ABSTRACT

Title of dissertation:	HEALTH, AGRICULTURE AND LABOR MARKETS IN DEVELOPING COUNTRIES
	Yeon Soo Kim, Doctor of Philosophy, 2010
Dissertation directed by:	Professor Maureen Cropper Department of Economics Assistant Professor Jeanne Lafortune Department of Economics

Rural households comprise a large share of the population in developing countries. This dissertation examines how the welfare of these households, whose economic activity mainly relies on agriculture, is affected by weather shocks and health shocks in the context of West Africa and Vietnam.

In the second chapter of the dissertation, I use the variation in rainfall within and across years at a detailed geographic level in West Africa to examine how rainfall shocks might affect the well-being of very young children. Variations in rainfall may affect not only income, but also the opportunity cost of time of parents, which may negatively impact child welfare. I find that high long-term rainfall averages for a particular location and month increase the probability of giving birth in the dry season, whereas positive deviations from this long-term mean ("rainfall shocks") have a small but statistically significant negative effect on the probability of giving birth in the rainy season. Further, contrary to what one might expect, rainfall shocks

do not appear to improve the survival chances of young children and shocks in the first year of life have an adverse effect on the survival of children that are born in the rainy season. This result may be partly attributable to the finding that rainfall shocks significantly reduce the time mothers breastfeed their children, which could be due to a trade-off with work. Breastfeeding is important for the health of young children since it provides not only essential nutrients but also effective protection against various diseases.

In the third chapter, I examine the effect of health shocks on the production decisions of agricultural households in Vietnam. I look at whether malaria illnesses experienced by the household have an effect on their agricultural production decisions. While I am not able to entirely overcome issues with endogeneity that are persistent in this literature, results show that profits are negatively associated with the share of household members experiencing malaria. This result is not explained by the decrease in the total number of labor days the household employed. Rather, households appear to change their crop choice to less labor-intensive, less profitable crops in anticipation of these seasonal health shocks.

HEALTH, AGRICULTURE AND LABOR MARKETS IN DEVELOPING COUNTRIES

by

Yeon Soo Kim

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2010

Advisory Committee:
Professor Maureen Cropper, co-Chair
Assistant Professor Jeanne Lafortune, co-Chair
Professor Mark Duggan
Assistant Professor Raymond Guiteras
Associate Professor Kenneth Leonard

Dedication

To my mother, who would have been proud

To F, who always believed in me

Acknowledgments

First and foremost, I would like to express my deepest gratitude to my advisors, Maureen Cropper and Jeanne Lafortune, for their continuous encouragement and support throughout this entire process. Their detail-oriented comments were indispensable and this dissertation would not have been possible without their guidance.

I would also like to thank Mark Duggan and Raymond Guiteras, who have provided valuable comments at various stages of this dissertation. I am also grateful to Kenneth Leonard who has agreed to serve as the Dean's representative on my dissertation committee. Thanks also to Ramanan Laxminarayan who kindly shared the data used in the third chapter.

Finally, I acknowledge the technical support through the Maryland Population Research Center. The handling of the large data involved in the second chapter has been greatly facilitated through access to their computing facilities.

Table of Contents

List of Tables

List of Figures

Chapter 1

Overview

Rural households comprise a large share of the population in developing countries and they face various types of shocks that might affect their well-being. The assessment of the impact of these shocks is complicated because unobservable characteristics of the household could be correlated with the likelihood of receiving such shocks.

A large body of literature has studied the vulnerability of agricultural households to shocks due to volatile weather conditions (e.g., Paxson (1992)) or illnesses (e.g., Gertler and Gruber (2002)). In general, households can mitigate the adverse effect of income risk either by managing or coping with it. Strategies of risk management include diversification of crops (Dercon (1996)) or occupation, while risk-coping measures include saving and borrowing behavior to smooth consumption across time or across households through risk-sharing (Deaton (1992), Townsend (1994), Grimard (1997); see Alderman and Paxson (1992) for an overview of the literature). While most studies reject perfect insurance they find some evidence of consumption smoothing.

Several studies examine the consequences of these shocks for children: Jensen (2000) shows that adverse weather shocks led to lower investments in education and health, measured by school enrollment, short-term nutritional status, and use of medical services in Côte d'Ivoire. Jacoby and Skoufias (1997) concludes that school attendance fluctuated with seasonal income in India. Foster (1995) finds that severe floods had an adverse impact on children's weight in rural Bangladesh.

The next two chapters of this dissertation examine how the welfare of households whose economic activity mainly relies on agriculture is affected by exogenous weather shocks and health shocks in the context of West Africa and Vietnam, respectively.

In the second chapter, I exploit the exogenous variation in rainfall within and across years at a detailed geographic level in West Africa to examine how rainfall shocks affect the health of very young children. Rainfall generates variation in income through its effect on agricultural output and more income is usually beneficial for the survival of children. However, rainfall also affects the opportunity cost of time of parents and may thus have a negative impact. I match detailed rainfall data from nearby weather stations to household data drawn from Demographic and Health Surveys from nine West African countries. I first examine how short- and long-run variations in rainfall affect the timing of birth of children, possibly due to the effect on the opportunity cost of their time. I find that high long-term rainfall averages for a particular location and month increase the probability of giving birth in the dry season, whereas positive deviations from this long-term mean ("rainfall shocks") have a small but statistically significant negative effect on the probability of giving birth in the rainy season. Further, contrary to what one might expect, rainfall shocks do not appear to improve the survival chances of young children and shocks in the first year of life have an adverse effect on the survival of children that are born in the rainy season. This result may be partly attributable to the finding that rainfall shocks significantly reduce the time mothers breastfeed their children, which could be due to a trade-off between work and child care. Breastfeeding is important for the health of young children since it provides not only essential nutrients but also immune benefits against respiratory, diarrheal and other infectious diseases. These account for a substantial share of child mortality in this region. While breastfeeding might be directly linked to infant mortality, it might as well be representative of the parental care the child receives in early age. Since households residing in rural areas are much more likely to engage in agricultural activities, one would expect these results to be stronger for rural households. This is indeed confirmed: results are driven by children in rural areas where households are more vulnerable to variations in rainfall.

In the third chapter, I examine the effect of health shocks on the production decisions of agricultural households in Vietnam. Previous literature has found little effect of health shocks on profits, which has been attributed to rather well-functioning input markets in the countries studied. I examine a particular type of health shock from a disease that, because it is endemic, might be largely anticipated by households on a recurring basis. Using household-level data from two rounds of the Vietnam Living Standard Measurement Surveys, I look at whether malaria illnesses experienced by the household have an effect on agricultural profits. While concerns remain about the endogeneity of the malaria illness variable, profits are found to be negatively associated with the share of household members experiencing a malaria episode. This result is not explained by the decrease in the total number of labor days the household employed. Rather, households appear to change their crop choice to less labor-intensive, less profitable crops in anticipation of these seasonal health shocks.

Chapter 2

The Impact of Rainfall on Early Child Health

2.1 Introduction

In West Africa, one child out of five dies before age five and one out of ten dies during the first year of life. According to the World Health Organization (WHO (2008)), 75% of childhood deaths in Africa are due to infectious, diarrheal or respiratory diseases.[1] Low income, high disease prevalence and lack of access to proper health care are among the factors that are known to contribute to high childhood mortality. Moreover, interventions regarding timely immunization, provision of micronutrients, access to clean water, distribution of bed nets for protection against malaria, and simple oral rehydration solutions are not yet reaching enough people, even though they could easily avert many deaths. The climate in Africa is certainly favorable to the transmission of communicable diseases and rainfall variability frequently raises concern over food security and water availability.

In this chapter, I use data from nine West African countries and exogenous variation in rainfall within and across years at a detailed geographic level to examine the impact of rainfall shocks on early child mortality. West Africa has had historically high variation in rainfall with occasional severe droughts, and those weather

[1] The causes of death for children under five in Africa are: diarrheal diseases (16%), acute respiratory diseases (21%), malaria (26%), other infectious/parasitic diseases (11%) and neonatal deaths (25%) (Boschi-Pinto and Shibuya (2008)).

shocks affected agricultural output directly. The literature has often used rainfall as a shock to household income, which, if positive, would benefit children's health.[2] However, rainfall creates not only variation in income, but also variation in the opportunity cost of time of agricultural labor. This might be particularly relevant for women who provide farm labor but are also responsible for non-market household production and thus may need to reallocate their time away from these tasks during busy times of the year. If women have to work on the field for most of the day, they might, for example, breastfeed infants less frequently or wean them earlier, and also spend less time preparing nutritious meals at home than they otherwise would. All these factors may have a *negative* impact on the health of young children. Therefore, the overall impact of rainfall shocks on child health remains ultimately an empirical question.

I first examine how the timing of birth of children may depend on rainfall variations across seasons and years. Given that a woman's opportunity cost of time is higher during the rainy season when most agricultural activities occur, one might expect that women would attempt to time their delivery at times when they are less likely to be busy. I find that average rainfall levels, as well as transitory shocks occurring in the rainy season affect households' fertility decisions, although the impact of transitory shocks is much smaller. One would expect this since fertility can be timed to occur in a given season but not based on anticipated short-run fluctuations.

[2]The fact that rainfall leads to fluctuations in income has been established and used extensively in the literature. Levine and Yang (2006) show that more rainfall resulted in increased rice output in Indonesia. Duflo and Udry (2004) look at how income earned by men and women from different crops is spent differently in the household, exploiting the fact that different crops have a different sensitivity to rainfall. See also Paxson (1992) and Dercon (2004).

These results are similar to those found by Pitt and Sigle (1997) in that they highlight the importance of opportunity cost of time. This paper differs from their study and another, similarly motivated paper by Artadi (2005) in the following way: in both papers, variations in opportunity costs affect child mortality only through their effect on the timing of births, which influences mortality through the seasonality in income and disease. Neither paper allows the opportunity cost of a woman's time to have a direct impact on mortality post-birth, for example by affecting the length of time a mother breastfeeds her child.

I subsequently estimate how rainfall shocks affect mortality in the first year of life, where rainfall "shocks" are defined as deviations from a 20-year long-run average. I find that rainfall shocks in the first year after birth have an *adverse* effect on the survival of young children that were born in the rainy season, with the effect being largely driven by children in rural areas. While increased disease prevalence related to seasonal rainfall levels may be one of the causes of higher mortality, part of the result may be attributed to the finding that positive rainfall shocks significantly reduce the time mothers spend breastfeeding during times when their value of time is higher, such as the rainy season. To the extent that there is a trade-off in the allocation of time between work and child care, a positive rainfall shock (or higher-than-usual rainfall levels) may induce women to wean their children prematurely, as more income could potentially be forgone.[3] Early weaning may weaken the child's immune system and lead to higher incidence of various diseases.

[3] In West Africa, extended kinship networks and the prevalence of polygyny provide for an institutional setting where the raising of young children is shared among extended family members or older siblings (Adepoju and Oppong (1994)).

I explore breastfeeding as a channel that links increases in mortality to higher opportunity costs, especially in a context where child mortality from diseases matters considerably and could potentially be averted through proper breastfeeding.

The benefits of breastfeeding have been extensively documented in the medical literature (Victora et al. (1987); Kramer et al. (2001)). Breast milk provides necessary nutrients to the infant as well as immune benefits against diseases until it fully develops its own immune system. In particular, exclusive breastfeeding in the first six months reduces the incidence of and mortality from respiratory, diarrheal and other infectious diseases.[4] Children under age two who are not breastfed have a higher risk of death, and exclusive breastfeeding has been shown to have greater benefits than complementary breastfeeding which combines breast milk with other foods and liquids (Black et al. (2003), WHO (2000)).[5] Therefore, as long as the child is breastfed, he or she will drink less water and thereby reduce exposure to water-borne diseases. This could be another avenue through which benefits of breastfeeding might accrue. Further evidence suggests that the positive effects of breastfeeding on survival extend beyond infancy to children aged 12 - 36 months (Briend et al. (1988)). Therefore, the negative effect of early weaning on child health may be exacerbated in places where the incidence of water- and food-borne diseases

[4]Immunoglobulin (IgA), which helps prevent diarrhea, is passed on to the infant during breastfeeding (Clemens et al. (1997)).

[5]Most studies in the past have relied on observational data (Victora et al. (1987); Betran et al. (2003); Yoon et al. (1996)) and maternal-level unobservables may have biased the results. Recently, randomized trials in the form of educational interventions have been conducted: see, for example, Kramer et al. (2001); Morrow et al. (1999); Bhandari et al. (2003). They find similar benefits of breastfeeding in terms of reduced incidence of diseases, as well as some longer-term benefits on cognitive ability. Based on these findings, the WHO and the American Academy of Pediatrics recommend that infants be exclusively breastfed for the first 6 - 12 months, with complementary feeding up to two years of age.

is high, as it is in West Africa.

Estimates of the impact of rainfall shocks on the length of breastfeeding, measured in months, show that mothers respond to positive rainfall shocks after birth by reducing the time they breastfeed their children, especially the ones born in the rainy season. The magnitude of the effect is even greater and statistically significant for shocks occurring in the second year of life. This is not surprising as children would have been breastfed for at least a year by then. Early weaning in the middle of the rainy season would be especially critical for survival since that is the time when diseases are rampant. Alternatively, as a woman's spare time available for household production becomes scarce, the meals that she prepares in the limited available time after a long day of field work might be of lower nutritional quality.

The remainder of the chapter is organized as follows: section 2.2.1 provides background information on women's role in agriculture in West African countries and the potential consequences for child welfare; section 2.2.2 reviews the existing literature on weather shocks and health outcomes in sub-Saharan Africa; section 2.3 outlines the empirical strategy; section 2.4 describes the data sources; section 2.5 presents the empirical results; and section 2.6 concludes.

2.2 Background and Literature Review

2.2.1 Women, Agriculture and Child Care in West Africa

Women in West Africa play a pivotal role in agriculture, providing a large share of farm labor and making key decisions for many agricultural activities. They are mainly responsible for the production of subsistence crops.[6] The seasonality of labor demand is very pronounced in this region because agriculture is mainly rain-fed and thus farming activities are largely defined by rainfall. The nine countries examined in this chapter exhibit either a unimodal rainfall pattern with a short rainy season lasting from May to September (Burkina Faso, Guinea, Mali and Niger), or a bimodal rainfall pattern with two rainy seasons lasting from March to October, with a short dry spell in between (Benin, Côte d'Ivoire, Ghana, Nigeria and Togo). Since the latter dry spell lasts in general only about two weeks, I treat these countries as having one long rainy season for practical purposes in the empirical section. This classification is also consistent with seasonal ups and downs in the demand for agricultural labor. The lean season occurs right before the main harvest, either around the middle or the end of the rainy season, depending on the rainfall pattern. This is another reason why we would expect to see less births occurring around this time.

During the rainy season, when labor requirements are high, women have to prioritize labor and time allocation between agricultural activities and non-market household production such as fetching water, cooking and child care. Women sow seeds, weed, apply fertilizer and pesticides, and harvest and thresh crops. While rural women in sub-Saharan Africa are responsible for a substantial part of food production, access to time-saving agricultural tools and technology is limited. Some even argue that those time-saving innovations have actually hurt women as "Tractors

[6] Major food crops that are grown in this region include maize, yam, cassava, rice, millet and sorghum. Doublecropping is practiced in regions with a longer rainy season, as is intercropping in some areas using cowpea and millet, or rice with cassava, maize or millet, for example.

and animal-drawn plows have been used by men to increase the acreage under cultivation, leaving women to struggle with an increase in weeding and harvesting, using only handheld tools" (World Bank (2009)). Therefore, the high burden of women during rainy seasons may put constraints on how much time women can devote to taking care of their children. More specifically, if the woman is trying to free up as much time as possible for field work during the day, she may not find enough time to breastfeed a newborn infant as often as needed, for example. Moreover, since there is little time left for food preparation, the infant may be introduced to porridge or solid family food earlier than recommended, which may lead to various food-borne diseases.

2.2.2 Existing Literature

This chapter builds on a literature that looks at the relationship between adverse weather shocks and health outcomes, such as anthropometric indicators (e.g., height-for-age). Hoddinott and Kinsey (2001) and Dercon and Hoddinott (2003) use data from Zimbabwe and find that exposure to drought at an early age reduces height-for-age.[7] The latter also finds that catch-up growth is limited, that adult women are affected more than adult men, and that there is no differential effect between boys and girls. Dercon and Krishnan (2000) examine adult Body Mass Index (BMI), defined as a person's weight in kilograms divided by squared height in meters, and find that the burden of shocks is borne disproportionately by women in

[7]Much of this literature has focused on the effect of droughts because rainfall data at a disaggregated geographic level was difficult to obtain.

poor households. In addition, there are studies showing that weather shocks in early life can have a permanent effect on longer-term outcomes. Alderman et al. (2006) show that pre-school exposure to drought results not only in lower height-for-age, but also in delays in school enrollment and fewer grades completed. Maccini and Yang (2009) examine the effect of rainfall shocks around the time of birth in Indonesia and find that more rainfall leads to better health in adulthood, more completed schooling, and higher asset accumulation for women.

The papers most closely related to this study are Pitt and Sigle (1997) and Artadi (2005). Both papers are motivated by the seasonality of child survival and the woman's opportunity cost of time. Pitt and Sigle (1997) argue that in Senegal, children are less likely to die when born in the dry season, which is also the time when women's opportunity cost is the lower. They estimate the effect of rainfall up to two years before birth on fertility and on survival until 24 months of age, and find that more rainfall increases the probability that a birth occurs, resulting in an effect on the average season of birth and therefore the permanent quantity of surviving children. Artadi (2005) constructs a country-level measure of the trade-off between child survival and opportunity cost by computing the difference in expected survival probabilities from being born in months with high and low demand for labor. Months with higher income coincide with months with higher child survival in some countries, while they do not coincide in others. She finds that households residing in countries with a high level of trade-off are more likely to give birth in months that have, on average, a high child mortality rate.

This paper stresses the importance of the opportunity cost of time for early child mortality with regards to the potential trade-off between work and child care, by exploring breastfeeding as one channel that may lead to higher child mortality. A small but parallel literature from developed countries identifies return to work as a common reason for stopping breastfeeding (Lindberg (1996); Noble and The ALSPAC Study Team (2001)). A problem in this literature is that the studies do not account for maternal or child-level unobservables. To circumvent this problem, Baker and Milligan (2008) exploit an increase in maternity leave entitlements in Canada and find that the policy change led to an increase in the incidence and duration of breastfeeding but had little effect on indicators of child health.

2.3 Empirical Strategy

2.3.1 Fertility

While there are various factors that a household may take into account in their family planning, my main interest is to explore how households' decisions depend on long- or short-run variations in rainfall across months and seasons. The goal is to estimate how rainfall, by varying the opportunity cost of women's time, affects whether or not a birth occurs in a given month. To investigate this, I construct a panel dataset which consists of observations at the woman-month level, starting in the month the woman turns 15.[8] This results in an unbalanced panel of all women who gave birth to at least one child. The main dependent variable is then an indi-

[8]More than 99% of births occur after age 15.

cator variable for whether the woman gave birth in each month.[9]

The distribution of births by month is shown in Figure 2.1, for countries exhibiting a single short rainy season and for countries that have two rainy seasons. The dark-colored bars in the graphs correspond to rainy season months and the light-colored bars to dry season months. The fraction of births occurring in each month is quite different from the fraction that would correspond to a uniform distribution of births across months. While the timing of birth may be influenced by several factors, I focus on variation due to the fact that the opportunity cost of women's time is lower during months in the dry season, since the time-consuming tasks of planting and harvest are over. More time is available to give birth, recover from pregnancy and care for children. Furthermore, diseases from which parents may want to shield their newly born children are more prevalent during the rainy season. Food availability also varies across seasons, as food is likely to be more plentiful starting at the end of the rainy season after harvests have occurred. This should provide better nutrition for mothers and their children. The lean season, which is when households run out of food, usually occurs right before the harvest and women may want to avoid childbirth around that time of the year.

Whether a woman gives birth in a given month is likely affected by the above considerations and also by factors that affect her nutrition before conception and during pregnancy. The latter may affect whether a child is carried to term. I therefore model the impact of rainfall on the probability that a woman gives birth during

[9]For example, if a woman is 20 years and 2 months old at the time of survey, there are 4 x 12 + 2 = 50 observations, one for each month since the month she turned 15.

month t using the following equation:

$$\begin{aligned} Birth_{jt} = \alpha + \gamma M_j + \theta_1 RainConcep_{jt} + \theta_2 RainPreg_{jt} + \delta Rainy_{jt} \\ + [\theta_1' RainConcep_{jt} + \theta_2' RainPreg_{jt}] * Rainy_{jt} \\ + [\lambda_1' LongConcep_{jt} + \lambda_2' LongPreg_{jt}] * Rainy_{jt} \\ + \lambda_1 LongConcep_{jt} + \lambda_2 LongPreg_{jt} + \xi Country_j + \tau Year_j + \epsilon_{jt} \end{aligned} \tag{2.1}$$

where the subscript j indexes the mother and $t = 1, 2, ...T_j$, where T_j is equal to the number of months since the woman's 15th birthday. The dependent variable $Birth_{jt}$ is a dummy that takes on the value one if woman j gave birth in month t.

The rainfall variables used in this regression are constructed in the following way. For each month of observation t, I first construct long-run rainfall variables for the period corresponding to the months before conception (specifically, $t-10$, $t-11$ and $t-12$) and during pregnancy ($t-1$ through $t-9$). So for example, for the month of October 1970, two long-run rainfall variables are created, one corresponding to the 20-year average of October through December, to measure the persistent trends of rainfall of the months leading up to conception, and another long-run rainfall variable that corresponds to the 20-year average of January through September, to measure long-running trends in the months during pregnancy. In contrast to these, rainfall "shock" variables are created that measure any deviations from these trends: $RainConcep_{jt}$, which measures the deviation of rainfall in the three months before the child was conceived and $RainPreg_{jt}$, which measures the deviation of rainfall in the nine months of pregnancy.[10]

Demographic controls include mother's characteristics, such as mother's age at birth (a linear and a quadratic term), education (dummies equal to one if mother received either primary education or secondary education or above), and dummies for whether place of residence is urban. $Rainy_{jt}$ is a country-specific dummy variable that indicates whether each month of observation falls in the rainy season. In addition, all rainfall variables are interacted with $Rainy_i$ to examine whether any effects of rainfall shocks differ by season of birth. $Country_j$ and $Year_j$ are vectors of country and year dummies that are intended to control for any country- or time-specific factors that are not observed in the data. Models with country fixed effects are estimated in the baseline model, and them replaced with region- and mother fixed effects. Finally, ϵ_i is the usual idiosyncratic error term.[11] Standard errors are robust to heteroskedasticity and clustered at the sampling cluster level to account for possible correlation of errors within the same sampling cluster.

2.3.2 Infant Mortality and Breastfeeding

There are at least three channels through which rainfall may affect infant mortality. First, rainfall has a direct effect on the agricultural income of rural households. Second, more rainfall is likely to increase the prevalence of infectious

[10]This variable would measure whether rainfall shocks during pregnancy affect the probability that a birth occurs. One way to interpret this would be to consider it as the effect of rainfall shocks on miscarriages. This is all assuming that the child was carried to full term because there is no data available on prematurity. Only later surveys asked whether the child was born prematurely, but the reported incidence is extremely low. Additionally, all rainfall variables are measured in meters.

[11]In specifications with mother dummies, any variable that is time-invariant is dropped from the regression.

diseases (e.g., malaria). Finally, in an agricultural setting, household members' opportunity cost of time fluctuates within and across years with varying rainfall levels. This may have implications for child health if women need to prioritize among different tasks during busy times and are not able to spend as much time taking care of their children. For example, women may not have enough time to breastfeed their newborn child frequent enough and may introduce the child to solid food early. It is well known that breast milk provides immunity to infectious diseases through the transfer of antibodies from mother to child and through improved child nutrition. If rainfall increases the opportunity cost of time, women might be induced to wean the children prematurely, which may have an adverse effect on child health. While the income channel has a positive impact on child health, the latter two exert a negative effect. Therefore, whether the overall effect of rainfall on child health is positive or negative is an empirical question and I explore breastfeeding as a possible channel explaining the empirical relationship between rainfall and infant mortality.

The impact of rainfall on the probability that a child dies before reaching age one and on the number of months breastfed are estimated using the following model:

$$\begin{aligned} Mortality_i \text{ or } Breastfeeding_i \ &= \alpha + \beta C_i + \gamma M_i + \lambda LongRain_i + \delta Rainy_i \\ &+[\theta_0 RainShock_{0,i} + ... + \theta_k RainShock_{k,i}] + \lambda' LongRain_i * Rainy_i \\ &+[\theta'_0 RainShock_{0,i} + ... + \theta'_k RainShock_{k,i}] * Rainy_i + \xi Country_i + \tau Year_i + \epsilon_i \end{aligned} \tag{2.2}$$

where i indexes the child, and C_i and M_i are sets of child and mother controls. C_i includes sex and birth order of the child, and whether the child was born in a multiple birth. When the outcome of question is length of breastfeeding, additional dummy variables are included that indicate whether the child was still being breastfed at the time the survey was carried out and whether the mother stopped breastfeeding because the child died. Similar to equation 2.1, a 20-year long-run rainfall variable is constructed that varies by cluster, month and year, however, now there is only one long-run variable that measures rainfall before birth. For example, for the month of April 1980, long-run rainfall is the average rainfall from April 1960 to March 1980. The mean of this variable, which is measured as a monthly average across 20 years, is around 82 mm (about 3.3 inches), which would correspond to an annual rainfall level of 984 mm (about 39.4 inches), with a standard deviation of 86 mm.

Rainfall shock variables are created as deviations from this long-run mean, and then aggregated to represent shocks for different periods around birth. $RainShock_{t,i}$ measures the deviation of rainfall from the long-run average, where the subscript $t = 0, ..., k$ indexes the year relative to the birth year of the child that the rainfall shock occurs. The index t runs from zero (which indicates the year before birth) to one, if outcome is infant mortality, and from zero to two, if outcome is the length of breastfeeding, to capture rainfall shocks in the first and second year after birth. For example, rainfall shock before birth is measured as the average deviation of rainfall in the year before birth from long-run average rainfall. Although breastfeeding obviously starts after birth, rainfall shock before birth is also controlled for when estimating the impact of rainfall on the length of breastfeeding because rainfall is correlated with agricultural labor demand across time. That is, a positive rainfall shock by the beginning of the season likely increases labor demand throughout the season. Rainfall shock in the first and second year of life is measured similarly.[12] Similarly, rainfall shock before birth is also included in the mortality regression because rainfall affects agricultural output and therefore income, not only in the seasons before birth when the rainfall actually occurs, but also in the following seasons, since it takes time for crops to grow during the rainy season and since harvests last until the next season.

$Rainy_i$ is a country-specific dummy variable that now indicates whether the child was born in the rainy season. For example, any child born in the months between May and September in Burkina Faso would be characterized as being born in the rainy season and be assigned a value equal to one for the $Rainy_i$ dummy. This variable therefore varies by country and birth month now. The rest of the variables are defined as previously.

After estimating the baseline model, the country dummies are gradually replaced with region and mother dummies in the mortality regression. These additional dummies are intended to control for any time-invariant and unobservable country-, region- or mother-specific characteristics that might influence the probability of the child surviving beyond its first birthday. In the breastfeeding regressions, only one additional specification with region dummies is estimated. This is because the questions on breastfeeding were asked only for children that were born within five years of the survey, and most women in the sample had one or two children

[12] These do not correspond to calendar years and allow for more variation in the variables.

at most during this time frame so there is not enough variation to estimate models with mother dummies.

2.4 Data Sources and Descriptive Statistics

The data used in this analysis come from the Demographic and Health Surveys (DHS). These are nationally representative household surveys that contain a wide range of information on demographic characteristics, and the health and nutrition of women and children in particular. For countries with no reliable census data, the DHS has been used to perform indirect estimation of important indicators of population dynamics, such as fertility and mortality. More recently, GIS data on the household sample cluster was collected along with household data for some surveys. I use 13 surveys from nine countries in West Africa that include data on the geographic coordinates of each sample cluster.[13] Clusters are usually census enumeration areas, villages in rural areas or city blocks in urban areas, and DHS cluster points were taken at the center of each cluster. The number of clusters per country ranges from 140 to 400, and each cluster originally sampled 30 to 40 women in rural areas and 20 to 25 women in urban areas.[14] Information was collected on the entire retrospective birth history of women aged 15 - 49, including data on

[13] See Table 2.12 for a complete list of surveys used. Surveys before 1990 did not collect sufficiently detailed data on recent births to be suitable for my analysis and surveys implemented after 1999 were excluded because the particular weather data used in this chapter relies on retroactive reporting, which requires years of a time lag until data is cleaned and becomes available for use.

[14] DHS GPS Manual, 2004 (Macro International Inc. (1996)). While the surveys provide nationally representative statistics, they are not suited for small area estimation. Comparing urban and rural population was an important aim in many surveys and oversampling was conducted in countries with a low share of urban population.

women's month and year of birth, education level, residential characteristics (region of residence, whether place of residence is urban or rural), children's month and year of birth, sex, birth order, and importantly, their survival status. For children born within five years from the time of the survey, further detailed questions regarding the child's health were asked, including for how long the child had been breastfed. Given that the individual country samples pooled together are all from surveys collected in the 1990s and that women between age 15 and 49 were sampled, the distribution of observations across birth years is not even and some birth years are over-represented, as shown in Figure 2.2, by country. In addition to that, the sample for four countries was drawn from two separate surveys.

The most important sample restriction criterion concerns linking the correct rainfall data to each household.[15] Since interest lies in the impact of rainfall before and after birth, it would be ideal to have geographic information on the cluster of residence at the time of birth of each child.[16] However, such data are not available and this information is inferred from the question on the number of years the household has lived in the current residence.[17] Combined with data on the child's age, it is possible to determine whether the child was born in the current sample cluster. This way, children who were not born in the cluster of current residence

[15]The sample used to estimate the impact on mortality was restricted to "unfinished cases". See Section 2.5 for details on additional sample restriction criteria.

[16]Child fostering is a common practice in West Africa. For example, an estimated fifth of non-orphaned children of age 7–14 were living away from their parents in Côte d'Ivoire in 1985. However, this percentage is very low for children less than two years old (Ainsworth (1992)). Child fostering could be of concern since rainfall in the cluster of residence is merged to each child, but it is unlikely to be a problem at least for the period of interest.

[17] Any women who were visitors to the household at the time of the survey were also excluded from the sample.

were dropped from the sample.[18]

Table 2.1 provides descriptive statistics on relevant child's and mother's characteristics and Table 2.2 presents length of breastfeeding by percentile. In the majority of cases, the child was weaned because he or she entered weaning age (60 %), followed by the death of child (17%) or because the mother became pregnant again (12%). Slightly more than half of the children are male (51%), which is as expected, 3.4% of them were born in a multiple birth, and average birth order is 3.55.[19] The infant mortality rate, which measures the probability that a child survives until his or her first birthday, is strikingly high at 11%. Only 18.6% of women have received any formal education (13.5% have primary education and 5.1% have secondary education or more), and 27.8% live in an urban area. While an average child was breastfed for about 13 months, 6.64% were not breastfed, 23.06% were breastfed less than 6 months, and 40.75% were breastfed for less than a year.

Rainfall data was obtained from the Global Historical Climatology Network (GHCN-Monthly, version 2) database, which collects weather station data from around the world. This data was checked against mislocation of weather stations and individual values were cleaned of discontinuities and inconsistencies before being

[18]Selective migration might be of concern if mothers with certain characteristics are more likely to move to sample clusters with more than average rainfall. This would result in a downward bias of estimates if mothers with healthier children were more likely to move away from the place of residence and therefore be dropped from the sample. Additionally, children born before 1960 are dropped from the sample because of the low number of observations per year.

[19]The average number of children per mother is slightly smaller than the total fertility rate for this region reported elsewhere. This is not surprising, given that the sample of women surveyed were between age 15 and 49 and many of them would not have completed their lifetime fertility. The average total fertility for the nine countries ranges from 6 to 7.5 according to UN Population Statistics for the period of 1950-2000 (United Nations Population Division (2008)).

made available for use.[20] Rainfall was matched to households at the sample cluster level using data from the nearest weather station. The median distance to the nearest weather station is 62 km in the birth month of the children in the sample.

2.5 Results

2.5.1 Does rainfall shift the timing of births?

If rainfall affects the opportunity cost of a woman's time, it may affect the timing of births. These results are presented in Table 2.3. The sample is constructed as described in section 2.1 and consists of approximately 8.8 million woman-month observations. Column (1) presents baseline results with country dummies, and columns (2) and (3) add region and mother fixed effects, respectively. Mother fixed effects control for persistent, unobservable differences across mothers, such as their fecundity or their ability to control the timing of conception, both factors that are likely to affect their fertility outcome. In addition to reporting the coefficient estimates of the regressors, test statistics for the impact of each variable in the rainy season are also reported at the bottom of the table.[21]

The results on estimated coefficients on mother's characteristics are not surprising: women residing in urban areas or who have achieved any formal education are less likely to give birth in any given month, and the age-fertility profile is increasing in a decreasing way. Estimated coefficients on long-run rainfall and rainfall

[20] The majority of rainfall data for Africa comes from the African Historical Precipitation Data, which contains a total of 1,239 weather stations.

[21] The impact of rainfall shock before conception during the rainy season is the sum of the coefficient on Rainfall Shock before Conception and its interaction with Rainy.

shocks show an interesting contrast across different birth seasons. Higher average monthly rainfall before conception significantly increases the probability of giving birth in the dry season, whereas it has a much smaller effect on a birth in the rainy season. However, the latter effect is not statistically significant when mother fixed effects are included in the model. Rainfall during pregnancy may have an effect on how likely it is that a pregnancy results in a birth.[22] Results suggest that having a baby in gestation during months with higher historical rainfall is more likely in the dry season, but the opposite effect for the rainy season is not statistically significant.[23] Rainfall shocks before conception have a very small but statistically significant negative impact on the probability of a birth during the rainy season, but no effect on a birth during the dry season. The magnitude of the coefficient on long-run rainfall is much larger than the coefficient on the shock variable. This is expected, as a woman does not know what the rainfall amount will turn out to be when she plans her pregnancy. In terms of the magnitude of the effects, a one standard deviation change in long-run rainfall increases the probability that a birth occurs by 0.7% points in the dry season, whereas a rainfall shock of the same magnitude increases the probability of birth by 0.03% points in the rainy season. These are not trivial effects considering that the mean probability of birth in any given month is 2%.

[22]Technically, a woman cannot give birth for nine months following a birth, since she cannot conceive again once she has conceived. For comparison, I estimate the same specifications excluding those observations. Estimation results, not reported here, are qualitatively very similar. The sum of the coefficients on the variables measuring rainfall shocks before conception and the interaction with the rainy dummy is even larger and statistically significant at 2% with mother fixed effects.

[23]If a child is born in the dry (rainy) season, a large part of the gestation months falls in the rainy (dry) season.

It is conceivable that extreme weather events have a very different effect on pregnancy decisions because floods and droughts might damage and kill the crops, thereby limiting agricultural labor demand during those times. In other words, there might be a nonlinear effect of rainfall on opportunity costs. In order to account for such extreme weather events, a dummy variable is first defined to indicate whether each month had a severe shortage or excess of rainfall: Specifically, the dummy is equal to one if the rainfall amount of that month fell in the extreme 5% tail of the overall distribution of rainfall. Then, variables measuring extreme weather are defined as the number of months that had such an event, either in the three months pre-conception or during the months of pregnancy. Table 2.4 reports regression results accounting for such possibly nonlinear effects. While the number of flood months before conception and the number of drought months in pregnancy seem to matter even in the specification accounting for mother-level unobservables, the coefficient estimates on long-run rainfall and rainfall shocks are remarkably similar, which indicates that the probability of births is affected very little by such weather events. A one standard deviation change in long-run rainfall increases the probability of birth by 0.7% in the dry season and the same magnitude of rainfall shocks decrease the probability of birth by 0.07%. These estimates are statistically significant at around 1%.

2.5.2 Reduced-form Impact on Infant Mortality

The sample for the infant mortality regression excludes any children that were born less than one year from the time of survey, whether alive or not. This leaves the final sample with 217,303 observations. The number of observations for each survey is listed in the appendix.

Table 2.5 presents estimation results for the infant mortality model in equation 2.2. The signs of the coefficients on the mother's and child's control variables are as expected: the child is less likely to reach his first birthday if the child is male, is born in a multiple birth, is of higher birth order, and lives in a rural cluster. The younger the mother, the lower the probability that the child dies before age one, but the relationship bottoms out at age 35. Additionally, the more education the mother has received, the more likely it is that the child survives.

The coefficient estimates on rainfall shocks one year before and after birth are not significant in the baseline regression with country dummies (column(1)), nor is long-run rainfall. Region dummies are added in column (2) to account for unobservable factors that are time-invariant and persistent within the region. Finally, mother dummies are included in the results in the last column. I focus on these results since they are the most robust ones. Models with mother dummies capture mother-level unobservables to the degree that they are time-invariant: for example, some mothers may have a better ability to shield their children from the consequences of negative rainfall shocks if they have better health knowledge. These estimates rely solely on the within-mother variation and thus the effect of variables that are constant within the mother (e.g., education) cannot be estimated anymore.

The results in column (3) show that while rainfall shocks before birth have a statistically insignificant effect on survival, rainfall shocks during the first year *after* birth negatively affect survival of children born in the rainy season (as implied by the statistically significant estimate of the sum of the variable and the interaction with the "rainy" dummy: see F-stat at the bottom of the table). The coefficient estimate suggests that conditional on other control variables, a positive one standard deviation shock in rainfall increases the probability of the child dying before reaching age one by about 1.15% if the child was born in the rainy season. This estimate is statistically significant at the 10% level in the specification with mother fixed effects.

The same sensitivity check that was performed in the previous section is done again to account for potentially nonlinear effects of rainfall. Table 2.6 reports these results for infant mortality. If anything, the effect of rainfall shocks on infant mortality are slightly greater after accounting for extreme weather events.

The fact that rainfall shocks have adverse effects on the survival of young children according to these results may seem surprising at first, given that higher rainfall is in general associated with more income, and therefore, one might expect positive shocks to benefit the survival of children.[24] However, more rainfall could increase mortality due to the fact that parents have less time to take care of children or because diseases such as malaria are more prevalent during the rainy season.

[24]Although not reported here, conditional on surviving the first year of life, rainfall shocks actually decrease mortality of children born in the rainy season, but this result is likely driven by selection.

While I am unable to eliminate the second channel as a possible cause, I explore whether there is any evidence of the first in my data by looking at the impact of rainfall shocks on breastfeeding decisions.

2.5.3 Rainfall shocks, Opportunity cost and Breastfeeding

The sample of children that reports length of breastfeeding has 51,912 observations, after dropping those that currently live in a residence different from the one at the time of birth and those with missing breastfeeding information. Some mothers report to have breastfed up to 5 years, and I remove those outliers. This leaves a total of 49,161 observations. Estimation results on the length of breastfeeding are shown in Table 2.7. The child is likely to be breastfed longer if the child is a girl, born in a singleton birth, of lower birth order, and if the mother is younger, resides in a rural area, and has no education.[25] Rainfall shocks before birth are positively associated with how long the child is breastfed for children born in the rainy season, which could possibly reflect an income effect. The signs of the coefficients of the rainfall variables are overall negative, and while not all of the coefficients on individual interaction terms are significant, the sum of the variable with the interaction term is significant at the 1% level for rainfall shocks occurring after birth, as reported at the bottom of the table. These results suggest that a positive deviation of rainfall after birth consistently decreases the length of time the child is breastfed. Regardless of season of birth, the effect is greater for shocks occurring in the second

[25]In developing countries, it is common for less educated mothers to breastfeed longer (Cleland and van Ginneken (1988)). There is no clear consensus on the urban-rural difference in breastfeeding practices, with some studies suggesting that rural women tend to breastfeed longer.

year of life relative to shocks in the first year. The effect is also greater for children born in the rainy season, which is as expected. This is true for shocks during the second year but not during the first. A shock in the magnitude of one standard deviation in the first year decreases the length of breastfeeding by a statistically significant 30 days, regardless of the birth season.[26]

The consequences of reduced breastfeeding for mortality could be manifested in several ways. It is possible that early weaning weakens immunity, or that supplemental foods or liquids are not nutritious enough. On the other hand, if women are restricted in their time they can devote to non-market household production, they may not have enough time to prepare a separate meal for the newborn and be provided with family food instead. The child might be exposed to food-borne diseases during that process of premature transition from breast milk to solid food. From a broader perspective, reduced breastfeeding during critical early childhood might be representative of less time for "child care", which may affect marginally sick children.

It is well known that breastfeeding can be an effective, although imperfect, method of contraception. It appears that rainfall shocks before birth actually increase the time children are breastfed if they are born in the rainy season. On the other hand, rainfall shocks in the first year of life reduce the length of breastfeeding for children born in the dry season, and reduce it even more for children born in

[26]The reason why the effect of breastfeeding on mortality is not estimated directly is because of obvious endogeneity issues. That is, there are mother-specific unobservables that affect both the length of breastfeeding and mortality and therefore, I only examine the impact of exogenous rainfall shocks on breastfeeding. Alternatively, to use rainfall as an instrument for breastfeeding would likely violate the exclusion restriction in the second stage.

the rainy season. If rainfall induces women to wean children early, their fertility may return sooner, resulting in another pregnancy, and this is consistent with what the fertility results show. So whether this is a result of a shift in timing due to fertility returning earlier because of weaning, or whether it is the direct consequence of conscious timing decisions, the implication that opportunity costs influence the timing of births still stands and is consistent with both explanations.

2.5.4 Falsification Test with Neonatal Mortality

In the previous section, I argue that rainfall might adversely affect the survival of infant children through a post-birth channel, which is the length of time the child is breastfed. To strengthen the case for post-birth channels leading to mortality, I perform a type of falsification test by looking at how rainfall affects neonatal mortality (mortality before reaching one month of age). If rainfall has an effect on infant mortality through factors such as low birth weight or maternal malnutrition, both of which are determined by conditions during pregnancy, then pre-birth factors might also influence infant mortality. Since detrimental *in utero* conditions are more likely to lead to death within one month of life rather than thereafter, I examine whether rainfall shocks right around birth affect neonatal mortality. Results are reported in Table 2.8, and across different specifications, including one that controls for mother fixed effects, rainfall does not have a statistically significant effect on mortality in the first month of life when the child is born in the rainy season. For children born in the dry season, there is a statistically significant effect of rainfall shock in the first month in columns (1) and (2) for specifications with country and region fixed effects. However, the estimate turns insignificant with the inclusion of mother fixed effects. This suggests that it is post-birth rather than pre-birth channels that result in increased infant mortality.

2.5.5 Further results by urban–rural

Considering that variations in the opportunity cost of time of agricultural labor created by fluctuations in rainfall is more relevant to rural households, it is natural to expect households in rural areas to respond more strongly than households in urban areas. To see if this is indeed true, the same regressions are run on subsamples divided by urban or rural area of residence. While the majority of household income in rural areas is generated by farm activities,[27] there are at least two reasons why urban areas may not be entirely free of seasonalities. First, women residing in urban areas may engage in agriculture as a secondary source of income. Because of growing food insecurity, urban agriculture has spread rapidly over the years.[28] Moreover, manufacturing industries that rely on the seasonal supply of raw material might also experience fluctuations in opportunity cost.[29] Therefore, women in urban areas may still see variations in their opportunity cost in response to rainfall, although at a smaller scale compared to women in rural areas.

Estimation results for the split sample are shown in Tables 2.9, 2.10, and 2.11, for fertility, infant mortality, and breastfeeding, respectively. The specifications are

[27] For example, in Côte d'Ivoire, 75% of income came from farming (Kozel (1990)).

[28] Gardening vegetables or raising micro livestock has become more widespread in Ghana (Danso et al. (2004)).

[29] The production of sorghum beer in Burkina Faso is one example.

the same as before. The impact on fertility is indeed greater in rural than urban areas, although it seems to persist in both (Table 2.9). The effect of rainfall shocks on infant mortality is also mainly driven by rural children and the estimate is even larger in magnitude than before. The results for breastfeeding are mixed: rainfall shocks in the first year negatively impact the length of breastfeeding of rural but not urban children who are born in the dry season. However, the opposite seems to hold for children born in the rainy season, as the estimates are actually smaller for rural children.

2.6 Conclusion

Households in developing countries are affected by various types of shocks and it is important to understand how they respond to them. Rainfall shocks are of particular interest given the high dependence on agriculture in many developing countries. Rainfall in the development literature has often been associated with positive outcomes given its positive effect on income. This chapter suggests that rainfall shocks can actually have adverse effects on the survival of young children through their impact on the opportunity cost of women across seasons and over time. While this result may come as a surprise, it may be partly attributed to the impact on the length of breastfeeding. More rainfall increases the mother's opportunity cost of time, which reduces the time children are breastfed and may weaken their immune system. The importance of opportunity costs is further substantiated by exploring the effect on the timing of birth: long-run rainfall increases the probability of giving birth in the dry season, whereas rainfall shocks have a small but statistically significant negative effect on the probability of giving birth in the rainy season. This suggests that women are more likely influenced by long-run variations in rainfall when making their fertility decisions. Altogether, these results highlight the importance of the opportunity cost of time. More work is warranted regarding how changes in the opportunity costs of parents affect the well-being of children.

Table 2.1: Descriptive Statistics (All households)

Mother's characteristics		*Child's characteristics*	
Age at birth	25.368	Male	0.51
	(6.508)		(0.5)
Primary education	0.135	Birth Order	3.547
	(0.342)		(2.30)
Secondary education or higher	0.051	Multiple birth	0.034
	(0.220)		(0.181)
Urban	0.278	Infant mortality rate	0.11
	(0.448)		(0.313)
Number of women	55,278	Number of children	217,293

Table 2.2: Breastfeeding in months

Mean (St. Dev)	13.06 (8.866)
Missing	1.42%
Zero months	6.64%
0 – 6 months	23.06%
0 – 12 months	40.75%
Observations	49,161

Table 2.3: Fertility

	(1)	(2)	(3)
Mother's age at birth	0.0039***	0.0039***	0.0024***
	(0.0000)	(0.0000)	(0.0002)
Mother's age at birth squared	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)
Urban	-0.0028***	-0.0023***	
	(0.0001)	(0.0002)	
Primary education	-0.0015***	-0.0012***	
	(0.0001)	(0.0001)	
Secondary education or higher	-0.0051***	-0.0048***	
	(0.0002)	(0.0002)	
Rainfall shock before conception	0.0073	0.0063	0.0036
	(0.0050)	(0.0050)	(0.0050)
Rainfall shock in pregnancy	0.0075**	0.0053	0.0041
	(0.0036)	(0.0036)	(0.0037)
Long-run rainfall before conception	0.0835***	0.0891***	0.0805***
	(0.0035)	(0.0038)	(0.0053)
Long-run rainfall in pregnancy	-0.0200***	-0.0207***	-0.0251**
	(0.0033)	(0.0040)	(0.0123)
Rainy	0.0009**	0.0010***	0.0013***
	(0.0004)	(0.0004)	(0.0004)
Interaction with Rainy			
Rainfall shock before conception	-0.0098*	-0.0097*	-0.0075
	(0.0054)	(0.0054)	(0.0054)
Rainfall shock in pregnancy	-0.0027	-0.0034	-0.0037
	(0.0056)	(0.0056)	(0.0057)
Long-run rainfall before conception	-0.0784***	-0.0845***	-0.0795***
	(0.0038)	(0.0039)	(0.0039)
Long-run rainfall in pregnancy	0.0191***	0.0209***	0.0201***
	(0.0034)	(0.0034)	(0.0035)
Constant	-0.0262***	-0.0271***	-0.0335***
	(0.0016)	(0.0016)	(0.0022)
Test for significance of variables on births in the rainy season			
Rainfall before conception			
Sum of coefficients	-0.0025	-0.0034	-0.0039
F-stat	1.93	3.48	4.19
Corresponding p-value	0.1648	0.0620	0.0407
Rainfall in pregnancy			
Sum of coefficients	0.0048	0.0019	0.0004
F-stat	1.42	0.22	0.01
Corresponding p-value	0.2339	0.6389	0.9338
Long-run rainfall before conception			
Sum of coefficients	0.0051	0.0046	0.001

F-stat	11.44	7.46	0.05
Corresponding p-value	0.0007	0.0063	0.8155
Long-run rainfall in pregnancy			
Sum of coefficients	-0.0009	0.0002	-0.005
F-stat	0.09	0.00	0.16
Corresponding p-value	0.7691	0.9499	0.6858
Country dummies	x		
Region dummies		x	
Mother dummies			x
Observations	8831987	8831987	8831987
R^2	0.0018	0.0018	0.0059

Note: This table reports linear probability model estimates for the effect of rainfall shocks on the probability of birth. Reported birth histories are used to construct a new sample that consists of one observation for each woman for each month starting when she turns 15. The dependent variable is equal to one if the woman gave birth to a child in that month and the unit of observation is a woman-month. Control variables include urban (dummy equal to one if place of residence is in an urban area), education (dummies equal to one if mother received either primary education or secondary education and above), and mother's age in each month. Sample is from 13 surveys from nine countries in West Africa. Long-run rainfall is the 20-year average rainfall in the sample cluster and varies by month and year. All rainfall shock variables are measured as an average relative to the month of observation, t. Rainy is a dummy variable that takes on the value one if the month of observation falls in the rainy season and zero otherwise, and varies by country and month. All regressions include year and month dummies. The urban dummy is dropped in columns (3) and (4) and mother's education is dropped in column (4). Standard errors are robust to heteroskedasticity and clustered at the sampling cluster level.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.4: Fertility results with nonlinearity

	(1)	(2)	(3)
Mother's age at birth	0.0039***	0.0039***	0.0024***
	(0.0000)	(0.0000)	(0.0002)
Mother's age at birth squared	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)
Urban	-0.0028***	-0.0022***	
	(0.0001)	(0.0002)	
Primary education	-0.0015***	-0.0012***	
	(0.0001)	(0.0001)	
Secondary education or higher	-0.0051***	-0.0048***	
	(0.0002)	(0.0002)	
Rainfall shock before conception	0.0035	0.0023	-0.0002
	(0.0053)	(0.0053)	(0.0053)
Rainfall shock in pregnancy	0.0120***	0.0095**	0.0084**
	(0.0039)	(0.0039)	(0.0040)
Long-run mean rainfall before conception	0.0835***	0.0892***	0.0811***
	(0.0035)	(0.0038)	(0.0053)
Long-run mean rainfall in pregnancy	-0.0195***	-0.0200***	-0.0232*
	(0.0033)	(0.0040)	(0.0123)
Rainy	0.0010**	0.0011***	0.0014***
	(0.0004)	(0.0004)	(0.0004)
# of flood months before conception	0.0005**	0.0005**	0.0004*
	(0.0002)	(0.0002)	(0.0002)
# of flood months in pregnancy	-0.0002**	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)
# of drought months before conception	-0.0001	-0.0001	-0.0002
	(0.0002)	(0.0002)	(0.0002)
# of drought months in pregnancy	0.0003***	0.0003***	0.0003**
	(0.0001)	(0.0001)	(0.0001)
Interaction with Rainy			
Rainfall shock before conception	-0.0078	-0.0076	-0.0056
	(0.0055)	(0.0054)	(0.0055)
Rainfall shock in pregnancy	-0.0027	-0.0034	-0.0037
	(0.0056)	(0.0056)	(0.0057)
Long-run mean rainfall before conception	-0.0785***	-0.0846***	-0.0797***
	(0.0038)	(0.0039)	(0.0039)
Long-run mean rainfall in pregnancy	0.0188***	0.0206***	0.0197***
	(0.0034)	(0.0034)	(0.0035)
Constant	-0.0370***	-0.0377***	-0.0518***
	(0.0027)	(0.0027)	(0.0030)
Test for significance of variablesn on births in the rainy season			
Rainfall before conception			
F-stat	3.91	6.11	6.92

Corresponding p-value	0.0482	0.0135	0.0086
Rainfall in pregnancy			
F-stat	4.31	1.79	0.98
Corresponding p-value	0.0379	0.1806	0.3227
Long-run rainfall before conception			
F-stat	11.06	7.42	0.11
Corresponding p-value	0.0009	0.0065	0.7418
Long-run rainfall in pregnancy			
F-stat	0.06	0.02	0.08
Corresponding p-value	0.8045	0.8819	0.7810
Country dummies	x		
Region dummies		x	
Mother dummies			x
Observations	8842131	8842131	8842131
R^2	0.0018	0.0018	0.0059

Table 2.5: Infant mortality

	(1)	(2)	(3)
Male	0.0145***	0.0146***	0.0134***
	(0.0015)	(0.0015)	(0.0020)
Multiple birth	0.2442***	0.2454***	0.2616***
	(0.0073)	(0.0073)	(0.0093)
Birth Order	0.0134***	0.0133***	0.0232***
	(0.0008)	(0.0007)	(0.0020)
Mother's age at birth	-0.0140***	-0.0139***	-0.0049
	(0.0011)	(0.0011)	(0.0031)
Mother's age at birth squared	0.0002***	0.0002***	0.0003***
	(0.0000)	(0.0000)	(0.0000)
Urban	-0.0309***	-0.0259***	
	(0.0022)	(0.0026)	
Primary education	-0.0141***	-0.0100***	
	(0.0026)	(0.0025)	
Secondary education or higher	-0.0219***	-0.0164***	
	(0.0033)	(0.0033)	
Rainfall shock before birth	-0.0823	-0.0439	0.0012
	(0.0698)	(0.0710)	(0.0954)
Rainfall shock in first year	-0.0765	-0.0443	-0.0518
	(0.0655)	(0.0663)	(0.0883)
Long-run rainfall	0.0005	0.0059	-0.0053
	(0.0045)	(0.0068)	(0.0295)
Rainy	0.0039	0.0024	0.0008
	(0.0037)	(0.0037)	(0.0049)
Interaction with Rainy			
Rainfall shock before birth	0.1068	0.0830	0.0794
	(0.0916)	(0.0916)	(0.1210)
Rainfall shock in first year	0.1256	0.1127	0.1857*
	(0.0853)	(0.0857)	(0.1132)
Long-run rainfall	-0.0002	0.0009	0.0007
	(0.0033)	(0.0034)	(0.0044)
Constant	0.1502	0.1461	-0.1194
	(0.1165)	(0.1174)	(0.1060)
Test for significance of variables on mortality in the rainy season			
Rainfall before birth			
F-stat	0.1397	0.3498	0.9868
Corresponding p-value	0.7086	0.5543	0.3206
Rainfall in first year			
F-stat	0.6336	1.1660	2.8402
Corresponding p-value	0.4261	0.2803	0.0920
Long-run rainfall			
F-stat	0.0067	1.0005	0.0253

Corresponding p-value	0.9349	0.3172	0.8737
Country dummies	x		
Region dummies		x	
Mother dummies			x
Observations	217293	217293	217293
R^2	0.0370	0.0388	0.3104

Note: This table reports linear probability model estimates for infant mortality (mortality before age one). The dependent variable is a dummy variable equal to one if the child died before reaching its first birthday. Control variables include male (dummy equal to one if child is male), a dummy for whether the child was born in a multiple birth, the birth order of the child, urban (dummy equal to one if place of residence is in an urban area), education (dummies equal to one if mother received either primary education or secondary education and above), and mother's age at birth. Sample is from 13 surveys from nine countries in West Africa. Birth year ranges from 1950 to 1999. Long-run rainfall is the 20-year average rainfall in the sample cluster and varies by month and year. Rainfall shock before birth is the deviation of average rainfall in the 12 months prior to birth from long-run rainfall. Rainfall shock in first year is the deviation of rainfall during the first year of life from the long-run average. Rainy is a dummy variable that takes on the value one if the child was born in the rainy season and varies by country and month. All regressions include year and month dummies. The urban dummy is dropped in columns (3) and (4) and mother's education is dropped in column (4). Standard errors are robust to heteroskedasticity and clustered at the sampling cluster level.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.6: Infant mortality results with nonlinearity

	(1)	(2)	(3)
Male	0.0145***	0.0146***	0.0134***
	(0.0015)	(0.0015)	(0.0020)
Multiple birth	0.2442***	0.2454***	0.2616***
	(0.0073)	(0.0073)	(0.0093)
Birth Order	0.0134***	0.0133***	0.0233***
	(0.0008)	(0.0007)	(0.0020)
Mother's age at birth	-0.0140***	-0.0139***	-0.0049
	(0.0011)	(0.0011)	(0.0031)
Mother's age at birth squared	0.0002***	0.0002***	0.0003***
	(0.0000)	(0.0000)	(0.0000)
Urban	-0.0310***	-0.0259***	
	(0.0022)	(0.0026)	
Primary education	-0.0140***	-0.0100***	
	(0.0026)	(0.0025)	
Secondary education or higher	-0.0219***	-0.0164***	
	(0.0033)	(0.0033)	
Rainfall shock before birth	-0.1073	-0.0606	0.0235
	(0.0778)	(0.0793)	(0.1045)
Rainfall shock in first year	-0.0724	-0.0337	-0.0436
	(0.0711)	(0.0717)	(0.0967)
Long-run rainfall	0.0002	0.0058	-0.0036
	(0.0045)	(0.0069)	(0.0296)
Rainy	0.0039	0.0024	0.0009
	(0.0037)	(0.0037)	(0.0049)
# months with excess rainfall before birth	0.0003	0.0005	-0.0012
	(0.0016)	(0.0016)	(0.0020)
# of flood months in dry season at age 1	-0.0005	-0.0003	-0.0002
	(0.0016)	(0.0016)	(0.0021)
# months with rainfall shortage before birth	-0.0021	-0.0007	0.0003
	(0.0014)	(0.0014)	(0.0018)
# of drought months in rainy season at age 1	-0.0009	0.0005	0.0004
	(0.0014)	(0.0014)	(0.0018)
Interaction with Rainy			
Rainfall shock before birth	0.1075	0.0839	0.0782
	(0.0916)	(0.0917)	(0.1211)
Rainfall shock in first year	0.1248	0.1119	0.1865*
	(0.0853)	(0.0858)	(0.1133)
Long-run rainfall	-0.0001	0.0009	0.0007
	(0.0033)	(0.0034)	(0.0044)
Constant	0.1512	0.1461	-0.1207
	(0.1165)	(0.1174)	(0.1060)
Test for significance of variables on mortality in the rainy season			

Rainfall before birth			
F-stat	0.1397	0.3498	0.9868
Corresponding p-value	0.7086	0.5543	0.3206
Rainfall in first year			
F-stat	0.5912	1.2417	2.5397
Corresponding p-value	0.4420	0.2652	0.1111
Long-run rainfall			
F-stat	0.0004	0.9557	0.0097
Corresponding p-value	0.9845	0.3283	0.9214
Country dummies	x		
Region dummies		x	
Mother dummies			x
Observations	217293	217293	217293
R^2	0.0371	0.0388	0.3104

Table 2.7: Breastfeeding

	(1)	(2)
Male	-0.1298*	-0.1277*
	(0.0665)	(0.0663)
Multiple birth	-1.4207***	-1.3796***
	(0.3271)	(0.3299)
Birth Order	-1.8533***	-1.8789***
	(0.1039)	(0.1032)
Mother's age at birth	0.1837***	0.1986***
	(0.0387)	(0.0386)
Mother's age at birth squared	-0.0029***	-0.0031***
	(0.0007)	(0.0007)
Urban	-0.6078***	-0.5512***
	(0.0961)	(0.1059)
Primary education	-0.6305***	-0.5153***
	(0.1028)	(0.1061)
Secondary education or higher	-1.0437***	-0.8355***
	(0.1339)	(0.1357)
Still breastfeeding	-3.6512***	-3.6375***
	(0.1432)	(0.1427)
Died while breastfeeding	-9.6772***	-9.6947***
	(0.1586)	(0.1609)
Rainfall shock before birth	1.4630	1.4199
	(3.5185)	(3.6820)
Rainfall shock in first year	-11.0923***	-11.1762***
	(3.7720)	(3.8478)
Rainfall shock in second year	-34.1548***	-35.3519***
	(3.7914)	(3.8383)
Long-run rainfall	-7.7195***	-10.5555***
	(2.2563)	(2.9872)
Rainy	0.7030***	0.5701***
	(0.1607)	(0.1583)
Interaction: Rainy		
Rainfall shock before birth	5.7832	5.4669
	(3.6932)	(3.7128)
Rainfall shock in first year	-0.5200	-0.5408
	(4.3340)	(4.3546)
Rainfall shock in second year	-10.1392**	-8.3804**
	(4.2024)	(4.1757)
Long-run rainfall	-9.5172***	-7.9672***
	(1.8349)	(1.7904)
Constant	23.6542***	25.1204***
	(0.7517)	(0.7662)
Country dummies	x	
Region dummies		x

Observations	49161	49161
R^2	0.3371	0.3447
Test for significance of variables on breastfeeding in the rainy season		
Rainfall shock before birth		
F-stat	4.54	3.75
Corresponding p-value	0.0332	0.0529
Rainfall shock in first year		
F-stat	11.63	10.82
Corresponding p-value	0.0007	0.0010
Rainfall shock in second year		
F-stat	138.93	129.25
Corresponding p-value	0.0000	0.0000
Long-run rainfall		
F-stat	81.78	47.59
Corresponding p-value	0.0000	0.0000

Note: This table reports ordinary least squares model estimates for the length of breastfeeding of the child. The dependent variable is the number of months the child was breastfed. Control variables include male (dummy equal to one if child is male), whether the child was born in a multiple birth, the birth order of the child, urban (dummy equal to one if place of residence is in an urban area), education (dummies equal to one if mother received either primary education or secondary education and above), and mother's age at birth. Sample is from 13 surveys from nine countries in West Africa. Birth year ranges from 1986 to 1999. Long-run rainfall is the 20-year average rainfall in the sample cluster and varies by month and year. Rainfall shock before birth is the deviation of average rainfall in the 12 months prior to birth from long-run rainfall. Rainfall shock in first year is the deviation of rainfall during the first year of life from the long-run average. Rainy is a dummy variable that takes on the value one if the child was born in the rainy season and varies by country and month. All regressions include year and month dummies. Standard errors are robust to heteroskedasticity and clustered at the sampling cluster level.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 2.8: Neonatal mortality

	(1)	(2)	(3)
Male	0.0132***	0.0132***	0.0140***
	(0.0011)	(0.0011)	(0.0015)
Multiple birth	0.1754***	0.1755***	0.1878***
	(0.0068)	(0.0067)	(0.0080)
Birth Order	0.0068***	0.0068***	0.0151***
	(0.0005)	(0.0005)	(0.0014)
Mother's age at birth	-0.0110***	-0.0110***	-0.0082***
	(0.0008)	(0.0008)	(0.0025)
Mother's age at birth squared	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)
Urban	-0.0114***	-0.0088***	
	(0.0015)	(0.0018)	
Primary education	-0.0061***	-0.0046**	
	(0.0018)	(0.0018)	
Secondary education or higher	-0.0115***	-0.0096***	
	(0.0023)	(0.0023)	
Rainfall shock before birth	-0.0721	-0.0475	-0.0590
	(0.0450)	(0.0458)	(0.0619)
Rainfall shock in first month	0.0607*	0.0668*	0.0349
	(0.0348)	(0.0348)	(0.0464)
Long-run rainfall	-0.0005	0.0047	-0.0218
	(0.0030)	(0.0044)	(0.0231)
Rainy	0.0012	0.0006	-0.0020
	(0.0026)	(0.0026)	(0.0032)
Interaction with Rainy			
Rainfall shock before birth	0.0380	0.0276	0.0614
	(0.0597)	(0.0600)	(0.0802)
Rainfall shock in first month	-0.0479	-0.0522	-0.0243
	(0.0373)	(0.0373)	(0.0488)
Long-run rainfall	0.0003	0.0008	0.0030
	(0.0023)	(0.0023)	(0.0029)
Constant	0.1686	0.1696	0.0641
	(0.1151)	(0.1159)	(0.0923)
Test for significance of variables on neonatal mortality in the rainy season			
Rainfall before birth			
F-stat	0.5905	0.1929	0.0017
Corresponding p-value	0.4423	0.6605	0.9670
Rainfall in first month			
F-stat	1.3573	1.7514	0.5172
Corresponding p-value	0.2441	0.1858	0.4721
Long-run rainfall			
F-stat	0.0037	1.5618	0.6642

Corresponding p-value	0.9512	0.2115	0.4152
Country dummies	x		
Region dummies		x	
Mother dummies			x
Observations	232170	232170	232170
R^2	0.0303	0.0312	0.3120

Table 2.9: Fertility by urban–rural with mother fixed effects

	(1) Urban	(2) Rural
Mother's age at birth	0.0026***	0.0023***
	(0.0003)	(0.0003)
Mother's age at birth squared	-0.0001***	-0.0001***
	(0.0000)	(0.0000)
Rainfall shock before conception	0.0011	0.0046
	(0.0074)	(0.0064)
Rainfall shock in pregnancy	-0.0054	0.0065
	(0.0058)	(0.0045)
Long-run mean rainfall before conception	0.0543***	0.0846***
	(0.0083)	(0.0063)
Long-run mean rainfall in pregnancy	-0.0180	-0.0411***
	(0.0218)	(0.0144)
Rainy	0.0019***	0.0011**
	(0.0006)	(0.0005)
Interaction with Rainy		
Rainfall shock before conception	-0.0076	-0.0077
	(0.0078)	(0.0069)
Rainfall shock in pregnancy	0.0020	-0.0055
	(0.0084)	(0.0072)
Long-run rainfall before conception	-0.0567***	-0.0869***
	(0.0060)	(0.0048)
Long-run rainfall in pregnancy	0.0108**	0.0226***
	(0.0047)	(0.0042)
Constant	-0.0592***	-0.0479***
	(0.0049)	(0.0035)
Test for significance of variables on births in the rainy season		
Rainfall before conception		
F-stat	6.22	1.61
Corresponding p-value	0.0128	0.2052
Rainfall in pregnancy		
F-stat	0.28	0.03
Corresponding p-value	0.5953	0.8587
Long-run rainfall before conception		
F-stat	0.10	0.22
Corresponding p-value	0.75337	0.6385
Long-run rainfall in pregnancy		
F-stat	0.11	1.62
Corresponding p-value	0.7428	0.2029
Observations	2776272	6065859
R^2	0.0068	0.0056

Table 2.10: Infant mortality by urban–rural with mother fixed effects

	(1) Urban	(2) Rural
Male	0.0133***	0.0134***
	(0.0035)	(0.0023)
Multiple birth	0.2305***	0.2685***
	(0.0178)	(0.0106)
Birth Order	0.0207***	0.0237***
	(0.0032)	(0.0023)
Mother's age at birth	-0.0055*	-0.0049
	(0.0032)	(0.0038)
Mother's age at birth squared	0.0003***	0.0003***
	(0.0000)	(0.0000)
Rainfall shock before birth	0.1912	-0.0470
	(0.1752)	(0.1114)
Rainfall shock in first year	-0.0145	-0.0593
	(0.1711)	(0.1020)
Long-run rainfall	-0.0146	0.0047
	(0.0480)	(0.0354)
Rainy	0.0014	0.0008
	(0.0089)	(0.0057)
Interaction with Rainy		
Rainfall shock before birth	-0.0568	0.1158
	(0.1970)	(0.1452)
Rainfall shock in first year	0.0390	0.2261*
	(0.1970)	(0.1339)
Long-run rainfall	-0.0021	0.0013
	(0.0075)	(0.0052)
Constant	-0.0949	-0.1287
	(0.0983)	(0.1310)
Test for significance of variables on mortality in the rainy season		
Rainfall before birth		
F-stat	0.9907	0.4940
Corresponding p-value	0.3197	0.4822
Rainfall in first year		
F-stat	0.0359	3.0547
Corresponding p-value	0.8498	0.0807
Long-run rainfall		
F-stat	0.1233	0.0295
Corresponding p-value	0.7255	0.8637
Observations	60416	156877
R^2	0.3353	0.3035

Table 2.11: Breastfeeding by urban–rural

	(1) Urban	(2) Urban	(3) Rural	(4) Rural
Male	-0.1558	-0.1459	-0.1204	-0.1153
	(0.1221)	(0.1198)	(0.0773)	(0.0773)
Multiple birth	-0.5352	-0.4860	-1.7001***	-1.6865***
	(0.4678)	(0.4663)	(0.3883)	(0.3904)
Birth Order	-1.4554***	-1.5206***	-1.9618***	-1.9648***
	(0.1773)	(0.1767)	(0.1227)	(0.1221)
Mother's age at birth	0.1808***	0.2072***	0.1925***	0.2036***
	(0.0668)	(0.0657)	(0.0447)	(0.0446)
Mother's age at birth squared	-0.0028**	-0.0032***	-0.0030***	-0.0032***
	(0.0012)	(0.0012)	(0.0008)	(0.0008)
Primary education	-0.9752***	-0.7923***	-0.5053***	-0.4150***
	(0.1512)	(0.1510)	(0.1324)	(0.1379)
Secondary education or higher	-1.6711***	-1.3625***	-0.2684	-0.0833
	(0.1688)	(0.1724)	(0.2136)	(0.2163)
Still breastfeeding	-4.5364***	-4.5617***	-3.3226***	-3.2910***
	(0.1858)	(0.1863)	(0.1841)	(0.1827)
Died while breastfeeding	-9.6250***	-9.7105***	-9.5943***	-9.5870***
	(0.3081)	(0.3072)	(0.1801)	(0.1826)
Rainfall shock before birth	1.0973	3.8473	2.8905	2.5454
	(5.6740)	(5.9890)	(4.1906)	(4.3591)
Rainfall shock in first year	-7.6245	-6.7117	-12.2300***	-12.2225***
	(6.0057)	(6.0913)	(4.5167)	(4.5777)
Rainfall shock in second year	-22.8753***	-20.5897***	-37.7421***	-40.1386***
	(5.4024)	(5.3928)	(4.5530)	(4.6184)
Long-run rainfall	-1.5222	-2.3587	-9.0577***	-13.0345***
	(4.0671)	(5.3582)	(2.6576)	(3.4080)
Rainy	1.3003***	1.2594***	0.5734***	0.4107**
	(0.2678)	(0.2685)	(0.1873)	(0.1841)
Interaction: Rainy				
Rainfall shock before birth	2.0624	0.3793	9.4954**	8.5722*
	(6.5244)	(6.4250)	(4.3692)	(4.4011)
Rainfall shock in first year	-13.4866*	-12.8076*	2.6124	2.0075
	(7.3265)	(7.2430)	(5.1867)	(5.2062)
Rainfall shock in second year	-12.1393**	-10.2075*	-10.2766**	-8.5823*
	(6.0374)	(5.9889)	(5.1377)	(5.1209)
Long-run rainfall	-11.7794***	-11.0232***	-9.2975***	-7.4075***
	(2.8664)	(2.8661)	(2.2015)	(2.1339)
Constant	19.8516***	20.6923***	24.2904***	26.0318***
	(1.2084)	(1.1508)	(0.8852)	(0.9091)
Observations	14765	14765	34396	34396
R^2	0.3160	0.3273	0.3502	0.3580

Test for significance of variables

on breastfeeding in the rainy season				
Rainfall before birth				
F-stat	0.32	0.54	9.15	6.84
Corresponding p-value	0.5689	0.4608	0.0025	0.0090
Rainfall in first year				
F-stat	17.08	14.09	5.25	5.52
Corresponding p-value	0.0000	0.0002	0.0221	0.0189
Rainfall in second year				
F-stat	54.29	39.36	103.14	101.91
Corresponding p-value	0.0000	0.0000	0.0000	0.0000
Long-run rainfall				
F-stat	15.25	7.26	68.38	47.20
Corresponding p-value	0.0001	0.0071	0.0000	0.0000
Country dummies	x		x	
Region dummies		x	x	

Table 2.12: Complete list of surveys

Country	Year of survey	Number of observations
Benin	1996	15,050
Burkina Faso	1992	16,376
	1998	17,990
Côte d'Ivoire	1994	16,786
	1998	7,055
Ghana	1993	9,214
	1998	9,799
Guinea	1999	22,138
Mali	1995	32,125
Niger	1992	19,142
	1998	23,586
Nigeria	1990	24,614
Togo	1998	19,078
Total		217,303

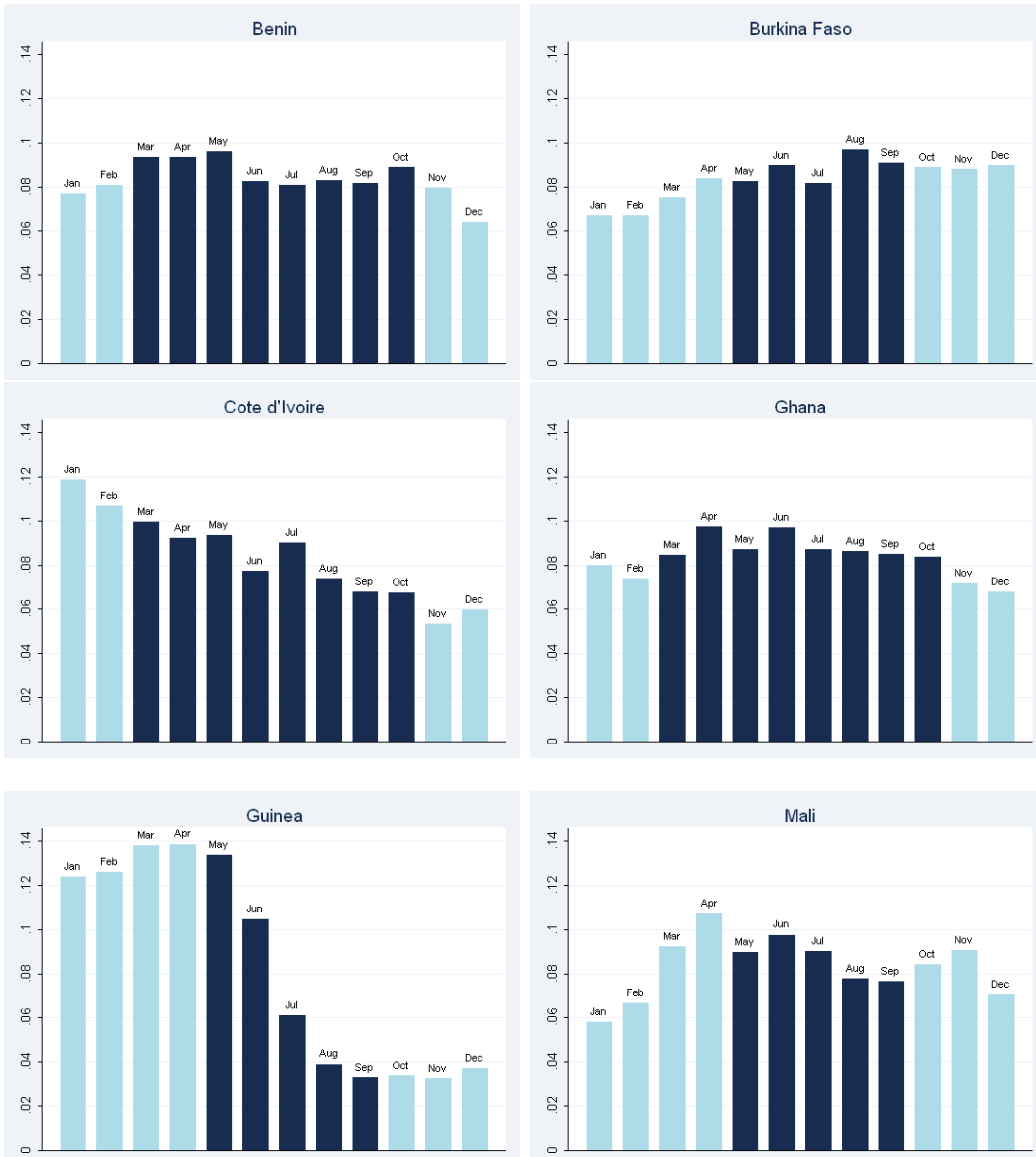
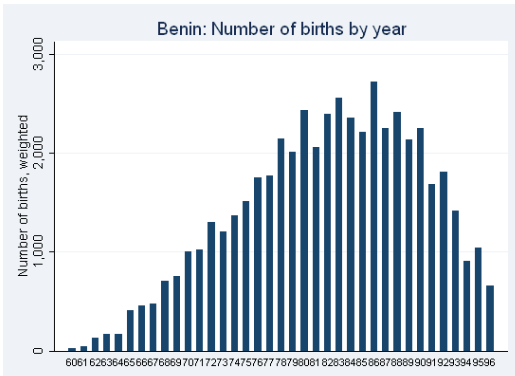
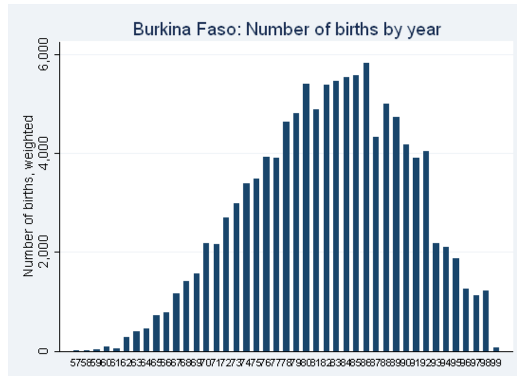
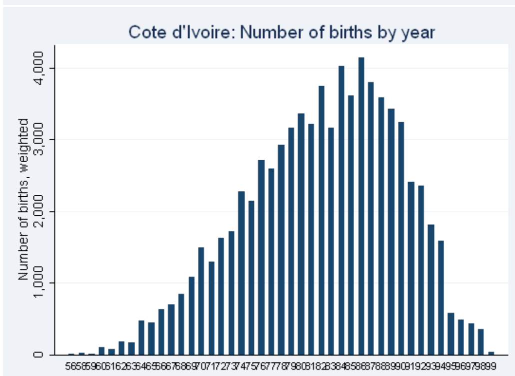
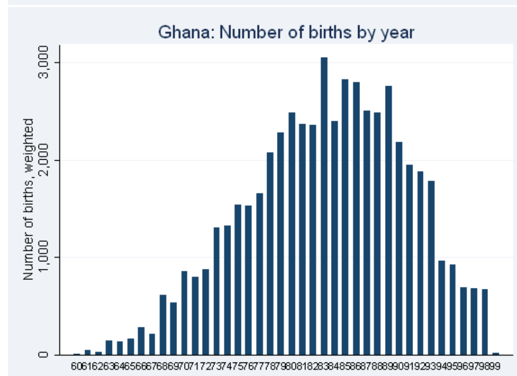

Benin
Burkina Faso
Cote d'Ivoire
Ghana
Guinea
Mali
0
.02
.04
.06
.08
.1
.12
.14
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

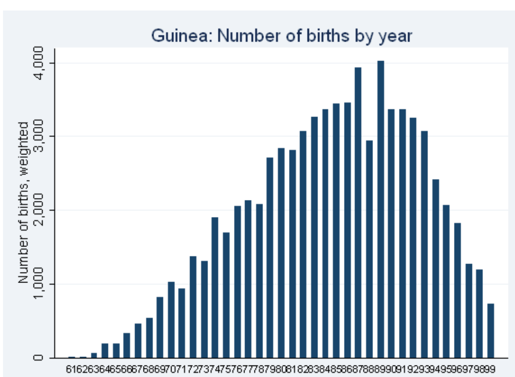
Figure 2.1: Fraction of births by birth month, by country
Dark-colored bars correspond to rainy season months and light-colored bars to dry season months.

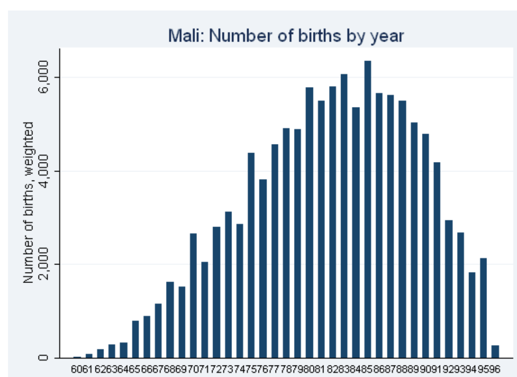

Benin: Number of births by year
Number of births, weighted
0
1,000
2,000
3,000


Burkina Faso: Number of births by year
Number of births, weighted
0
2,000
4,000
6,000


Cote d'Ivoire: Number of births by year
Number of births, weighted
0
1,000
2,000
3,000
4,000


Ghana: Number of births by year
Number of births, weighted
0
1,000
2,000
3,000


Guinea: Number of births by year
Number of births, weighted
0
1,000
2,000
3,000
4,000


Mali: Number of births by year
Number of births, weighted
0
2,000
4,000
6,000

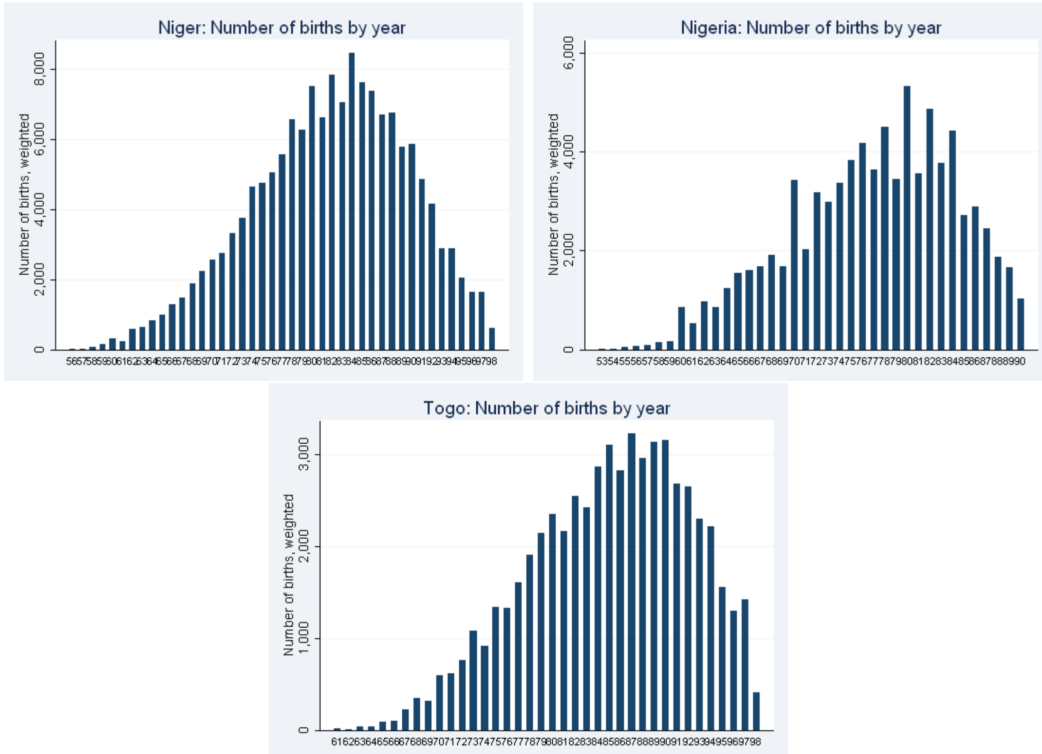


Figure 2.2: Distribution of births by birth year, by country

Chapter 3

Health Shocks and Production Decisions of Agricultural Households

3.1 Introduction

There is an extensive literature linking health and work productivity, and thus a farmer's capacity to work (e.g., Strauss (1986)). However, as long as markets are competitive, it can be shown that farm profits should not be impacted by supply factors to the agricultural household, such as health shocks. Tests of this so-called separation hypothesis have generally found support for it (see Lopez (1984) and Benjamin (1992) for example). This chapter examines whether health shocks generated by malaria infections affect the production decisions of agricultural households.

Pitt and Rosenzweig (1986) extend the traditional consumer-cum-producer agricultural household model to incorporate an explicit health production function (as developed by Grossman (1972)). Their model essentially shows that with well-functioning input and output markets, farm profits and the health of the farmer are independent of each other. Using data from Indonesia, they test whether illness episodes affect farm profits and male labor supply. They find that while the labor supply of males is reduced as a result of an illness, profits are not, which most likely suggests that households were able to substitute family labor with hired labor, confirming the separation between production and health.

Malaria is a disease that is recurring and thus anticipation of the disease may involve adjustments in production decisions by the households affected. I explore the adjustment of households in response to malaria along two different margins: First, whether households adjust their labor input, and second, whether households choose to grow a less labor-intensive crop mix in anticipation of the disease.

The analysis in this chapter is complicated by the fact that the estimates may be biased for several reasons. First, malaria incidence could be correlated with unobservable factors, such as household-specific managerial abilities, that are omitted from the regression but also affect the outcomes of interest. Second, the measure of malaria being used may not be a good proxy for the true incidence of malaria, in which case, measurement error would lead to an attenuation bias. Finally, there is the possibility of reverse causality: agriculture and health are linked in a way that causality might go in both directions. Agriculture is essential for the production of health through the production of food, whereas bad health might reduce labor productivity, which would further reduce income and result in further ill health (Hawkes and Ruel (2006)). This last issue in particular is not present in some recent studies that look at economic outcomes later in life, such as completed schooling or earnings as an adult (as for example, Cutler et al. (2007) or Bleakley (2010)). While the use of household fixed effects regressions in some of the specifications may deal with the issue of household-level unobservables, it does not address the other issues mentioned above, which call for the use of an instrumental variable. Moreover, the attenuation bias due to measurement error is magnified with the use of fixed effects. An ideal instrument in this case would be one that is a strong determinant of malaria transmission (or in other words, that would result in a strong first stage regression) and not be a direct determinant of the outcomes of interest, i.e., profits or labor use. While the first condition is easier to satisfy, it proved to be very difficult to find one that satisfies the second condition as well.

The first candidate for an instrument for malaria incidence would be environmental factors that govern the intensity of malaria transmission, i.e., rainfall, temperature, humidity and altitude. Peak malaria transmission occurs during the wet season because of its direct relationship with rainfall, which raises relative humidity and promotes breeding activity of mosquitoes by increasing the breeding surface. While rainfall is critical, excessive rainfall may interrupt transmission as the breeding grounds might be flushed away. The parasite develops best and transmission is highest when mean temperature is between 20°C and 30°C. Low relative humidity shortens the life of the mosquito and high relative humidity enhances mosquito activity (Pampana (1963)). Finally, mosquitoes are inactive at altitudes 1500 meters and above. In Vietnam, most of the rice is grown in lowlands, while some fruit crops are grown above certain altitudes (Food and Agriculture Organization (1999b)). Due to their direct relationship with malaria transmission, different combinations of these factors have been used as instruments to look at how early-life exposure to malaria affects education and wealth later in life (Barreca (2010), Cutler et al. (2007) and Hong (2007)). Temperature is not used as an instrument since Vietnam is geographically located in a tropical region close to the equator and there is comparably little interannual variation in temperature. Thus transmission is mainly influenced by rainfall.[1]

Regardless of their impact on malaria transmission, these variables cannot be used as instruments in this analysis. The outcomes of interest are agricultural outcomes, which are directly affected by all of these factors. Altitude is not a valid instrument since it determines land cover and other geographical features (Hong (2007)) and may therefore influence which crops are grown in the high- and lowlands. The exclusion restriction in the second stage of the instrumental variables regression is not satisfied since these environmental factors strongly impact crop growth and therefore, profits.

Another candidate, for which data is available, is province-specific expenditure on antimalarial drugs. These drugs were dispensed through the National Malaria Control Program over the same period as the surveys, as part of a nationwide effort to control malaria. It is indeed the case that the central government allocated

[1] Therefore, exploiting differences in ideal temperatures for malaria transmission and agriculture is not an option (see Barreca (2010) who developed this approach).

more budget to provinces that had a higher prevalence of malaria (resulting in a strong first-stage regression); however, program expenses are likely correlated with the error term in the second stage, to the extent that government expenditures on antimalarial drugs are correlated with other government expenditures.[2]

Acknowledging the difficulties of finding a suitable instrument that would alleviate potential endogeneity concerns of the malaria illness variable, I alternatively exploit the panel nature of the survey by using a fixed-effects estimation approach. I first look at which characteristics are associated with having at least one individual in the household reporting to have had a malaria episode. While certain household and farm characteristics are significant determinants of malaria incidence, the relationship largely disappears as household fixed effects are added, suggesting that the endogeneity of malaria illness is less of concern once these time-invariant unobservables are accounted for. I subsequently look at the relationship between malaria incidence of household members and agricultural profits. I find a negative and statistically significant relationship between the household's profits and the likelihood that any household member experienced a malaria infection in the four weeks leading up to the household survey. While I am cautious in claiming that the effect is causal, there is reason to believe that at least some of the effect might be, since malaria infections would significantly impede the productivity of affected household members.

To explain why profits might have gone down, I next look at whether total agricultural labor input is affected. The effect of the likelihood of illness incidence on the number of total person-days employed in the household's agricultural activities is examined, where total labor input is the sum of all person-days worked by household members, plus the total days of exchanged labor and hired labor. Surprisingly, total

[2] If the only bias associated with the malaria incidence variable was classical measurement error, then household-level, reported malaria incidence could be instrumented using these official malaria statistics. This is not the only issue however.

days of labor does not seem to be affected even though profits are reduced. One explanation could be that while farmers still go to the field regardless of their illness and work when ill, they may not be able to work the same number of hours or work as efficiently as when they are not. It is also possible that since the value of time that household members work on farms is not explicitly accounted for in calculating profits, that profits might be going down because households substitute hired labor for their own labor. As will be discussed in more detail later, none of this appears to be the case. When looking at hours worked by household members instead of days worked, the results are qualitatively similar in that hours worked do not respond to malaria episodes of household members. Moreover, disaggregating labor days into household- and non-household labor does not make a difference either.

Yet another potential explanation could be that, if malaria transmission is seasonal, farmers may come to expect productivity losses during certain periods of the year and grow a different mix of crops in anticipation of the disease. Some crops, notably rice and cash crops, are highly labor-intensive and need to be planted, tended to and harvested at certain times of the year. Delays in the process may harm the quality of the crop or result in crop loss. These are however also crops that generate on average higher returns. On the other hand, crops such as cassava, corn and sweet potatoes demand less labor input, are less sensitive to the timing of harvest, but are also of low-return. I exploit these differences across crops to look at whether variations in the likelihood of illness is related to the crop choice of households.[3] More specifically, I group the crops into highly labor-intensive, high-return crops and less labor-intensive, low-return crops. Detailed information on agricultural activities of households allows me to construct the share of land allocated to each type of crops at the household level. I find that the share of land devoted to rice and annual crops is smaller for households whose province

[3]Laxminarayan and Moeltner (2003) investigate whether malaria illness affects crop yields. Fisher and Datta (2007) examine whether malaria affects how land is allocated to different crops.

experienced a greater prevalence of malaria illness in the past. This adjustment in crop choice could have led to the decrease in profits. While not a direct cost of malaria, these are indirect consequences of the disease that need to incorporated into the calculation of the burden of the disease.

The remainder of this chapter proceeds as follows. Section 3.2 briefly summarized related literature. Section 3.3 explains some background on malaria in Vietnam. Section 3.4 explains the empirical strategy. Section 3.5 describes the data sources. Section 3.6 presents the results and section 3.7 concludes.

3.2 Literature Review

The notion that health may affect the productivity of farmers is not new. Basta et al. (1979) implemented an iron and food supplementation treatment to a group of plantation workers in Indonesia where anemia rates were high, to examine the effect of the treatment on labor productivity. They find that workers' physical performance was improved, as measured by work output, physical capacity and morbidity. Antle and Pingali (1994) find that pesticide use has a negative impact on farmer health and that farmer health is positively related to productivity in two rice-growing regions in the Philippines. This stream of literature has found consistent evidence that better health status improves physical capacity and therefore improves labor productivity.

Some papers in this literature measure nutritional status by anthropometric indicators such as height, weight, or body mass index (BMI). For example, Schultz (2002)) estimates the effect of height on hourly wages using local food prices and parental education as instrumental variables. His estimates suggests that a one centimeter increase in height results in an eight to ten percent increase in wages in Ghana and Brazil. A handful of these studies specifically focus on how diseases may affect farmers' health and their labor productivity. Baldwin and Weisbrod (1974) and Weisbrod and Helminiak (1977) examine the impact of parasitic disease on labor labor productivity but do not find a strong link to earnings. Kim et al. (1997), using data from coffee plantation workers in Ethiopia, find that onchocerciasis (a skin disease) reduces daily earnings of permanent workers by 10 to 15 percent.

The stream of literature that examines the relationship between health and wages, income, and profits finds more mixed results, which could be because the majority of studies are not able to perfectly account for the endogeneity of health or missing variables owing to data limitation. Deolalikar (1988) finds that wages are affected by long-run nutritional status as measured by weight-for-height, but not by short-run caloric intake, concluding that the human body cannot compensate for chronic malnutrition. Sahn and Alderman (1988) find that calories affect the wage offer since better nutrition boosts labor productivity. Strauss (1986) uses local food prices as an instrument and finds that higher caloric intake raises family farm labor productivity. Behrman et al. (1997) find that planting-stage calorie consumption has productivity effects that are realized in the harvest stage. All of the aforementioned papers measure nutritional status by caloric consumption. Liu et al. (2008) use self-reported health status and find a positive association with income, with returns to health larger in rural areas where work is more likely to be manual.

While many studies are not able to address the issue of heterogeneity in health and unobservable characteristics, some notable exceptions are Schultz and Tansel (1997) who use instrumental variables to estimate how sickness affects the wages of individuals and find that disability days reduce daily wages and hours. Pitt and Rosenzweig (1986) also use health program variables to instrument for illness and find that while there is a reduction in labor supply, profits are unaffected.

The main contribution of this chapter is that I explore the effects on agricultural outcomes of a disease which is endemic and recurs over time in a community. While I am not able to overcome the methodological issues using an instrumental variable, I instead exploit the panel nature of the survey to estimate a household-fixed effects model. The analysis by Audibert and Etard (2003) is similar in that they test the link between health and agricultural productivity and labor input. They find no effect on either profits or labor use and suggest that the absence of an effect of improvement in health on hired labor could be because the additional time available might be spent on leisure or the cultivation of crops other than rice, the main cash crop.[4]

This chapter is also related to the literature that studies the economic burden of malaria. Malaria, along with other tropical diseases, has been documented as a factor constraining economic development (Conley (1972), Gallup and Sachs (2001)). At the micro-level, researchers have attempted to gauge the economic burden of malaria, by estimating the number of workdays or wages lost due to malaria infections (see for example, Leighton and Foster (1994), Cropper et al. (1999), Chima et al. (2003)). More recently, researchers have looked at broader and long-run implications of the disease. Hong (2007) finds that malarial risk leads to adverse long run health outcomes, lower labor force participation, and lower wealth. Barecca (2009) finds that in utero and postnatal malaria exposure leads to lower educational attainment. Bleakley (2010) studies the effect of malaria eradication campaigns on the income and education of native males in the United States, Brazil, Colombia, and Mexico. Using malaria mortality rates and an ecology index to identify pre-eradication disease prevalence, he finds that childhood exposure to malaria lowers labor productivity and leads to lower adult income. Cutler et al. (2007) use geographic variation in malaria prevalence in India prior to a nationwide eradication program in the 1950s to study the effect of malaria on educational attainment and income. They find a positive effect of the program on the income of men only, which they attribute to differences between men and women in their improvements

[4] Audibert et al. (2009) do not find an effect of malaria prevalence on yields or the use of family labor. On the other hand, Audibert et al. (2003) find that malaria had a large impact on cotton production in Côte d'Ivoire, which could be because cotton is a labor intensive crop.

in labor market productivity. I extend this literature by showing that there could be further economic costs to the disease if households possibly adapt to the disease environment by adjusting their production decisions ex-ante, thereby hurting their profits.

3.3 Background on Malaria in Vietnam

Vivax malaria is the prevalent malaria strain in Vietnam. Although it is the more benign type of malaria and has a low fatality rate, it is accompanied by potentially severe symptoms.[5] These include recurring fever, chills, severe headache, vomiting, and thirst, followed by a sweating stage, after which the symptoms subside. These symptoms would leave the farmer bedridden for days, hurting his productivity and possibly profits (see Chima et al. (2003) for a review on Africa and Morel et al. (2008) for a study in Vietnam).[6] Even after individuals resume work, their productivity may not immediately revert to pre-infection levels, especially for those working in labor-intensive occupations (Hong (2007)). These attacks recur until the infection is treated. Unlike many other diseases, immunity to malaria does not last for a lifetime. Acquired immunity may develop and get stronger as the infection proceeds, but even adults in hyperendemic areas do not develop full immunity to the disease.

Malaria transmission in Vietnam is highly seasonal. Transmission peaks during and after the wet season (from April through November), which coincides with the period of high labor demand (Nam et al. (2005)). The first malaria eradication effort in Vietnam was started in 1958 and continued for two decades. There was a dramatic reduction in malaria morbidity and mortality that was sustained until

[5] The prevalent malaria strain in Africa that carries a high fatality rate is *Falciparum* malaria.

[6] In the data used in this chapter, the average length of an episode is reported at approximately 7.5 days, out of which 6.3 days individuals reported to have been unable to carry on their usual activities.

the early 1980s. However, the situation reversed due to increasing lack of resources, post-war migration and insufficient health infrastructure. The number of malaria cases peaked in 1991, with more than 1.6 million cases and nearly five thousand deaths resulting from about 150 outbreaks (Ettling (2002), Hung et al. (2002)).

In 1991, the central government made malaria a top health priority. A national malaria control program was begun, which provided clear control guidelines for intervention strategies based on the level of endemicity. The program focused on prevention, early diagnosis, and efficient treatment. Primary health Care (PHC) networks were extended, and surveillance and response to outbreaks was strengthened. Insecticide-treated bednets and antimalarial drugs were distributed and extensive indoor residual spraying was carried out. A stronger economy facilitated access to treatment options and contributed to an increase in the government's health budget. This concerted effort resulted in a 92% reduction in the number of epidemic outbreaks per year, near elimination of malaria fatalities and a large decline in the number of cases over the following 5-6 years. However, Vietnam has not succeeded in eliminating malaria until today and downward trends in number of cases started to reverse in the late 1990s.

3.4 Empirical Strategy

I estimate the impact of malaria on farm profits using data from the 1992/93 and 1997/98 Living Standard Measurement Surveys. In the health section of the survey, each household member is asked about any illness episodes in the four weeks prior to the survey. I construct an illness shock variable that measures the number of self-reported malaria cases in the household and divide it by household size.[7]

[7] One might argue that the effect on profits might depend on who in the household experiences malaria. In other words, the effect on profits might differ whether an adult, child or elderly person had malaria. To explore this, I replace the original variable, which measures the share of household members who experienced a malaria illness, with the same variable but measured by demographic group: i.e., I include in the regression the share of adults, elderly and children in the household

Unfortunately, the survey underwent a considerable change in the format of the questionnaires between the two waves. In the 1997/98 wave, instead of asking for the specific diseases experienced, households were asked which symptoms they had experienced in the prior four weeks. In the second wave of the survey, I use any responses that were coded as "fever" to proxy for malaria illness. Fever is one of the main symptoms of malaria, but could be an indication of an illness other than malaria (e.g., dengue fever). This variable therefore suffers from measurement error. I also define a narrower proxy for malaria, which is a combination of headache, fever, vomiting and cough. The results are qualitatively the same when this definition of malaria is used but are shown as an alternative nevertheless.

To study the impact of malaria on agricultural profits and labor use, the following equation is estimated:

$$Y_i = \alpha + \beta X_i + \gamma A_i + \delta Malaria_i + \lambda Landtitle_i + Year_i + Province_i + \epsilon_i \quad (3.1)$$

where the subscript i notates the household. Y_i is either the logarithm of profits or the logarithm of the total number of person-days used by each household. Total labor use of the household is constructed as the sum of any household labor employed in the last 12 months, plus unpaid or exchanged labor, and hired labor. X_i includes household composition variables (share of adult females, elderly people and children,[8] logarithm of household size, age, sex and education of household head) and A_i initially includes the logarithm of total land area cultivated by the household and the number of pieces of farming equipment (such as a tractor or insecticide pumps) owned by the household.[9] $LandTitle_i$ measures the number of land use certificates

who experienced malaria in the prior four weeks. These variables are set to zero if there are zero members of the corresponding demographic group in the household. Results appear strongest for children. The negative relationship between profits and malaria illness of adults is present in the baseline model but disappears with the inclusion of additional variables and fixed effects.

[8]Share of adult males is the omitted category.

[9]Farming equipment for livestock food processing and aquaculture are excluded.

distributed in the province by 1998, divided by the total number of households. $Year_i$ and $Province_i$ control for year- and province-specific trends, respectively, and ϵ_i is the idiosyncratic error term. To the baseline regression, I subsequently add whether the household has access to irrigation by looking at whether it cultivated any irrigated land, and variables indicating the share of land of good and medium quality (with share of land of bad quality being the omitted category). Province- and year- fixed effects are then replaced by Province x Year fixed effects, to see whether the results are robust to time-varying, province-specific unobservables.

I consider only households that report to be "farm" households, which reduces the sample to a little less than two thirds of the original sample. The relationship between profits and the likelihood of a malaria infection of any household member is examined first. Profits are calculated as the sum of crop revenue from food crops (including rice, corn and sweet potatoes), other annual crops (e.g., soy beans, peanuts, sesame), perennial crops (e.g., tea, coffee, rubber) and fruit crops (e.g., oranges, pineapples, mangoes) minus any expenses. Revenue from crop byproducts are also included, as well as revenue from agricultural sideline activities such as livestock, agro-forestry, and aquaculture. Expenses from the purchase of seeds, fertilizers, insecticides, transport, storage and hired labor are deducted from total revenue. The value of any output that was given to laborers or landlords and any payments for use of land are also excluded. These payments include cash or in-kind payments on allocated, auctioned or rented-in annual land. If payment was for land use over multiple years, the amount was rescaled to reflect annual payments. Finally, profits are adjusted for inflation between the years using an overall price index.[10]

[10] As a caveat, "priced" own labor is not accounted for in the measure of profits. Therefore, the impact of malaria on profits, when they do not include the cost of the household's own labor, would be expected to be automatically negative as the farm would replace the labor of their own (which costs nothing) with that of outside workers (which would be subtracted from the profits). Attempts to subtract the value of the time each household member works on the farm proved to be difficult as these attempts led profits to be negative for a large fraction of households in the data.

The resulting measure of profits has some extreme outliers, which is likely due to the many pieces of information that were put together (also reported in McCaig et al. (2009)). In order for those outliers to not bias my estimates, observations in the extreme 1% of each tail are dropped from the sample used in the regressions. In the labor use model, observations are dropped if the household reported zero days of total labor input.

I am interested in whether the impact of malaria on profits could possibly be explained by its impact on crop choice. Rice is by far the most important crop in Vietnam, most of which is planted on irrigated lowland. Other major crops include corn, sweet potato, cassava, legume, soybean, peanut, sugar cane, coffee and black pepper. The planting and harvesting of rice and other cash crops is extremely labor intensive. Moreover, those activities need to be carried out in a timely manner. Despite advances in modern technology, many tasks are still performed manually. On the other hand, some food crops such as corn, sweet potato and cassava are less labor intensive in general, but they also yield lower profits.[11].

My hypothesis is that households, based on past illness experiences, may anticipate malaria and choose to grow a less labor-intensive crop mix in an effort to minimize loss in profits. Since those crops also tend to be less profitable in general, this would reduce farm profits. The following equation is estimated to test this hypothesis:

$$\begin{aligned} Land\_high_{i,98} = \alpha + \beta X_{i,98} + \gamma A_{i,98} + \delta_1 Malaria_{i,92} + \delta_2 Malaria_{p,92} \\ + \lambda Landtitle_{p,98} + Year_{i,98} + Province_{i,98} + \epsilon_i \end{aligned} \tag{3.2}$$

where i denotes the household and p the province of residence. The dependent

[11]There are three main cropping seasons in Vietnam: The main season, with planting occurring from May to August and harvesting from September to December, the winter-spring season and the summer-autumn season.[12] The wet season occurs from April to November. Temperatures are higher year-round in central and southern Vietnam, and more temperate in the North (Food and Agriculture Organization (1999a)

variable $Land\_high_{i,98}$ is the share of land allocated to high-return, highly labor intensive crops by household i. All regressors are measured in 1998, except for $Malaria_{i,92}$, which measures the number of malaria episodes in the household in 1992, weighted by household size.[13] Since the disease is endemic at the community level, I use province-level malaria prevalence data to proxy for the intensity of the disease that households may expect to experience on average. This is measured by $Malaria_{p,92}$. Thus I look at how malaria illness in the household and at the province-level in 1992 affects the household's own crop choice decisions 5-6 years later, conditional on other household characteristics which might also influence how agricultural land is allocated to crops of different labor intensity.

While the specification to be estimated is very similar to equation 3.1, there are a few differences. First, I use only the sample of households that was surveyed in both years, to look at whether their own or province-level past malaria illness affects subsequent crop choice of the household. Of the 4800 households originally interviewed in 1992/93, 495 households were not reinterviewed either because they were not available or because they refused to be surveyed. These households were replaced with a randomly selected household in the same village.[14] The households that were interviewed again for the second wave of the survey were either still living in the same residence or they moved to a different residence within the same village. Second, since the outcome is measured as "share of land", perennial and fruit crops are excluded since many households report how much perennial and fruit crops they grew in number of trees instead of land area cultivated, which would have created an aggregation issue.

There are two reasons why I look at later (instead of contemporaneous) crop

[13]The correlation between malaria illness in 1992 and 1998 is rather low, indicating that malaria incidence does not necessarily repeat itself in the same household and providing another argument against the endogeneity of the disease.

[14]The households that dropped out of the sample from 1992 were on average smaller in size, cultivated less land, and the household head was younger, less likely to be male and more likely to have received formal education.

choice. One reason is that information on malaria illness is available only for the same year as the household reports its agricultural activities, creating a timing issue: planting decisions have already been made by the time households experience malaria. Another is that households may not change their crop mix from one year to another: in other words, crop choice might be "sticky" and it may take time to adjust production decisions. This is confirmed by the fact that the share of land allocated to high-return, highly labor intensive crops changes little between the two waves.[15]

3.5 Data Sources

3.5.1 Vietnam Living Standard Measurement Survey (LSMS)

The household surveys used in this study are the Vietnam Living Standard Measurement Surveys (VLSS) from 1992/93 and 1997/98. Data collection was funded by the UNDP and the Swedish International Development Authority (SIDA), and implemented with technical assistance from the World Bank as part of the Living Standard Measurement Study (LSMS) Household Surveys. Each survey consisted of three parts: a household survey, price survey and community survey. The household survey contains information on the demographic characteristics of all household members, as well as information on education, health, migration, housing, fertility, and most importantly, agricultural activities. The price survey includes observed prices of important food and non-food commodities. The commune questionnaires were administered in rural areas only and contain information on demographics, education and health infrastructure, and main employment activities. Sample selection was based on the 1989 Census. There were 4800 households originally sampled in 1992-93 and 6002 households in 1997-98, representing 7 regions,53 provinces (61

[15]The mean change in the share of land devoted to high-return, highly labor intensive crops is just over 3%.

provinces in 1998, after a reorganization of provinces) and 150 communes, of which 80% were rural.[16] Households were interviewed from October 1992 to October 1993 in the first wave, and from December 1997 to December 1998 in the second. Approximately 4300 of the households surveyed in 1992 were reinterviewed in 1998, allowing the data set to be used as a panel. The final sample includes households from 51 provinces: 2 provinces, Kon Tum and Lai Chau, did not have any households who grew crops in either of the years of the survey.

3.5.2 Economic Reform and Land Title Data

Vietnam went through a series of structural economic reforms (called "Doi Moi") starting around 1986. These reforms were aimed at transforming the economy from a centrally planned to a market-oriented system and encompassed liberalization of product and input markets, agricultural diversification, assignment of individual land rights and trade liberalization (Benjamin and Brandt (2002)), Kirk and Tuan (2009)). These economic reforms continued during the period 1992-1998. Trade restrictions on rice and fertilizers were relaxed in 1996 and the rice export quota was increased, which led to a significant increase in the price of rice. While land was officially still the property of the State, non-tradeable land use rights were assigned to individuals for up to fifteen years.

The Land Law of 1993 finally granted households the permission to transfer, inherit, exchange, lease or mortgage their land-use rights by distributing Land Use Certificates (LUC, hereafter), which guaranteed effective land ownership. The law

[16] The 7 regions are Northern Uplands, Red River Delta, North Central Coast, Central Coast, Central Highlands, Southeast and Mekong Delta. There were 53 provinces in 1992 and 61 provinces in 1998. The difference in the number of provinces is due to the fact that 8 provinces were split into two provinces in 1996. Bac Thai province split into Bac Can and Thai Nguyen, Ha Bac province split into Bac Giang and Bac Ninh, Hai Hung province split into Hai Duong and Hung Yen, Minh Hai province split into Bac Lieu and Ca Mau, Nam Ha province split into Ha Nam and Nam Dinh, Quang Nam-Da Nang province split into Quang Nam province and Da Nang municipality, Song Be province split into Binh Duong and Binh Phuoc, and Vinh Phu province split into Phu Tuo and Vinh Phuc.

increased tenure over the land that farms had been allocated and was seen as setting the grounds for a formal market for land (Do and Iyer (2007)). The first two reforms were implemented at the national level and are therefore less likely to affect the results. However, the distribution of LUCs was carried out by communal authorities and thus did not occur in a uniform way across communes. By the end of 1998, there was considerable variation across provinces in how far the process had proceeded.

Land tenure is of concern as far as it might affect factors that are related to farm profits, labor input and crop choice decisions. Studies have shown that land tenure or property rights increase labor supply (Field (2007)) and investment in the land (Besley (1995), Goldstein and Udry (2008)). Although it would be ideal to have information on whether the household itself held a registered LUC, this data is not available, and instead data on the proportion of households in a province who had a registered land title is used to control for the effect of the reform. The data comes from the records of the General Department of Land Administration (GDLA) in Hanoi.[17] Using this data, Do and Iyer (2007) find that provinces that made greater progress in land titling issuance had a greater increase in the proportion of cultivated area devoted to multi-year crops in Vietnam. Following their approach, I take province-level differences in registration level of LUCs as plausibly exogenous.[18]

[17]Data was obtained from Quy-Toan Do at the World Bank who used the data to examine the impact of land titles on land use and crop investment (see Do and Iyer (2007)).

[18]Heterogeneity across provinces in registration levels could result from a variety of factors, including some that might affect the agricultural outcomes of interest. Do and Iyer (2007) argue that province- level differences are due to bureaucratic and other reasons exogenous to the household. They run alternative specifications controlling for household expenditure that might be related to registration but find similar results.

3.6 Results

3.6.1 Description of the Data

The means and standard deviations of all variables are presented by survey year in Tables 3.1 and 3.2, for the pooled sample and the panel sample, respectively. While profits on average increased over the years, total days worked on the farm went down, as did total hours worked by household members. This might be due to substitution to capital (ownership of farm equipment went up). Nearly 80% of households were headed by a male, who is older in 1997/98 compared to 1992/93. This is not surprising given that a large share of households in 1998 were reselected from 1992. The size of total land cultivated by households slightly increased, as did the share of households with access to irrigation. Somewhat surprisingly, land quality seems to have deteriorated over the years: however, this may be largely attributed to measurement error, in particular stemming from the format change in the questionnaires.

The last two rows in the tables report means of the two malaria illness measures, as calculated by the number of cases per household, divided by household size. The mean of the first proxy, which uses fever as a proxy for malaria in 1998, actually increases by about two-fold despite the national downward trend in malaria cases over this period. As noted above, the use of fever to proxy for malaria likely overestimates the incidence of the disease. Malaria is not the only disease that is accompanied by fever: influenza and dengue fever are also characterized by fever and are not uncommon in Vietnam, although the incidence of dengue fever is lower than malaria. I therefore construct construct an alternative measure of malaria which combines four symptoms reported in the survey: headache, fever, vomiting and cough. Some of the symptoms may overlap with other diseases, but not all of them.[19] Since individuals who experienced malaria may report some, but not all of these symptoms, this proxy may lead to an underestimate of the actual incidence. Thus, it might be informative to look at the association of both measures of malaria and agricultural outcomes. The share of land allocated to labor-intensive, high-return crops is greater than 76%. Rice is the single most important crop in Vietnam and therefore it usually takes up a large proportion of the land for most households, which explains why the means are all in the higher range.

Descriptive statistics for panel households are overall comparable, although due to possible changes in the household composition, the change in the share of individuals in each demographic group is slightly larger compared to the corresponding change in the variable from the cross-sectional sample. Panel households are slightly larger in size, and the share of good quality land is higher in 1998 compared to non-panel households. They also own more farm equipment and are more likely to hold a land use certificate in 1998.[20]

Table 3.3 shows the geographic distribution of households across seven major regions in Vietnam and Table 3.4 presents, by province, the percentage of households that held a land use certificate as of 1998. The number ranges widely from 11.89% to 100%.[21] Since the registration of land use certificates started to roll out after the Land Reform Law of 1993, the equivalent variable for households in 1992 is set to zero.

3.6.2 Models of Malaria Incidence

I first examine which households are more likely to report anyone in the household having had malaria in the four weeks prior to the survey. Specifically, I estimate

[19] Using this measure, illness incidence goes down to about 0.002 in 1998.

[20] The number of pieces of farm equipment measures how many pieces of tractors, water pumps, threshing machines, etc were owned by the household.

[21] Two provinces are not shown since there were no households in the final regression sample residing in those provinces.

a logit model to analyze which characteristics of the household are associated with malaria incidence. Table 3.5 reports marginal effects from this logit model. Columns (1) and (2) report results for the malaria measure that proxies malaria illness in 1998 using only fever, whereas columns (3) and (4) report results using the alternative malaria proxy which combines multiple symptoms to measure malaria illness in the 1998 survey. Further, specifications in columns (1) and (3) include province and year fixed effects, and columns (2) and (4) include province x year fixed effects. To account for the possibility that the stochastic error terms are correlated within the household's province of residence, standard errors are clustered by province.

Interview month dummies are included to account for the seasonality of the disease since households were interviewed during different months of the year and the health questions were asked in reference to the four weeks prior to the survey. Not surprisingly, the coefficients on some of the wet season months such as July and August are positive and statistically significant, indicating that households are more likely to experience malaria during this period relative to January (the omitted month). In particular, households interviewed in July are more likely to report having had an illness even after controlling for province-year-specific fixed effects. This relationship, however, is not present when using the narrow proxy for malaria.

Across all specifications, there are statistically significant associations between the likelihood that there was a malaria episode in the household and household size and education of the household head. While the coefficient on whether the household had any irrigated land iss insignificant in columns (2) and (4) with province-year fixed effects, the coefficients on some household characteristics remain large and statistically significant. Moreover, the results using the alternative malaria proxy in columns (3) and (4) suggest that land quality may matter as well. Along with household head's education, these are all factors that are likely to be positively correlated with income, which raises the possibility of reverse causality. The number of observations in column (4) is lower by about a quarter of the sample because of the large number of households who report no malaria incidence using the narrow measure in 1998. This causes some provinces to drop out of the sample entirely when province-year fixed effects are included and if they have no households reporting a malaria case.

Columns (1) and (2) in Table 3.6 report estimates of the same model as in Table 3.5, but with household fixed effects. This is to see whether controlling for unobservables at the household-level decreases the correlation between certain household characteristics and malaria incidence, and thus the potential for reverse causality. Here the within-household variation in malaria incidence and regressors is exploited to purge any unobservable household-level heterogeneity. The dependent variable is the malaria proxy using fever in column (1), and the narrow malaria proxy in column (2). Many households had no variation in their malaria responses between 1992 and 1998. Therefore, the number of observations used in the panel regression drops substantially.

Compared to estimates in Table 3.5, the statistically significant relationship between malaria incidence and some of the variables (e.g., share of good quality land) disappears, partly alleviating concerns that malaria incidence is endogenous at the household-level. The sign on the age of household head switches and is now positive and significant at the 10% level. Moreover, the number of pieces of farm equipment owned has a positive and statistically significant association with malaria illness. In column (2), where malaria incidence is proxied using the alternative measure, the only factor that still matters is the share of elderly people in the household.

3.6.3 Malaria Illness and Farm Profits

Table 3.7 reports estimates of equation 3.1 where the dependent variable is total agricultural profits. The relationship between profits and malaria illness is negative and statistically significant at the 1% level in the baseline results in column (1). Lower farm profits are associated with more members of a household suffering from malaria, although the relationship may not be entirely causal. Reverse causality could be present if households who earn more farming profits can afford better treatment and thus suffer from fewer illness episodes. The magnitude of the malaria coefficient indicates that in a household consisting of six people, if one additional individual becomes sick from malaria, profits are lower by roughly 4%. This statistically significant, negative relationship largely holds up to the inclusion of province x year fixed effects in column (3) that control for province-time-specific trends although estimates are smaller.

Other variables also explain variation in farm profits. Across columns, total land area and the number of pieces of farm equipment owned by the household are positively associated with farm profits, although the latter is measured very imprecisely in column (4). Profits are higher if the household head is older, male and received formal education. Column (2) adds land quality variables and an irrigation dummy to the specification, where the latter measures whether the household cultivated any irrigated land. Land quality variables are shown to have a positive association with profits. The proportion of households in a province that received a formal land use certificate has a positive sign, but the coefficient is not statistically significant in any of the specifications. Province x year fixed effects are further added in column (3) to account for province-year specific, unobservable trends. The land title variable drops out because it varies only at the province-year level. These results are overall similar to the ones in column (2). Again, standard errors are clustered by province and are robust to heteroskedasticity.

While I am not able to deal with the measurement error problem associated with malaria and potential reverse causality in a rigorous way, I try to address the issue of omitted variables using household fixed effects, which will capture household-specific omitted variables that are time-invariant. These results are shown in column (4). The drop in the number of observations is obviously due to the fact that not all households were reinterviewed in 1997/98. The coefficient measuring the intensity of malaria illness in the household is still negative and statistically significant at the 10% level. Although there is a loss of precision, the size of the coefficient is comparable to column (2). Except for the household head's education and the share of female adults, most household characteristics are now insignificant.

The 4-week malaria illness variable is an imperfect measure of the extent that the household is exposed to the disease over the year, due to the length of the reporting period and the fact that transmission is seasonal. To capture seasonality in transmission, I include dummies for the month the household was interviewed, and interact those dummies with the household's malaria illness variable. The interview month dummies may also capture any other sort of measurement error that is related to which month of the year the household is interviewed: households may remember more or less precisely how much they earned in yields and profits depending on how much time has passed since the main harvest, even though all households were asked about agricultural activities over the entire past 12 months.

These results with interview month dummies are presented in Table 3.8. Profits are persistently higher for households that were interviewed in the main agricultural season, from May through October. Testing for joint significance of the malaria illness variable and its interaction terms with interview months, it does appear to matter when the household was interviewed: The negative relationship between profits and malaria illness is statistically significant when households were interviewed in May through August and December in column (1), and additionally in February in column (2). In columns (3) and (4), only the interaction terms with June and August, and February and July are jointly significant, respectively. All of these months fall in the wet season, when malaria transmission is higher. The size of the effect is also greater by at least a quarter.

As previously mentioned, households were not specifically asked in 1997/98 which illness they suffered from, but which symptoms they experienced (and recognized). To see the impact of using symptoms other than fever to proxy for malaria, the same specifications as in Table 3.7 are estimated with this alternative proxy, which combines several malaria symptoms. These are presented in Table 3.9. Coefficient estimates on malaria illness are larger in column (4) compared to those in Table 3.7, which is to be expected if fever was indeed capturing measurement error by including other diseases. According to estimates with household fixed effects in column (4), one more case of malaria illness in a household of six is associated with around 10% lower profits.

3.6.4 Malaria Illness and Use of Agricultural Labor

Given the negative relationship between profits and malaria illness, the next question is whether any of the effect could result because farmers fall ill and are not able to provide sufficient labor. In order to investigate this, I examine how the total number of person-days employed is associated with malaria illness. These estimates are presented in Table 3.10. Across all specifications, the total number of person-days employed by the household in the past 12 months is positively associated with total land area, household size and number of farm equipment owned. The larger the share of children and elderly in the household, the lower the number of total labor days used. This may not be surprising given that households largely rely on their own labor input rather than exchanged or paid labor.

The important result is that malaria illness shocks do not appear to impact total labor use of the household. This result persists throughout different specifications: with the inclusion of land quality and irrigation variables, with the addition of province x year fixed effects and even with household fixed effects. Since total labor is measured as the sum of household and non-household labor, the question is whether there are no effects overall because households reduce their labor supply and substitute paid labor for their own. In order to address that concern, I run the same model on total labor days worked by members of the household. These results are reported in Table 3.11, which indicate that there is no evidence of such substitution. Using the alternative proxy for malaria illness does not change the results, as reported in Table 3.12. Another possibility is that while household members still opt to work the same number of days on the field, they may reduce the number of hours spent working per day. I examine whether illness episodes due to malaria affects number of total hours worked by household members, but do not find any evidence of this (results not reported here). [22]

3.6.5 The Impact of Malaria on Crop Choice

If malaria does not affect labor employed in agriculture, what explains the impact on profits? An alternative explanation could be that households, in anticipation of the seasonal disease, choose to grow less rice, soy beans and peanuts, which are crops that are highly labor-intensive and offer higher returns, and instead grow more corn, cassava and sweet potatoes, which are crops that are less labor-intensive, but also less profitable. This might be especially true in a context where the disease is endemic and occurs during seasons when labor demand peaks, as in Vietnam.

In order to test whether households, in making their crop choice decisions, take into account how likely it is that they will contract malaria, which might weaken their productivity and ultimately hurt profits, I estimate equation 3.2 to see whether previous malaria experience at the household- or province-level affects households' crop choice decisions 5-6 years later. While previous household-level malaria illness measures the household's own propensity to contract the illness (possibly related to

[22] This result also suggests that the negative relationship between malaria and profits is not driven by the fact that own-labor is not factored in.

household-specific factors), province-level malaria prevalence measures how likely it is for a household on average to become ill.

The estimation results for models of crop choice are shown in Table 3.13. In order to look at how households' health shocks affected their own crop choice later on, here I consider only panel households who were surveyed in both years. The larger the area of the land cultivated and the better the quality of the land, the more land the household allocated to such profitable crops. While household-level malaria illness is not significant in columns (1) and (2), province-level malaria is statistically significant once it is added in column (3). These findings suggest that households respond to previously experienced province-level malaria prevalence, but that they do not respond to their own experience of malaria incidence. Interestingly, these results suggest that households do not necessarily take into account their own illness experience, but rather, how likely it was for a household in their province to have suffered from malaria. Past experience may serve as a proxy for how likely members of a household think they might become ill in any given year. This result is also in line with the fact that the correlation of malaria illness variables in 1992 and 1998 is not very high, suggesting that malaria illness may not be as recurring as often suggested.

3.7 Conclusion

Malaria is still endemic in a number of developing countries and an estimated three billion people are said to be at risk of malaria each year (Boschi-Pinto and Shibuya (2008)). In this chapter, I show that malaria illness measured at the household level is negatively correlated with agricultural profits. However, this does not appear to be due to a decrease in the total number of labor days the household employed. As an alternative explanation for the decrease in profits, I present evidence that the household's land allocation decisions might be affected. Since malaria is a seasonal and endemic disease in Vietnam, households living in an area where the likelihood of contracting malaria is higher may choose to allocate less land to highly labor-intensive, but also more profitable crops in anticipation of the disease. Results seem to confirm this: more malaria episodes experienced on average in a province are associated with a smaller share of land devoted to rice and cash crops five years later.

As Hong (2007) notes, most papers in the literature that aim at calculating the impact of malaria on losses in economic activities fail to capture long-term consequences of the disease and therefore the impact on economic activities could likely be underestimated. Along the same line, I argue that the welfare of agricultural households can still be negatively impacted even if no effect on labor supply is found, as households may adjust their production decisions *ex-ante*.

Table 3.1: Descriptive Statistics (All households)

	1992			1998		
Variable	**Mean**	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**
Ln(profits)	7.919	1.06	2802	8.559	0.945	3229
Ln(Total labor days)	6.416	0.771	2796	6.163	0.873	3098
Ln(Total labor days worked by HH members)	6.219	0.799	2791	6.191	0.737	3020
Ln(Total hours worked by HH members)	7.966	0.912	2791	7.859	0.812	3020
Share of adult female in household	0.301	0.172	2802	0.307	0.183	3229
Share of elderly in household	0.066	0.175	2802	0.089	0.214	3229
Share of children in household	0.376	0.231	2802	0.333	0.23	3229
Ln(household size)	1.541	0.456	2802	1.486	0.469	3229
Age of household head	45.277	14.775	2802	47.486	13.752	3229
Whether household head is male	0.787	0.41	2802	0.787	0.41	3229
Whether household head has education	0.873	0.333	2802	0.897	0.305	3229
Ln(Total land area)	8.346	0.864	2802	8.544	1.003	3229
Whether household has access to irrigation	0.971	0.168	2802	0.983	0.131	3229
Share of good quality land	0.276	0.367	2802	0.241	0.341	3229
Share of medium quality land	0.509	0.387	2802	0.37	0.362	3229
# of farm equipment	0.926	1.021	2802	1.478	1.304	3229
% households in province with LUC	0	0	2082	0.714	0.249	3229
Share of land growing high-return crops	0.767	0.236	2790	0.769	0.261	3090
Malaria incidence of HH members	0.048	0.143	2802	0.097	0.199	3229
Malaria incidence of HH members (narrow)	0.048	0.143	2802	0.002	0.026	3229

Table 3.2: Descriptive Statistics (Panel households)

Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**N**
Ln(Profits)	7.982	0.989	8.566	0.909	2141
Ln(Total labor days)	6.478	0.729	6.222	0.830	2066
Ln(Total labor days worked by HH members)	6.308	0.753	6.231	0.741	2029
Share of adult female in household	0.297	0.167	0.311	0.187	2141
Share of elderly in household	0.064	0.167	0.095	0.219	2141
Share of children in household	0.383	0.23	0.327	0.232	2141
Ln(household size)	1.56	0.448	1.49	0.473	2141
Age of household head	45.412	14.553	47.894	13.612	2141
Whether household head is male	0.8	0.4	0.785	0.411	2141
Whether household head has education	0.87	0.337	0.893	0.309	2141
Ln(Total land area)	8.385	0.821	8.505	0.956	2141
Whether household has access to irrigation	0.972	0.164	0.984	0.127	2141
Share of good quality land	0.27	0.361	0.271	0.345	2141
Share of medium quality land	0.5	0.379	0.352	0.343	2141
# of farm equipment	0.998	1.034	1.56	1.312	2141
% households in province with LUC	0	0	0.735	0.244	2141
Share of land growing high-return crops	.761	.225	.802	.226	2110
Malaria incidence of HH members	0.05	0.147	0.087	0.185	2141
Malaria incidence of HH members (alternative)	0.05	0.147	0.002	0.023	2141

Table 3.3: Geographic distribution of households

Region	Number of households (% of total)
Northern Uplands	1176 (19.5)
Red River Delta	1366 (22.65)
North Central Coast	965 (16)
South Central Coast	652 (10.81)
Central Highlands	375 (6.22)
Southeast	388 (6.43)
Mekong River Delta	1109 (18.39)

Table 3.4: Means by province, grouped by region

Province	**% HH with land title in 1998**
Northern Uplands	*65.9*
Bac Can	93.91
Bac Giang	31.25
Cao Bang	77.14
Ha Giang	75.72
Hoa Binh	100.00
Lang Son	87.20
Lao Cai	85.88
Phu Tho	35.84
Quang Ninh	91.88
Son La	31.13
Tuyen Quang	95.62
Yen Bai	50.49
Red River Delta	*81.72*
Ha Nam	74.04
Ha Tay	11.89
Hai Phong	97.34
Hanoi	35.02
Hung Yen	92.48
Ninh Binh	99.48
Thai Binh	50.12
North Central Coast	*74.39*
Ha Tinh	90.98
Nghe An	91.45
Quang Binh	99.57
Quang Tri	40.54
Thanh Hoa	98.87

Thua Thien Hue	49.15
Central Coast	*77.26*
Binh Dinh	93.95
Binh Thuan	76.67
Khanh Hoa	84.78
Ninh Thuan	77.71
Phu Yen	88.02
Quang Nam	70.69
Quang Ngai	37.37
Central Highlands	*60.09*
Dac Lac	83.12
Gia Lai	29.91
Lam Dong	89.04
Southeast	*78.58*
Ba Ria Vung Tau	65.87
Binh Duong	64.42
Dong Nai	57.99
Ho Chi Minh City	68.74
Tay Ninh	81.42
Mekong Delta	*88.97*
An Giang	91.72
Ben Tre	89.59
Ca Mau	89.82
Can Tho	86.32
Dong Thap	85.94
Kien Giang	31.95
Long An	90.53
Soc Trang	74.77
Tien Giang	75.52
Tra Vinh	80.09
Vinh Long	80.01

Table 3.5: Determinants of malaria illness

	(1)	(2)	(3)	(4)
Dependent variable	Malaria	Malaria	Alt. malaria	Alt. malaria
Ln(Total land area)	-0.0046	-0.0148	0.0027	0.0024
	(0.0815)	(0.0682)	(0.0864)	(0.0897)
Whether household has access to irrigation	-0.6887*	0.0991	-0.5602*	-0.1511
	(0.3993)	(0.1957)	(0.3125)	(0.3245)
Share of good quality land	-0.3576	-0.1231	-1.0208***	-0.9046**
	(0.2535)	(0.2200)	(0.3838)	(0.3778)
Share of medium quality land	-0.3155	0.0142	-0.6502**	-0.5056*
	(0.2507)	(0.1843)	(0.2875)	(0.2883)
Share of adult female in household	-0.0741	-0.1872	-0.7464	-0.8969*
	(0.2607)	(0.2831)	(0.4995)	(0.5329)
Share of elderly in household	-0.4305	-0.4371	-1.3913***	-1.4841***
	(0.3102)	(0.2997)	(0.5196)	(0.5493)
Share of children in household	0.3219	0.2326	-0.4008	-0.5210
	(0.2703)	(0.2736)	(0.4721)	(0.5067)
Ln(household size)	0.5295***	0.5996***	0.3829**	0.4589**
	(0.1317)	(0.1242)	(0.1691)	(0.1836)
Age of household head	-0.0062**	-0.0071***	-0.0073	-0.0082
	(0.0028)	(0.0025)	(0.0061)	(0.0064)
Whether household head is male	0.0070	-0.0523	0.2747*	0.2547
	(0.0761)	(0.0853)	(0.1475)	(0.1580)
Whether household head has education	-0.5842***	-0.5232***	-0.5929***	-0.6160***
	(0.1501)	(0.1545)	(0.1884)	(0.2256)
# of farm equipment	-0.0472	-0.0686	-0.0635	-0.1031*
	(0.0420)	(0.0457)	(0.0576)	(0.0549)
Year = 1998	1.3288*	0.0481	-2.8776*	-16.9849***
	(0.7177)	(0.2869)	(1.7369)	(0.3017)
Interview month = Feb	-0.1218	0.2598	-0.0689	1.2923
	(0.3356)	(0.3704)	(1.2433)	(1.0958)
Interview month = Mar	0.2355	0.4944	-0.4943	0.7265
	(0.3839)	(0.3974)	(1.3453)	(1.1232)
Interview month = Apr	0.2951	0.5606*	-0.2135	1.2458
	(0.3150)	(0.3349)	(1.3272)	(1.0668)
Interview month = May	0.3229	0.5060	-0.4877	0.6325
	(0.2796)	(0.3231)	(1.2898)	(1.1295)
Interview month = Jun	0.4580*	0.4534	-0.4675	0.4529
	(0.2749)	(0.2853)	(1.3503)	(1.1977)
Interview month = Jul	0.6707**	0.9588***	0.2449	1.4264
	(0.2844)	(0.2603)	(1.2495)	(1.1323)
Interview month = Aug	0.3353	0.6005**	-0.7194	0.3152
	(0.2830)	(0.2909)	(1.3496)	(1.2323)
Interview month = Sep	0.0954	0.4186	-1.2384	-0.0942
	(0.2714)	(0.3164)	(1.3306)	(1.2044)
Interview month = Oct	0.2911	0.6010*	-0.2570	1.0969

	(1)	(2)	(3)	(4)
	(0.3275)	(0.3490)	(1.3284)	(1.1688)
Interview month = Nov	-0.0248	0.3036	-0.8926	0.4245
	(0.3143)	(0.3165)	(1.3052)	(1.1030)
Interview month = Dec	0.0614	0.4142*	-0.3569	0.8658
	(0.2808)	(0.2483)	(1.2169)	(1.1010)
% households with land titles in province	-0.5666		-0.8546	
	(0.9110)		(2.3556)	
Province FE, Year FE	x		x	
Province x Year FE		x		x
Observations	6336	6336	6276	4579
Pseudo R^2	0.1172	0.1767	0.3212	0.2700

This table reports marginal effects from logit regressions on the determinants of malaria illness in the household. The dependent variable in columns (1) and (2) is a dummy equal to one if the household reported at least one household member to have had a malaria episode in the four weeks prior to the survey. The dependent variable in columns (3) and (4) is the alternative malaria measure, which in 1998, proxies malaria using a combination of several symptoms (fever, cough, chill, and headache). Standard errors are robust to heteroskedasticity and clustered at the province level.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3.6: Determinants of malaria illness (Households fixed effects)

	(1)	(2)
Dependent variable	Malaria	Alt. malaria
Ln(Total land area)	-0.0701	0.1091
	(0.2807)	(0.2768)
Whether household has access to irrigation	-1.5543**	-0.2623
	(0.6717)	(0.6713)
Share of good quality land	-0.3768	-0.4998
	(0.4270)	(0.8661)
Share of medium quality land	-0.0815	-0.2270
	(0.4169)	(0.4177)
Share of adult female in household	0.7118	-1.2741
	(0.5878)	(2.2654)
Share of elderly in household	-0.2771	-1.9420*
	(0.6912)	(1.1229)
Share of children in household	0.8040	0.9777
	(0.5361)	(1.8000)
Ln(household size)	0.4554	-0.0084
	(0.2796)	(0.8096)
Age of household head	0.0136*	0.0294
	(0.0077)	(0.0196)
Whether household head is male	0.3882	-0.3324
	(0.2529)	(0.6654)
Whether household head has education	-0.0205	0.5282
	(0.3353)	(0.4962)
# of farm equipment	0.1223**	0.0902
	(0.0484)	(0.2664)
% households with land titles in province	-0.3489	-0.3847
	(0.8384)	(1.7112)
Interview month = Feb	-0.5413	-2.5238
	(0.6486)	(1.8827)
Interview month = Mar	0.0374	-0.7373
	(0.6793)	(1.7489)
Interview month = Apr	0.3863	-1.9223
	(0.6936)	(1.8309)
Interview month = May	0.1060	-2.1639
	(0.5594)	(1.8293)
Interview month = Jun	0.4608	-0.8686
	(0.4857)	(1.7979)
Interview month = Jul	0.2886	-1.8095
	(0.6345)	(1.6362)
Interview month = Aug	0.0033	-2.3881
	(0.6326)	(1.8430)
Interview month = Sep	-0.1339	-0.6437

	(0.5684)	(1.4236)
Interview month = Oct	0.2891	-1.9171
	(0.5226)	(1.6909)
Interview month = Nov	-0.4036	-2.1263
	(0.6011)	(1.5362)
Interview month = Dec	-0.4697	-0.3739
	(0.5402)	(1.2073)
Year = 1998	1.1425	-2.9920**
	(0.6963)	(1.2320)
Observations	1904	864
Pseudo R^2	0.1940	0.7317

This table reports marginal effects from conditional logit regressions on the determinants of malaria illness in the household using household fixed effects. The dependent variable in column (1) is a dummy equal to one if the household reported at least one household member to have had a malaria episode in the four weeks prior to the survey. The dependent variable in column (2) is the alternative narrow malaria measure, which in 1998, proxies malaria using a combination of several symptoms (fever, cough, chill, and headache). Standard errors are robust to heteroskedasticity and clustered at the province level.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3.7: Relationship between malaria illness and farm profits

	(1)	(2)	(3)	(4)
Malaria illness of household members	-0.3342***	-0.2881***	-0.1609**	-0.2652*
	(0.0714)	(0.0608)	(0.0745)	(0.1461)
Ln(Total land area)	0.4987***	0.5271***	0.5433***	0.3307***
	(0.0440)	(0.0471)	(0.0444)	(0.1030)
Whether household has access to irrigation		0.0848	0.0649	-0.0616
		(0.0926)	(0.0950)	(0.2498)
Share of good quality land		0.4905***	0.4795***	-0.3728
		(0.0845)	(0.0799)	(0.2775)
Share of medium quality land		0.2766***	0.2562***	-0.1120
		(0.0731)	(0.0688)	(0.1985)
Share of adult female in household	-0.0084	-0.0511	-0.0780	0.3667***
	(0.1062)	(0.1064)	(0.1019)	(0.1295)
Share of elderly in household	-0.2378***	-0.2789***	-0.2867***	0.0039
	(0.0795)	(0.0783)	(0.0718)	(0.0027)
Share of children in household	-0.1253	-0.1109	-0.0950	-0.0915
	(0.0859)	(0.0865)	(0.0867)	(0.0989)
Ln(household size)	0.3477***	0.3045***	0.2907***	0.0243
	(0.0510)	(0.0551)	(0.0510)	(0.1373)
Age of household head	0.0018*	0.0021*	0.0022**	0.0462
	(0.0011)	(0.0011)	(0.0010)	(0.0345)
Whether household head is male	0.0533*	0.0612*	0.0612*	0.1627
	(0.0313)	(0.0359)	(0.0350)	(0.2975)
Whether household head has education	0.1745***	0.1488***	0.1317***	0.4420*
	(0.0448)	(0.0461)	(0.0442)	(0.2303)
# of farm equipment	0.1526***	0.1420***	0.1455***	0.1500
	(0.0193)	(0.0179)	(0.0181)	(0.1924)
% households with land titles in province	0.0566	0.0274		0.1696
	(0.2334)	(0.2195)		(0.1777)
Year = 1998	0.4577**	0.5281***	0.7972***	0.1056
	(0.1838)	(0.1761)	(0.0165)	(0.1268)
Constant	2.4667***	2.1696***	1.9551***	4.3186***
	(0.3555)	(0.3869)	(0.3647)	(0.8664)
Province FE, Year FE	x	x		
Province x Year FE			x	
Household FE				x
Observations	6185	6031	6031	4282
Adjusted R^2	0.4776	0.4903	0.5161	0.7826

This table reports results from ordinary least square regressions estimating the relationship between farm profits and malaria illness in the household. Malaria incidence is measured as the number of episodes reported by the household, weighted by household size. Standard errors are robust to heteroskedasticity and clustered at the province level.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3.8: Relationship between malaria illness and farm profits, controlling for interview month

	(1)	(2)	(3)	(4)
Malaria illness of household members	0.2635	0.3129	0.3993	0.4126
	(0.3398)	(0.3065)	(0.2936)	(0.5027)
Ln(Total land area)	0.4948***	0.5234***	0.5380***	0.3265***
	(0.0432)	(0.0450)	(0.0424)	(0.0984)
Whether household has access to irrigation		0.1081	0.0684	0.1159
		(0.0909)	(0.0948)	(0.1500)
Share of good quality land		0.5013***	0.4879***	0.2020
		(0.0835)	(0.0743)	(0.1605)
Share of medium quality land		0.2684***	0.2444***	0.0781
		(0.0750)	(0.0687)	(0.1203)
Share of adult female in household	-0.0033	-0.0511	-0.0839	-0.0394
	(0.1051)	(0.1040)	(0.0998)	(0.2502)
Share of elderly in household	-0.2351***	-0.2804***	-0.2895***	-0.3325
	(0.0802)	(0.0776)	(0.0712)	(0.2799)
Share of children in household	-0.1224	-0.1053	-0.0992	-0.0648
	(0.0868)	(0.0870)	(0.0890)	(0.2055)
Ln(household size)	0.3524***	0.3074***	0.2967***	0.3586***
	(0.0508)	(0.0543)	(0.0501)	(0.1232)
Age of household head	0.0018*	0.0022**	0.0023**	0.0042
	(0.0010)	(0.0010)	(0.0010)	(0.0027)
Whether household head is male	0.0504	0.0576	0.0561	-0.0719
	(0.0323)	(0.0363)	(0.0366)	(0.0983)
Whether household head has education	0.1736***	0.1521***	0.1365***	0.0195
	(0.0449)	(0.0456)	(0.0453)	(0.1403)
# of farm equipment	0.1544***	0.1440***	0.1486***	0.0483
	(0.0161)	(0.0149)	(0.0153)	(0.0313)
% households with land titles in province	0.0454	0.0242		0.0789
	(0.2339)	(0.2246)		(0.2788)
Interview month = Feb	0.1440	0.1333	0.0760	0.2922
	(0.1228)	(0.1154)	(0.1095)	(0.2175)
Interview month = Mar	-0.0245	0.0112	-0.0690	0.1720
	(0.1101)	(0.1121)	(0.0994)	(0.1814)
Interview month = Apr	0.1874*	0.1994*	0.1443	0.2356
	(0.1106)	(0.1056)	(0.1173)	(0.1494)
Interview month = May	0.1967	0.1950*	0.1328	0.2964**
	(0.1228)	(0.1087)	(0.1307)	(0.1374)
Interview month = Jun	0.1900	0.2166	0.1796	0.4234**
	(0.1334)	(0.1337)	(0.1587)	(0.1597)
Interview month = Jul	0.2840***	0.3142***	0.2542**	0.4240***
	(0.0932)	(0.0901)	(0.1234)	(0.1484)
Interview month = Aug	0.1259	0.1696	0.0962	0.4166**
	(0.1227)	(0.1253)	(0.1271)	(0.1691)
Interview month = Sep	0.3084**	0.3501***	0.3008**	0.3793**

	(0.1221)	(0.1232)	(0.1232)	(0.1539)
Interview month = Oct	0.1371	0.1775*	0.1017	0.3754**
	(0.1148)	(0.1021)	(0.1143)	(0.1572)
Interview month = Nov	0.1086	0.1208	0.1074	0.2603
	(0.1209)	(0.1165)	(0.1158)	(0.1605)
Interview month = Dec	0.0675	0.0638	-0.0272	0.2261
	(0.0682)	(0.0700)	(0.0605)	(0.1454)
Interaction with HH malaria illness				
Interview month = Feb	-0.7102	-0.8274*	-0.7589*	-1.2945**
	(0.4739)	(0.4450)	(0.4382)	(0.5207)
Interview month = Mar	-0.4951	-0.5037	-0.4443	-0.8498
	(0.3366)	(0.3249)	(0.3029)	(0.5352)
Interview month = Apr	-0.4080	-0.4420	-0.3135	-0.2467
	(0.3429)	(0.2963)	(0.2927)	(0.5210)
Interview month = May	-0.8039**	-0.8043**	-0.6769**	-0.6994
	(0.3999)	(0.3369)	(0.3218)	(0.7746)
Interview month = Jun	-0.7196*	-0.7690**	-0.7801**	-0.9195
	(0.4102)	(0.3738)	(0.3687)	(0.6586)
Interview month = Jul	-0.8112**	-0.6702**	-0.3965	-1.0860*
	(0.3643)	(0.3190)	(0.4359)	(0.6010)
Interview month = Aug	-0.6669*	-0.6389*	-0.8736**	-0.2529
	(0.3782)	(0.3442)	(0.3342)	(0.6964)
Interview month = Sep	-0.1663	-0.3046	-0.3791	-0.7023
	(0.3942)	(0.3848)	(0.3694)	(0.6229)
Interview month = Oct	-0.5311	-0.5423	-0.5260	-0.5149
	(0.4657)	(0.4088)	(0.3914)	(0.8859)
Interview month = Nov	-0.5287	-0.6485*	-0.5506*	-0.6700
	(0.3858)	(0.3750)	(0.3257)	(0.8055)
Interview month = Dec	-0.9086**	-0.9008**	-0.7494**	-0.8687
	(0.3622)	(0.3598)	(0.3318)	(0.5530)
Year = 1998	0.4584**	0.5202***	0.5455***	0.4871**
	(0.1821)	(0.1818)	(0.0889)	(0.2260)
Constant	2.3575***	2.0014***	2.0016***	4.0480***
	(0.3592)	(0.3925)	(0.3770)	(0.8533)
Test for significance of variables by interview month				
Interview month = Feb				
Sum of coefficients	-0.4467	-0.5145	-0.3596	-0.8820
p-value	0.1450	0.0901	0.1909	0.0218
Interview month = Mar				
Sum of coefficients	-0.2316	-0.1908	-0.0450	-0.4373
p-value	0.2841	0.4865	0.8670	0.4071
Interview month = Apr				
Sum of coefficients	-0.1445	-0.1291	0.0858	0.1659
p-value	0.4193	0.3917	0.6136	0.5818
Interview month = May				
Sum of coefficients	-0.54048	-0.4914	-0.2776	-0.2869

p-value	0.0407	0.0137	0.1281	0.6357
Interview month = Jun				
Sum of coefficients	-0.4561	-0.4561	-0.3808	-0.5069
p-value	0.0383	0.0260	0.0895	0.2252
Interview month = Jul				
Sum of coefficients	-0.5477	-0.3573	0.0028	-0.6735
p-value	0.0001	0.0019	0.9932	0.0477
Interview month = Aug				
Sum of coefficients	-0.4034	-0.3260	-0.4744	0.1597
p-value	0.0055	0.0305	0.0085	0.7358
Interview month = Sep				
Sum of coefficients	0.0972	0.0083	0.0201	-0.2897
p-value	0.5924	0.9684	0.9208	0.3428
Interview month = Oct				
Sum of coefficients	-0.2676	-0.2294	-0.1267	-0.1024
p-value	0.3103	0.3191	0.5893	0.8558
Interview month = Nov				
Sum of coefficients	-0.2652	-0.3356	-0.1513	-0.2575
p-value	0.1995	0.1061	0.3924	0.5085
Interview month = Dec				
Sum of coefficients	-0.6451	-0.5879	-0.3502	-0.4562
p-value	0.0053	0.0204	0.1215	0.4583
Province FE, Year FE	x	x		
Province x Year FE			x	
Household FE				x
Observations	6185	6031	6031	4282
Adjusted R^2	0.4830	0.4959	0.5218	0.5693

This table reports results from ordinary least square regressions estimating the relationship between farm profits and malaria illness in the household. Malaria incidence is measured as the number of episodes reported by the household, weighted by household size. Compared to Table 4, specifications additionally control for the month the survey was administered on the household, to account for the seasonality of the disease and the fact that households reported on illness episodes in the four weeks prior to the survey. Standard errors are robust to heteroskedasticity and clustered at the province level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3.9: Relationship between profits and malaria illness using alternative malaria measure

	(1)	(2)	(3)	(4)
Malaria illness of household members	-0.5656***	-0.4911***	-0.1390	-0.6651***
	(0.1259)	(0.1153)	(0.2179)	(0.2279)
Ln(Total land area)	0.4984***	0.5266***	0.5428***	0.3295***
	(0.0443)	(0.0472)	(0.0446)	(0.0990)
Whether household has access to irrigation		0.0637	0.0651	0.0842
		(0.0951)	(0.0934)	(0.1616)
Share of good quality land		0.4901***	0.4819***	0.1528
		(0.0845)	(0.0804)	(0.1754)
Share of medium quality land		0.2695***	0.2563***	0.0764
		(0.0737)	(0.0697)	(0.1221)
Share of adult female in household	-0.0171	-0.0596	-0.0824	-0.0499
	(0.1066)	(0.1068)	(0.1010)	(0.2541)
Share of elderly in household	-0.2439***	-0.2846***	-0.2891***	-0.3564
	(0.0791)	(0.0780)	(0.0708)	(0.2805)
Share of children in household	-0.1447*	-0.1277	-0.1039	-0.1270
	(0.0854)	(0.0866)	(0.0854)	(0.1970)
Ln(household size)	0.3504***	0.3071***	0.2926***	0.3617***
	(0.0513)	(0.0554)	(0.0513)	(0.1258)
Age of household head	0.0018	0.0021*	0.0022**	0.0041
	(0.0011)	(0.0011)	(0.0010)	(0.0027)
Whether household head is male	0.0562*	0.0637*	0.0619*	-0.0834
	(0.0316)	(0.0359)	(0.0351)	(0.0996)
Whether household head has education	0.1733***	0.1478***	0.1339***	0.0174
	(0.0457)	(0.0463)	(0.0444)	(0.1353)
# of farm equipment	0.1526***	0.1424***	0.1461***	0.0442
	(0.0192)	(0.0179)	(0.0181)	(0.0337)
% households with land titles in province	0.0858	0.0503		0.1781
	(0.2289)	(0.2164)		(0.2857)
Year = 1998	0.3935**	0.4736***	0.7901***	0.3847*
	(0.1784)	(0.1736)	(0.0194)	(0.2232)
Constant	2.4912***	2.2144***	1.9556***	4.4337***
	(0.3555)	(0.3836)	(0.3608)	(0.8578)
Province FE, Year FE	x	x		
Province x Year FE			x	
Household FE				x
Observations	6185	6031	6031	4282
Adjusted R^2	0.4773	0.4900	0.5156	0.5647

This table is analogous to Table 4 except that the alternative malaria proxy is used, which proxies malaria using a combination of several symptoms (fever, cough, chill, and headache). Malaria incidence is measured as the number of episodes reported by the household, weighted by household size. Standard errors are robust to heteroskedasticity and clustered at the province level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3.10: Malara incidence and total agricultural labor use of household

	(1)	(2)	(3)	(4)
Malaria illness of household members	0.0083	0.0389	-0.0164	0.1417
	(0.0704)	(0.0760)	(0.0708)	(0.1371)
Ln(Total land area)	0.2195***	0.2300***	0.2360***	0.1355*
	(0.0322)	(0.0351)	(0.0367)	(0.0709)
Whether household has access to irrigation		0.1788*	0.1915*	0.1202
		(0.0918)	(0.1089)	(0.1102)
Share of good quality land		0.0965	0.0686	0.1905
		(0.0803)	(0.0825)	(0.1527)
Share of medium quality land		0.1011	0.0603	0.0772
		(0.0738)	(0.0696)	(0.1143)
Share of adult female in household	0.0339	0.0365	0.0065	0.0153
	(0.0749)	(0.0749)	(0.0714)	(0.2495)
Share of elderly in household	-0.6043***	-0.6096***	-0.6273***	-0.5408**
	(0.0892)	(0.0909)	(0.0842)	(0.2505)
Share of children in household	-0.6169***	-0.6044***	-0.6564***	-0.3414**
	(0.0725)	(0.0754)	(0.0675)	(0.1699)
Ln(household size)	0.6660***	0.6508***	0.6420***	0.6469***
	(0.0411)	(0.0428)	(0.0417)	(0.1027)
Age of household head	0.0023***	0.0021***	0.0014	0.0042
	(0.0008)	(0.0008)	(0.0009)	(0.0030)
Whether household head is male	0.0389*	0.0452*	0.0309	0.1149
	(0.0224)	(0.0230)	(0.0235)	(0.0953)
Whether household head has education	0.0389	0.0231	0.0359	-0.0027
	(0.0341)	(0.0347)	(0.0345)	(0.1237)
# of farm equipment	0.0840***	0.0790***	0.0778***	0.0792**
	(0.0143)	(0.0151)	(0.0117)	(0.0390)
% households with land titles in province	-0.1310	-0.1241		-0.0764
	(0.2515)	(0.2590)		(0.3703)
Year = 1998	-0.2535	-0.2521	-0.0406**	-0.2347
	(0.1856)	(0.1901)	(0.0171)	(0.2861)
Constant	3.5823***	3.3346***	3.1952***	3.9071***
	(0.2501)	(0.2962)	(0.3017)	(0.5752)
Province FE, Year FE	x	x		
Province x Year FE			x	
Household FE				x
Observations	6045	5894	5894	4132
Adjusted R^2	0.3926	0.3944	0.4626	0.3817

This table reports results from ordinary least square regressions estimating the relationship between total number of household and non-household (hired and exchanged) labor days employed by the household, and malaria illness experienced by household members. Malaria incidence is measured as the number of episodes reported by the household, weighted by household size. Standard errors are robust to heteroskedasticity and clustered at the province level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3.11: Malaria incidence and total labor use of household members only (excluding non-household labor)

	(1)	(2)	(3)	(4)
Malaria illness of household members	0.0457	0.0630	0.0839*	0.0743
	(0.0557)	(0.0561)	(0.0476)	(0.1121)
Ln(Total land area)	0.1609***	0.1641***	0.1723***	0.0645
	(0.0243)	(0.0279)	(0.0277)	(0.0724)
Whether household has access to irrigation		0.1946***	0.1559*	0.1844
		(0.0683)	(0.0808)	(0.1172)
Share of good quality land		-0.0193	-0.0713	0.1582
		(0.0737)	(0.0723)	(0.1479)
Share of medium quality land		0.0014	-0.0333	0.0318
		(0.0512)	(0.0538)	(0.1008)
Share of adult female in household	0.0047	0.0094	-0.0125	-0.0523
	(0.0662)	(0.0671)	(0.0667)	(0.2193)
Share of elderly in household	-0.6723***	-0.6787***	-0.6870***	-0.7245***
	(0.0887)	(0.0898)	(0.0876)	(0.2567)
Share of children in household	-0.7820***	-0.7738***	-0.7775***	-0.5257***
	(0.0597)	(0.0600)	(0.0629)	(0.1352)
Ln(household size)	0.7767***	0.7702***	0.7583***	0.8373***
	(0.0314)	(0.0322)	(0.0316)	(0.0931)
Age of household head	0.0021***	0.0019***	0.0019**	0.0010
	(0.0007)	(0.0007)	(0.0008)	(0.0024)
Whether household head is male	0.0376*	0.0407*	0.0292	0.0839
	(0.0224)	(0.0222)	(0.0219)	(0.0865)
Whether household head has education	0.0443	0.0308	0.0371	0.0653
	(0.0356)	(0.0361)	(0.0356)	(0.0960)
# of farm equipment	0.0652***	0.0628***	0.0646***	0.0397
	(0.0135)	(0.0139)	(0.0117)	(0.0349)
% households with land titles in province	-0.0275	-0.0520		-0.0482
	(0.1937)	(0.1924)		(0.3045)
Year = 1998	-0.0903	-0.0757	-0.0437***	-0.0348
	(0.1496)	(0.1461)	(0.0140)	(0.2383)
Constant	3.8281***	3.6306***	3.5947***	4.2544***
	(0.1981)	(0.2384)	(0.2315)	(0.5967)
Province FE, Year FE	x	x		
Province x Year FE			x	
Household FE				x
Observations	5961	5811	5811	4058
Adjusted R^2	0.4469	0.4454	0.4826	0.4738

This table reports results from ordinary least square regressions estimating the relationship between total number of labor days worked by household members only, and malaria illness among household members. Malaria incidence is measured as the number of episodes reported by the household, weighted by household size. Standard errors are robust to heteroskedasticity and clustered at the province level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3.12: Total labor use regressions with alternative malaria measure

	(1)	(2)	(3)	(4)
Malaria illness of household members	0.0069	0.1103	0.0835	0.1063
	(0.1538)	(0.1538)	(0.0915)	(0.3602)
Ln(Total land area)	0.2195***	0.2300***	0.2357***	0.1343*
	(0.0325)	(0.0353)	(0.0370)	(0.0697)
Whether household has access to irrigation		0.1866*	0.1926	0.1130
		(0.0854)	(0.1089)	(0.1202)
Share of good quality land		0.0981	0.0700	0.1882
		(0.0791)	(0.0821)	(0.1502)
Share of medium quality land		0.1039	0.0612	0.0782
		(0.0729)	(0.0694)	(0.1176)
Share of adult female in household	0.0340	0.0375	0.0077	0.0182
	(0.0749)	(0.0748)	(0.0712)	(0.2475)
Share of elderly in household	-0.6043***	-0.6083***	-0.6260***	-0.5463**
	(0.0896)	(0.0912)	(0.0842)	(0.2507)
Share of children in household	-0.6166***	-0.6023***	-0.6558***	-0.3308*
	(0.0729)	(0.0762)	(0.0678)	(0.1679)
Ln(household size)	0.6659***	0.6507***	0.6427***	0.6482***
	(0.0412)	(0.0429)	(0.0419)	(0.1037)
Age of household head	0.0023**	0.0021*	0.0014	0.0042
	(0.0008)	(0.0008)	(0.0009)	(0.0030)
Whether household head is male	0.0389	0.0446	0.0309	0.1163
	(0.0225)	(0.0229)	(0.0235)	(0.0944)
Whether household head has education	0.0387	0.0244	0.0377	-0.0020
	(0.0359)	(0.0363)	(0.0355)	(0.1255)
# of farm equipment	0.0839***	0.0790***	0.0781***	0.0800**
	(0.0143)	(0.0151)	(0.0118)	(0.0390)
% households with land titles in province	-0.1315	-0.1277		-0.0836
	(0.2498)	(0.2578)		(0.3725)
Year = 1998	-0.2523	-0.2421	-0.0380*	-0.2181
	(0.1834)	(0.1881)	(0.0182)	(0.2850)
Constant	3.5822***	3.3208***	3.1881***	3.9155***
	(0.2496)	(0.2926)	(0.3002)	(0.5554)
Province FE, Year FE	x	x		
Province x Year FE			x	
Household FE				x
Observations	6045	5894	5894	4132
Adjusted R^2	0.3926	0.3945	0.4627	0.3811

This table reports results from ordinary least square regressions estimating the relationship between total number of labor days employed by the household and an alternative malaria measure, which proxies malaria using a combination of several symptoms (fever, cough, chill, and headache). Malaria incidence is measured as the number of episodes reported by the household, weighted by household size. Standard errors are robust to heteroskedasticity and clustered at the province level.

Table 3.13: Effect of malaria incidence at the household- and province-level in 1992 on crop choice in 1998

	(1)	(2)	(3)
Malaria illness of household members in 1992	-0.0730	-0.0560	-0.1225
	(0.0739)	(0.0691)	(0.0803)
Malaria cases per 1000 in population in 1992			-0.0028***
			(0.0009)
Ln(Total land area)	0.0422**	0.0562***	0.0475***
	(0.0170)	(0.0143)	(0.0157)
Whether household has access to irrigation		0.0161	0.0121
		(0.0403)	(0.0452)
Share of good quality land		0.1792***	0.1599***
		(0.0530)	(0.0493)
Share of medium quality land		0.1351***	0.1153***
		(0.0309)	(0.0333)
Share of adult female in household	0.0494	0.0440	0.0503
	(0.0322)	(0.0338)	(0.0396)
Share of elderly in household	0.0009	0.0029	0.0165
	(0.0314)	(0.0314)	(0.0371)
Share of children in household	0.0359	0.0478*	0.0764**
	(0.0287)	(0.0283)	(0.0365)
Ln(Household size)	0.0334**	0.0151	0.0003
	(0.0166)	(0.0175)	(0.0222)
Age of household head	-0.0003	-0.0002	0.0005
	(0.0005)	(0.0005)	(0.0006)
Whether household head is male	0.0082	0.0100	0.0142
	(0.0135)	(0.0128)	(0.0117)
Whether household head has education	-0.0606*	-0.0527	0.0151
	(0.0333)	(0.0319)	(0.0463)
# of farm equipment	-0.0031	-0.0063	-0.0044
	(0.0093)	(0.0091)	(0.0091)
% households with land titles in province			0.0590
			(0.0452)
Constant	0.1036	-0.0459	0.2150
	(0.1515)	(0.1211)	(0.1634)
Observations	2571	2571	2571
Adjusted R^2	0.3005	0.3289	0.1205

This table reports ordinary least sqaure results on how malaria incidence reported by the household or at the province-level affects households decision to allocate land to crops of different labor intensity 5-6 years later. The dependent variable measures the share of land each household devoted to highly labor- intensive, high-return crops such as rice and industrial crops such as peanut and soybean. Malaria incidence of the household is measured as the number of episodes reported by the household, weighted by household size. Province malaria measures the number of reported, slide-positive malaria cases per 1000 people in the population. Specifications in columns (1) and (2) include province fixed effects. Standard errors are robust to heteroskedasticity and clustered at the province level.

Bibliography

Adepoju, A. and C. Oppong (1994). *Gender, Work and Population in Sub-Saharan Africa*. International Labor Organization.

Ainsworth, M. (1992). Economic Aspects of Child Fostering in Côte d'Ivoire. World Bank, LSMS Working Paper No. 92.

Alderman, H., J. Hoddinott, and B. Kinsey (2006). Long Term Consequences of Early Child Malnutrition. *Oxford Economic Papers 58*, 450–474.

Alderman, H. and C. Paxson (1992). Do the Poor Insure? A Synthesis of the Literature on Risk and Consumption in Developing Countries. World Bank Policy Research Working Paper No. 1008.

Antle, J. and P. Pingali (1994). Pesticides, Productivity, and Farmer Health: A Philippine Case Study. *American Journal of Agricultural Economics 76*, 418–430.

Artadi, E. V. (2005). Going into Labor: Earnings vs. Infant Survival in Rural Africa. Working paper.

Audibert, M., J.-F. Brun, J. Mathonnat, and M. Henry (2009). Malaria, Production and Income of the Producers of Coffee and Cocoa: an Analysis from Survey Data in Côte d'Ivoire. CERDI, Working Paper Series, E 2006.31.

Audibert, M. and J.-F. Etard (2003). Productive Benefits after Investment in Health in Mali. *Economic Development and Cultural Change 51*, 769–782.

Audibert, M., J. Mathonnat, and M.-C. Henry (2003). Social and Health Determinants of the Efficiency of Cotton Farmers in Northern Côte d'Ivoire. *Social Science & Medicine 56*, 1705–1717.

Baker, M. and K. Milligan (2008). Maternal Employment, Breastfeeding and Health: Evidence from Maternity Leave Mandates. *Journal of Health Economics 27*(4), 871–887.

Baldwin, R. and B. Weisbrod (1974). Disease and Labor Productivity. *Economic Development and Cultural Change 22*, 414–435.

Barreca, A. (2010). The Long Term Impact of *In Utero* and Postnatal Exposure to Malaria. *Journal of Human Resources Forthcoming*.

Basta, S. S., M. Soekirman, D. Karyadi, and N. Scrimshaw (1979). Iron Deficiency Anemia and the Productivity of Adult males in Indonesia. *American Journal of Clinical Nutrition 32*, 916–25.

Behrman, J., A. Foster, and M. Rosenzweig (1997). The Dynamics of Agricultural Production and the Calorie-Income Relationship: Evidence from Pakistan. *Journal of Econometrics 77*, 187–207.

Benjamin, D. (1992). Household Composition, Labor Markets, and Labor Demand: Testing for Separation in Agricultural Household Models. *Econometrica 60*(2), 287–322.

Benjamin, D. and L. Brandt (2002). Agriculture and Income Distribution in Rural Vietnam under Economic Reforms: A Tale of Two Regions. University of Toronto Working Paper.

Besley, T. (1995). Property Rights and Investment Incentives: Theory and Evidence from Ghana. *Journal of Political Economy 103*, 903–937.

Betran, A., M. de Onis, J. A. Lauer, and J. Villar (2003). Ecological Study of Effect of Breastfeeding on Infant Mortality in Latin America. *British Medical Journal 323*, 1–5.

Bhandari, N., R. Bahl, S. Mazumder, J. Martines, R. Black, M. Bhan, and the other members of the Infant Feeding Study Group (2003). Effect of Community-based Promotion of Exclusive Breastfeeding on Diarrhoeal Illness and Growth: A Cluster Randomised Controlled Trial. *The Lancet 361*, 1418–23.

Black, R., S. Morris, and J. Bryce (2003). Where and Why are 10 Million Children Dying Every Year? *The Lancet 361*, 2226–34.

Bleakley, H. (2010). Malaria Eradication in the Americas: A Retrospective Analysis of Childhood Exposure. *American Economic Journal: Applied Economics 2*, 1–45.

Boschi-Pinto, L. V. and K. Shibuya (2008). Estimating Child Mortality due to Diarrhoea in Developing Countries. *Bulletin of the World Health Organization 86*, 710–717.

Briend, A., B. Wojtyniak, and M. Rowland (1988). Breast feeding, Nutritional State, and Child Survival in Rural Bangladesh. *British Medical Journal 296*, 879–882.

Chima, R. I., C. Goodman, and A. Mills (2003). The Economic Impact of Malaria in Africa: a Critical Review of the Evidence. *Health Policy 63*, 17–36.

Cleland, J. G. and J. K. van Ginneken (1988). Maternal Education and Child Survival in Developing Countries: The Search for Pathways of Influence. *Social Science Medicine 27*(12), 1357–1368.

Clemens, J. D., M. Rao, J. Chakraborty, M. Yunus, M. Ali, B. Kay, F. P. L. van Loon, A. Naficy, , and D. Sack (1997). Breastfeeding and the Risk of Life-threatening Enterotoxigenic coli Diarrhea in Bangladeshi Infants and Children. *Pediatrics 100*(6), e2.

Conley, G. N. (1972). The Impact of Malaria on Economic Development: A Case Study. *The American Journal of Tropical Medicine and Hygiene 21*, 668–674.

Cropper, M., M. Haile, J. Lampietti, C. Poulos, and D. Whittington (1999). The Value of Preventing Malaria in Tembien, Ethiopia. Washington DC: The World Bank.

Cutler, D., W. Fung, M. Kremer, M. Singhal, and T. Vogl (2007). Mosquitoes: The Long-term Effects of Malaria Eradication in India. NBER Working paper No. 13539.

Danso, G., O. Cofie, L. Annang, E. Obuobie, and B. Keraita (2004). Gender and Urban Agriculture: The Case of Accra, Ghana. International Water Management Institute.

Deaton, A. (1992). Household Saving in LDC's Credit Markets, Insurance, and Welfare. *Scandinavian Journal of Economics 94*.

Deolalikar, A. (1988). Nutrition and Labor Productivity in Agriculture: Estimates for Rural South India. *Review of Economics and Statistics 70*, 406–413.

Dercon, S. (1996). Risk, Crop Choice, and Savings: Evidence from Tanzania. *Economic Development and Cultural Change 44*, 485–513.

Dercon, S. (2004). Growth and Shocks: Evidence from Rural Ethiopia. *Journal of Development Economics 74*, 309–329.

Dercon, S. and J. Hoddinott (2003). Health, Shocks and Poverty Persistence. World Institute for Development Economics Research Discussion Paper No. 2003/08.

Dercon, S. and P. Krishnan (2000). In Sickness and in Health: Risk Sharing within Households in Rural Ethiopia. *Journal of Political Economy 108*(4), 688–727.

Do, Q.-T. and L. Iyer (2007). Land Titling and Rural Transition in Vietnam. World Bank Policy Research Working Paper.

Duflo, E. and C. Udry (2004). Intrahousehold Resource Allocation in Côte d'Ivoire: Social Norms, Separate Accounts, and Consumption Choices. NBER Working paper, No.10498.

Ettling, M. (2002). The Control of Malaria in Vietnam from 1980 to 2000: What went right? WHO Regional Office for the Western Pacific.

Field, E. (2007). Entitled to Work: Urban Property Rights and the Labor Supply in Peru. *Quarterly Journal of Economics 122*, 1561–1602.

Fisher, M. and S. Datta (2007). Malaria Risk, Crop Choice, and Agricultural Income in Northern Tanzania. Abstract accessed at http://www.aaea.org/2007am/abstracts/default.asp?mode=detail&abstractid=174603 on March 13, 2008.

Food and Agriculture Organization (1999a). Aquastat: Viet Nam. http://www.fao.org/nr/water/aquastat/countries/viet_nam/index.stm.

Food and Agriculture Organization (1999b). Deciduous Fruit Production in Asia and the Pacific. FAO/RAP Publication: 1998/10.

Foster, A. (1995). Prices, Credit Markets and Child Growth in Low-Income Rural Areas. *Economic Journal 105*, 551–70.

Gallup, J. L. and J. D. Sachs (2001). The Economic Burden of Malaria. *American Journal of Tropical and Medical Hygiene 64*, 85–96.

Gertler, P. and J. Gruber (2002). Insuring Consumption against Illness. *American Economic Review 92*, 51–70.

Goldstein, M. and C. Udry (2008). The Profits of Power: Land Rights and Agricultural Investment in Ghana. *Journal of Political Economy 116*, 981–1022.

Grimard, F. (1997). Household Consumption Smoothing through Ethnic Ties: Evidence from Côte d'Ivoire. *Journal of Development Economics 53*, 391–422.

Grossman, M. (1972). On the Concept of Health Capital and the Demand for Health. *The Journal of Political Economy 80*, 223–255.

Hawkes, C. and M. Ruel (2006). The Links between Agriculture and Health: an Intersectoral Opportunity to improve the Health and Livelihoods of the Poor. *Bulletin of the World Health Organization 84*.

Hoddinott, J. and B. Kinsey (2001). Child Health in the Time of Drought. *Oxford Bulletin of Economics and Statistics 63*, 409–436.

Hong, S. C. (2007). Malaria and Economic Productivity: The American Case. University of Chicago mimeo.

Hung, L. Q., peter J. de Vries, P. T. Giao, N. V. Nam, T. Q. Binh, M. Chong, N. Quoc, T. Thanh, L. Hung, and P. Kager (2002). Control of Malaria: a Successful Experience from Viet Nam. *Bulletin of the World Health Organization 80*, 660–666.

International Rice Research Institute, Rice statistics, Info by country (n.d.). http://www.irri.org/science/cnyinfo/vietnam.asp.

Jacoby, H. and E. Skoufias (1997). Risk, Financial Markets, and Human Capital in a Developing Country. *Review of Economic Studies 64*.

Jensen, R. (2000). Agricultural Volatility and Investments in Children. *American Economic Review, Papers and Proceedings 90*, 399–404.

Kim, A., A. Tandon, A. Hailu, and Others (1997). Health and Labor Productivity: The Economic Impact of Onchocercal Skin Disease. World Bank Policy Research Working Paper No. 1836.

Kirk, M. and N. D. A. Tuan (2009). Land-Tenure Policy Reforms: Decollectivization and the *Doi Moi* System in Vietnam. International Food Policy Research Institute Discussion Paper 00937.

Kozel, V. (1990). The Composition and Distribution of Income in Côte d'Ivoire. Technical Report, World Bank LSMS Working Paper No. 68.

Kramer, M., B. Chalmers, E. Hodnett, and et al (2001). Promotion of Breastfeeding Intervention Trial (PROBIT): A Randomized Trial in the Republic of Belarus. *Journal of the American Medical Association 285*(4), 413–420.

Laxminarayan, R. and K. Moeltner (2003). Malaria, Adaptation and Crop Choice. Working paper.

Leighton, C. and R. Foster (1994). Economic Impacts of Malaria in Kenya and Nigeria. Abt Associates, Health Financing and Sustainability Project, Bethesda, Maryland.

Levine, D. and D. Yang (2006). A Note on the Impact of Local Rainfall on Rice Output in Indonesian Districts. mimeo.

Lindberg, L. D. (1996). Women's Decisions about Breastfeeding and Maternal Employment. *Journal of Marriage and Family 58*(1), 239–251.

Liu, G. G., W. H. Dow, A. Z. Fu, J. Akin, and P. Lance (2008). Income Productivity in China: On the Role of Health. *Journal of Health Economics 27*, 27–44.

Lopez, R. (1984). Estimating Labour Supply and Production Decisions of Self-employed Farm Producers. *European Economic Review 24*, 61–82.

Maccini, S. and D. Yang (2009). Under the Weather: Health, Schooling and Economic Consequences of Early-Life Rainfall. *American Economic Review 99*(3), 1006–26.

Macro International Inc. (1996). Sampling Manual. DHS-III Basic Documentation No. 6 Calverton, Maryland.

McCaig, B., D. Benjamin, and L. Brandt (2009). The Evolution of Income Inequality in Vietnam, 1993-2006 (data appendix). Working Paper.

Morel, C. M., N. D. Thang, N. X. Xa, L. X. Hung, L. K. Thuan, P. V. Ky, A. Erhart, A. J. Mills, and U. D'Alessandro (2008). The Economic Burden of Malaria on the household in South-Central Vietnam. *Malaria Journal 7*.

Morrow, A., M. L. Guerrero, J. Shults, J. Calva, C. Lutter, J. Bravo, G. Ruiz-Palacios, R. Morrow, and F. Butterfoss (1999). Efficacy of Home-based Peer Counselling to Promote Exclusive Breastfeeding: A Randomised Controlled Trial. *Lancet 353*, 1226–1231.

Nam, N. V., P. de Vries, L. V. Toi, and N. Nagelkerke (2005). Malaria Control in Vietnam: the Binh Thuan Experience. *Tropical Medicine and International Health 10*, 357–365.

Noble, S. and The ALSPAC Study Team (2001). Maternal Employment and the Initiation of Breastfeeding. *Acta Paediatrica 90*(4), 423–428.

Pampana, E. (1963). *A Textbook of Malaria Eradication*. London: Oxford University Press.

Paxson, C. H. (1992). Using Weather Variability to Estimate the Response of Savings to Transitory Income in Thailand. *American Economic Review 82*(1), 15–33.

Pitt, M. and M. Rosenzweig (1986). Agricultural Prices, Food Consumption and the Health and Productivity of Indonesian Farmers. In *Agricultural Household Models: extensions, Applications, and Policy*. Johns Hopkins University Press, Baltimore.

Pitt, M. and W. Sigle (1997). Seasonality, Weather Shocks and the Timing of Births and Child Mortality in Senegal. Working Paper.

Sahn, D. and H. Alderman (1988). The Effect of Human Capital on Wages and the Determinants of Labor Supply in a Developing Country. *Journal of Development Economics 29*, 157–183.

Schultz, T. (2002). Wage Gains associated with Height as a Form of Health Human Capital. Economic Center Discussion Paper, Yale University.

Schultz, T. and A. Tansel (1997). Wage and Labor Supply Effects of Illness in Côte d'Ivoire and Ghana: Instrumental Variable Estimates for Days Disabled. *Journal of Development Economics 53*, 251–286.

Strauss, J. (1986). Does Better Nutrition raise Farm Productivity? *Journal of Political Economy 94*, 297–320.

Townsend, R. (1994). Risk and Insurance in Village India. *Econometrica 62*, 539–91.

United Nations Population Division (2008). World Population Prospects. http://esa.un.org/unpp/index.asp.

Victora, C., P. Vaughan, C. Lombardi, S. Fuchs, L. Gigante, P. Smith, L. Nobre, A. M. Texiera, L. Moreira, and F. Barros (1987). Evidence for a Strong Protective Effect of Breastfeeding against Infant Death due to Infectious Diseases in Brazil. *Lancet 330*(8554), 318–322.

Weisbrod, B. and T. Helminiak (1977). Parasitic Diseases and Agricultural Labor Productivity. *Economic Development and Cultural Change 25*, 505–522.

WHO (2000). Who Collaborative Study Team on the Role of Breastfeeding in the Prevention of Infant and Child Mortality due to Infectious Diseases in Less Developed Countries: A Pooled Analysis. *Lancet 355*, 451–455.

WHO (2008). The Global Burden of Disease: 2004 update. World Health Organization.

World Bank (2009). *Gender in Agriculture Sourcebook.* World Bank: Washington DC.

Yoon, P. W., R. E. Black, L. H. Moulton, and S. Becker (1996). Effect of Not Breastfeeding on the Risk of Diarrheal and Respiratory Mortality in Children under 2 Years of Age in Metro Cebu in the Philippines. *American Journal of Epidemiology 143*(11), 1142–1148.