisory channel into the three key sources of information: pesticide sellers, AFEWs, and peer farmers. We find that information from sellers significantly increases farmers' risk perception when controlling for district fixed effects (column 1), sub-district fixed effects (column 2) or farmer characteristics (column 3). Note, that overall adding these additional regressors slightly lowers the magnitude of the coefficients. To be conservative, we control for the sub-district fixed effects and these individual characteristics in all further estimations.

We note, that our point estimate of interest, pesticide sellers, remains robust to the inclusion or exclusion of farmers' individual characteristics: namely age, education, income, value of farming equipment, quantity of pesticide used and spatial fixed effects (columns 2 and 3). This set of control variables arguably includes the most important factors behind farmer

[17] We use the responses to question (1) 'What is the main information source of the following instructions that you may have received: While spraying pesticides, you should wear precautionary equipment' as our key information source variable.

precautionary behavior, and is hence likely correlated with any missing variables that could explain further unobserved heterogeneity. This robustness suggests that this form of endogeneity is unlikely to be a major concern in our data. We note here that in all regressions below, the inclusion or exclusion of this set of additional set of regressors (or including independent variables one by one) never qualitatively affects our point estimates of interest. Hence, this provides suggestive evidence that endogenous sorting should not be of first order concern.

Next, we disaggregate the information sources into the direct channel and the advisory channel.[18] In column (4) we find that pesticide sellers have a significant effect through the direct channel and column (5) shows that the sellers continue to have a significant effect when controlling for the types of 'trained peers' in the advisory channel. The coefficients of information sources in the direct channel remain robust even after adding the variables representing advisory channel. This robustness suggests that multicollinearity between direct and advisory channel is not a concern for our estimates. Finally, one can argue that labels on pesticide containers (as required by Pesticide Rules (1985)) by itself represents an information source. Controlling for this[19] in column 6, we find no qualitative difference in the main estimates of interest (the parameter of pesticide sellers changes slightly from 0.232 to 0.228). Finally, we find that peer farmers and AFEWs have no significant effect for any of these specifications.

Do information sources differentially impact the adoption of health protection products? Table 3.6 shows the impact of (A) to (C) on the likelihood of using any of the three most

[18] In some cases farmers list the same source as *both* the direct and advisory information source. As a robustness, we test alternative coding schemes. For those farmers that report to have obtained the same information from both the direct channel and the advisory channel, the coding can be either as advisory channel only, direct channel only, or a separate variable for these special cases of multiple sources. In all of these robustness tests, we find that our main results are unaffected from these alternative categorization schemes.

[19] The specific variables used are 'follow instruction of label' and 'understanding instructions on flyer'.

important PPEs: gloves, mask and boots. Column (1) shows that pesticide sellers and peer farmers increase the likelihood of farmers' adoption of PPEs. The effect persists when we control for reading instructions on pesticide containers (column 2). Disaggregating the sources by channel in column 3, we again find that pesticide sellers as a direct channel significantly increase farmers' adoption of PPEs. As a robustness check, we add glasses (column 4) and hats (column 5) to the list of PPEs and find that sellers maintain the significant effect, but the effect for peer farmers disappear. [20]

In Table 3.7 we continue the analysis of the relationship between (A) to (C) on the precautionary behavior.[21] . Column (1) shows that all three key sources significantly increase the likelihood of *reading* labels or seeking assistance for those unable to read. We find a similar effect when disaggregating the sources in column 2. However, when we examine the influence of these sources on farmers *actually following* the instructions on labels (columns 3 and 4) or applying the prescribed dose (columns 5 and 6), we find that only pesticide sellers (both on the aggregate and also as the direct and advisory channel) significantly increase the likelihood of following those precautionary actions. In contrast peer farmers and AFEWs do not have such consistent significant effects. Finally, in column (7), (using responses to question 3) we again find that pesticide sellers as a direct channel significantly increase the likelihood of not using bare hands to mix pesticides.

Summarizing our results, we consistently find that pesticide sellers improve the risk perception and precautionary behavior of farmers. However, does this also translate into

[20] For the interpretation of these results, note that although technically inadequate, farmers can wear reading glasses or religious caps as protective equipment. Our data does not allow to distinguish between protective glasses and reading glasses, and similarly for religious caps or protective hats.

[21] In Table 3.7, displays the marginal probability effects of the probit estimation. The 'information variable' informs the farmer of the necessity of reading labels, i.e. the response to question (2) quoted in our data section.

improved health outcomes? Table 3.8 reports probit marginal probability effects of the sources (A) to (C) on illness.[22] In column (1) we find that pesticide seller and peer farmers significantly reduce the likelihood of illness. In column (2) and (3), we disaggregate sources by channel and again find that sellers as a direct channel significantly decrease the likelihood of illness. Sellers continue to remain significant when we control for instructions on labels and fliers (column 4) as well as the specific instruction that it is dangerous to mix pesticide using bare hands (column 5). Finally, in all of the specifications, in terms of social learning we find that the 'average' peer has a positive but negligible effect on other farmers' health. However, the learning effect is particularly strong from the very small fraction of the more educated 'trained' peers, serving as important social multipliers into the farmers' network.

In summary, our regression results in Tables 3.5 to 3.8 suggest that advice from pesticide sellers consistently leads to enhanced risk perception, adoption of health products, precautionary actions, and reduced likelihood of illness. These results are significant and in contrast to the notion in the previous literature that sellers misguide farmers. We also find that *trained* peer farmers (advisory channel) have a positive effect on precautionary measures and health outcomes, but that peers over the direct channel (who are likely untrained) do not have any effect. This underlines the importance that formal training has positive spill-over effects on neighboring peers. It is remarkable that such small fraction of trained peer farmers (7.25%) provide significant results, whereas we cannot find a significant effect for the 10.3% of AFEWs on risk perception, precautionary measures or health.[23]

[22] To code this, in Table 3.8 we use the responses with respect to question (1) quoted in our data section.
[23] The only exception is column 7 of Table 3.7 (where AFEWs have a positive effect on the instruction that farmers must not use bare hands when mixing pesticides).

6. Conclusion

Our study has important policy implications. We show that pesticide sellers play a crucial role for information dissemination that improves health in developing countries. Future regulations should hence consider making explicit use of the network of pesticide sellers present in rural areas, which are often difficult to reach via the extension workers. According to our results, sellers do raise awareness and are already present in all relevant agricultural rural areas. Over 50% of farmers report that they do not have access to masks or gloves. Therefore, supply side regulations should consider selling protective equipment through the network of pesticide sellers. A required bundling policy of sales of protective equipment together with pesticides (i.e. one mask per container) could increase awareness and the use of protective equipment. Our results further suggest that the government should reconsider demand side strategies with which extension workers are used to disseminate information. We do not find AFEWs having any significant influence on farmers. Finally, we find that the very small fraction of trained farmers have a particularly positive effect on peers suggesting that more targeted training programs to social multipliers could be valuable to enhance the information flow.

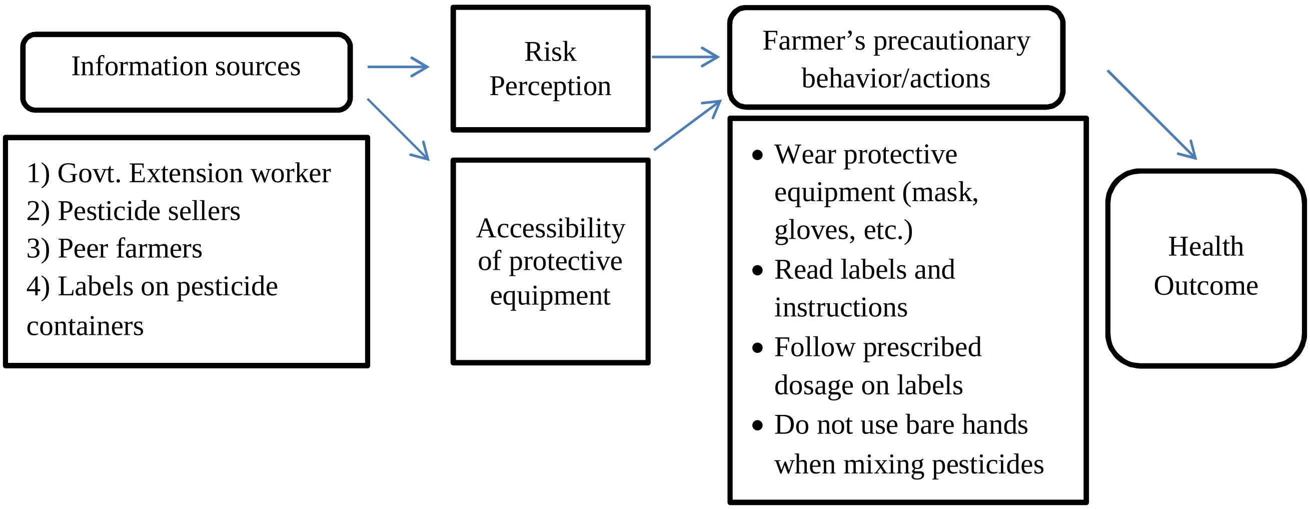

Figure 1: The pathway through which information sources affect risk perception, precautionary behavior, use of health products and health outcomes.

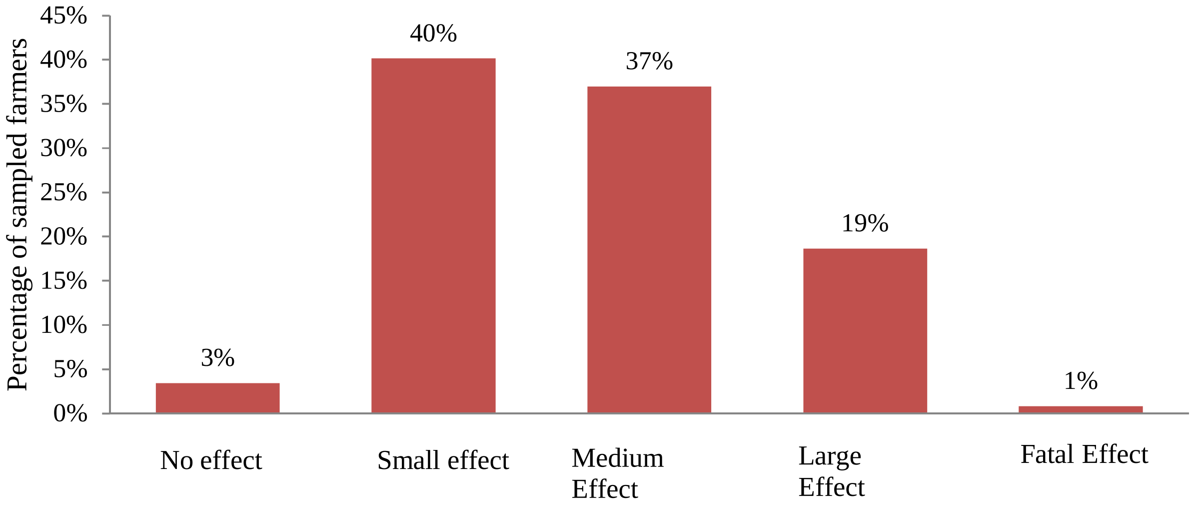

Figure 2: Perceived long-term effects of pesticide exposure for the sampled farmers.

Table 3.1: Break-down of sources by information channels

Section (i): Direct Information Channel

	Precautionary measures are necessary	Reading label is necessary	Bare hands should not be used
Ministry AFEWs	10.3%	5.8%	7.5%
Pesticide Seller	26.2%	45.6%	33.7%
Peer farmers	43.6%	39.5%	42.8%
Total	80.1%	90.9%	84%
No knowledge	19.9%	9.1%	16%

Section (ii): Advisory Channel: Types of trained peers

Trained peers	
- Ministry AFEWs	9.75%
- Pesticide Sellers	7.25%
- Peer farmers	7.25%
Total	24%
Do NOT have a trained peer	76%
Number of observations	759

Note: Section (i) provides a break-down of information sources provided through direct channels. Information sources are mutually exclusive to each other as each farmer can provide only one answer. Section (ii) provides a break-down of types of trained peers. Type of trained peers are also mutually exclusive to each other.

Table 3.2: Farmer's knowledge versus precautionary behavior: Do farmers follow *knowledge* with *actions*?

	No of obs	Percent
Knowledge: Read the labels on the pesticide container	691	
- of them, how many read labels	399	58%
- of them, how many follows the instruction on labels	315	46%
- of them, how many follows prescribed dose	195	28%
Knowledge: Precaution and protection is needed	611	
- of them, how many use any protection	85	14%
- of them, how many use mask	45	7%
- of them, how many use gloves	11	2%
- of them, how many use hats	37	6%
- of them, how many use glasses	23	4%
- of them, how many use boots	8	1%
Knowledge: Do not mix pesticide with bare hands	640	
- of them, how many do not use bare hand	292	46%
When purchasing pesticide, are you supplied with info in fliers?	593	
- of them, how many reads and understand	368	62%
Number of observations: 759		

Table 3.3: Percentage of farmers citing different reasons for not adopting PPE

Protections	Use	Unnecessary	Unavailable	Uncomfortable
Mask	7%	54%	31%	13%
Hat/Head-cover	6%	56%	22%	18%
Glasses	3%	55%	24%	13%
Gloves	2%	52%	26%	19%
Boots/Shoes	1%	34%	14%	45%

Note: Only farmers who do not use the certain Personal Protective Equipment (PPE) are asked about the reason for not using that PPE. The three set of responses: 'Unnecessary', 'Unavailable', and 'Uncomfortable' are mutually exclusive as farmers can only choose one response.

Table 3.4: Summary Statistics of Farmer Characteristics

		Sick		Not Sick		
Number		364		395		
Percentage		48%		52%		
Farmer characteristics		Mean	St Dev	Mean	St Dev	p-values
Number of household members		6.3	(3.0)	6.1	(2.9)	0.27
Farm size (in acres)		1.5	(1.5)	1.4	(1.4)	0.28
Yearly HH percapita income		17337	(12956)	15916	(14363)	0.17
Farm Equipment value		5591	(10262)	5531	(11959)	0.94
Age		34	(10.99)	36	(11.29)	0.026**
Education	Below Primary	26%	(0.44)	24%	(0.43)	0.53
	Primary & above	27%	(0.44)	23%	(0.42)	0.27
	Secondary & above	12%	(0.32)	11%	(0.31)	0.61
Body Mass Index (BMI)		19.7	(2.24)	19.5	(2.07)	0.3
Smoke cigarette		56%	(0.50)	58%	(0.49)	0.45
Pesticide quantity - solid (in Kg)		5.9	(8.30)	4.5	(6.74)	0.012**
Pesticide quantity - liquid (in Liters)		4.5	10.5	2.2	5.5	0.00***

Number of observations: 759

Note: p-values in the last column compares the mean of characteristics of sick farmers to non-sick farmers. *** indicates significance at 1% level; ** at 5%; * at 10%. In the data set farm sizes are enumerated in 7 distinct bins of farm areas. We approximate the farm size by assuming the mid-point of each bin.

Table 3.5: Effect of information sources on farmer's perceived long-term effects

Specification: OLS	Dependent variable: Farmer's perceived long-term effects					
	(1)	(2)	(3)	(4)	(5)	(6)
Pesticide seller (Aggregate)	0.203*	0.191*	0.176*			
	(0.111)	(0.100)	(0.097)			
Extension worker (Aggregate)	0.159	0.108	0.065			
	(0.107)	(0.112)	(0.118)			
Peer farmer (Aggregate)	0.204	0.154	0.137			
	(0.118)	(0.109)	(0.113)			
Per-capita Income			0.003	0.004	0.003	0.004
			(0.003)	(0.003)	(0.003)	(0.002)
Value of Equipment			0.003	0.003	0.003	0.003
			(0.003)	(0.003)	(0.003)	(0.003)
Age			-0.006	-0.006	-0.006	-0.006
			(0.004)	(0.004)	(0.004)	(0.004)
Education - Primary (1-5 yrs)			0.071	0.075	0.074	0.088
			(0.061)	(0.060)	(0.061)	(0.064)
Education - Junior High (6-10 yrs)			0.009	0.011	0.009	0.016
			(0.070)	(0.067)	(0.070)	(0.092)
Education - Secondary (11+ yrs)			0.114	0.122	0.115	0.116
			(0.152)	(0.155)	(0.162)	(0.128)
Direct Channel - Pesticide seller				0.209***	0.232***	0.228***
				(0.045)	(0.065)	(0.063)
- AFEW				0.089	0.113	0.113
				(0.163)	(0.175)	(0.183)
- Peer farmers				0.159	0.181	0.162
				(0.104)	(0.119)	(0.131)
Advisory Channel - Pesticide seller					0.082	0.083
					(0.216)	(0.220)
- AFEW					0.036	0.037
					(0.095)	(0.097)
- Peer farmers					0.074	0.074
					(0.148)	(0.130)
Follow instruction on labels						0.213***
						(0.052)
Understand instructions on fliers						-0.047
						(0.099)
District Fixed-Effects	Yes	No	No	No	No	No
Sub-District Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
R-squared	0.067	0.106	0.128	0.130	0.131	0.145
Number of observations	717	717	717	717	717	717

Note: Standard errors are in parentheses. Standard errors are computed after correcting for heteroskedasticity and correlation within district clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. The regressions in columns (3) - (6) further control for farm size, quantity of pesticide used, BMI and smoking dummy.

Table 3.6: Influence of information sources on use of farmers' personal protective equipment

Dependent variable	Mask, gloves or boots	Mask, gloves or boots	Mask, gloves or boots	Mask, gloves, boots or glasses	Mask, gloves, boots, glasses or hats
	Specification: OLS				
	(1)	(2)	(3)	(4)	(5)
Pesticide seller (Aggregate)	0.057**	0.056**			
	(0.021)	(0.020)			
Extension worker (Aggregate)	0.016	0.015			
	(0.022)	(0.022)			
Peer farmer (Aggregate)	0.025**	0.020*			
	(0.011)	(0.009)			
Direct Channel - Pesticide seller			0.049**	0.042**	0.046**
			(0.020)	(0.015)	(0.019)
- AFEW			-0.009	0.024	0.019
			(0.042)	(0.024)	(0.023)
- Peer farmers			0.004	0.005	0.000
			(0.011)	(0.013)	(0.013)
Advisory Channel - Pesticide seller			0.050	0.033	-0.009
			(0.051)	(0.054)	(0.063)
- AFEW			0.030	0.005	-0.015
			(0.040)	(0.031)	(0.030)
- Peer farmers			0.062*	0.042	0.042
			(0.031)	(0.033)	(0.042)
Follow instruction on labels		0.049**	0.050**	0.075***	0.093***
		(0.019)	(0.019)	(0.021)	(0.022)
Understand instructions on fliers		0.022	0.019	-0.001	-0.002
		(0.035)	(0.034)	(0.037)	(0.031)
Number of observations	757	757	757	757	757
R-squared	0.153	0.161	0.164	0.188	0.201

Note: Standard errors are in parentheses. Standard errors are computed after correcting for correlation and heteroskedasticity within district clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. All regression further include farm size, per-capita income, equipment, education, age, quantity of pesticide used, BMI, smoking-dummy, and sub-district fixed effects as additional regressors.

Table 3.7: Influence of information sources on use of farmers' precautionary behavior using Probit specification

Dependent variable	Read label or seek assistance if unable to read labels		Follow instructions on label		Follow prescribed dose as indicated on label		Hands not used for mixing pesticide
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pesticide seller (Aggregate)	0.089***		0.113**		0.180***		
	(0.025)		(0.052)		(0.053)		
Extension worker (Aggregate)	0.045**		0.084		0.180*		
	(0.018)		(0.116)		(0.101)		
Peer farmer (Aggregate)	0.108***		0.138		0.162***		
	(0.036)		(0.102)		(0.062)		
Direct Channel - Pesticide seller		0.085***		0.159**		0.114*	0.194***
		(0.027)		(0.062)		(0.063)	(0.063)
- AFEW		0.045**		0.215		0.149	0.143
		(0.022)		(0.165)		(0.139)	(0.091)
- Peer farmers		0.110***		0.201**		0.082	0.150*
		(0.026)		(0.098)		(0.061)	(0.078)
Advisory Channel - Pesticide seller		0.063***		0.159**		0.317***	0.171
		(0.009)		(0.075)		(0.088)	(0.117)
- AFEW		0.039		0.040		0.202**	0.238***
		(0.024)		(0.116)		(0.101)	(0.053)
- Peer farmers		0.047*		0.083		0.328***	0.178***
		(0.028)		(0.127)		(0.116)	(0.049)
Number of observations	743	743	744	744	746	746	749
R-squared	0.21	0.22	0.09	0.09	0.13	0.14	0.11

Note: The Table presents marginal probability effects of the probit estimation along with the estimated standard errors in parenthesis.Standard errors are computed after correcting for heteroskedasticity and correlation within district clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. All regression further include farm size, per-capita income, education, age, value of farm equipment, BMI, smoking dummy, quantity of pesticides used and sub-district fixed effects as additional regressors.

Table 3.8: Impact of information sources on illness

Dep. variable: Illness		Specification: Probit				
		(1)	(2)	(3)	(4)	(5)
Pesticide seller (Aggregate)		-0.177***				
		(0.053)				
Extension worker (Aggregate)		-0.051				
		(0.057)				
Peer farmer (Aggregate)		-0.163**				
		(0.067)				
Direct Channel	- Seller		-0.122**	-0.179***	-0.182***	-0.183***
			(0.061)	(0.068)	(0.070)	(0.070)
	- AFEW		0.005	-0.053	-0.053	-0.075
			(0.106)	(0.117)	(0.112)	(0.131)
	- Peer Farmer		-0.087	-0.149*	-0.143	-0.148
			(0.084)	(0.089)	(0.088)	(0.095)
Advis. Channel	- Seller			-0.156***	-0.155***	-0.151***
				(0.059)	(0.059)	(0.056)
	- AFEW			-0.049	-0.044	-0.041
				(0.039)	(0.035)	(0.033)
	- Peer Farmer			-0.235***	-0.228***	-0.224***
				(0.053)	(0.052)	(0.050)
Follow instruction on labels					-0.065	-0.066
					(0.040)	(0.041)
Understand instr. on fliers					-0.079	-0.080
					(0.053)	(0.052)
Not use hand:	- Seller					0.007
						(0.034)
	- AFEW					0.044
						(0.130)
	- Farmer					0.015
						(0.060)
Number of observations		748	748	748	748	748
R-squared		0.09	0.09	0.09	0.1	0.1

Note: The Table presents marginal probability effects of the probit estimation along with the estimated standard errors in parenthesis. Standard errors are computed after correcting for heteroskedasticity and correlation within district clusters. *** indicates significance at 1% level; ** at 5%; * at 10%. All regression further include farm size, farm equipment value, per-capita income, education, age, BMI, smoking dummy, quantity of pesticide used and sub-district fixed effects as additional regressors.