(Job Market Paper)

Going into Labor:
Earnings vs. Infant Survival in Rural Africa

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In Sub-Saharan Africa, variation in weather and nutrition causes children born in certain months to be up to three percentage points more likely to die. This seasonal variation is large relative to the annual average of eleven percent infant mortality. Parents do not always time births for low-mortality months. Agricultural cycles may help explain why: in some areas, low-mortality months coincide with high demand for women's labor. Thus, parents are faced with a stark trade-off between their newborn's health and family income. I show that families who live in areas with a larger trade-off tend to choose birth months that are worse for infant survival. Families who face less of a trade-off – those less dependent on female wages or subject to less seasonal labor demand – choose lower mortality months. Access to family planning exacerbates these effects by helping families target a specific birth-month more accurately. The results suggest that policies that smooth seasonality in labor demand and consumption could substantially improve infant survival.

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1 Introduction

In Sub-Saharan Africa, the predictable seasonal variation in infant mortality is high. If all children were born in the best possible month, infant mortality would fall by at least three percentage points— as much as it has fallen over the last fifteen years. Early-life circumstances have long-term consequences for children who survive infancy in terms of their educational attainment, productivity, and adult health.[1] Evidence suggests that children born in the "wrong" season suffer from an array of health problems and perform worse in school.[2] Improving conditions that determine infant survival can also increase adult human capital.

In this paper, I model the fertility decisions of families in developing countries. In particular, I ask: why do families not optimize childbearing to coincide with the months of minimal infant mortality? One possibility is that, due to agricultural cycles, parents often face a trade-off between their income and the health of their newborn. Thus, even in places with high infant mortality, choosing a month that assures a greater chance of infant survival might not be optimal if it implies a reduction in income that jeopardizes the health and well-being of the entire family. I posit that this family-income versus infant-health trade-off affects the seasonal pattern of childbirth in Sub-Saharan Africa.

I start by showing that month of birth is a strong predictor of infant mortality in African countries.[3] Environmental diseases and nutrition vary during the year, affecting both maternal and infant health. Combining data on monthly precipitation and food

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[1] See, for example, Barker (1992 and 1994), Almond (2005), and Behrman and Rosenzweig (2004).

[2] For summary of this literature, see Doblhammer (2004) and Bound and Jaeger (1996).

[3] This seasonality has been documented in the medical literature, but has barely been used by economists.

availability with birth and death records from 28 Sub-Saharan countries, I construct country and regional measures of the relative risk of infant mortality.[4]

Using agricultural calendars, I compare the above data with measured differences in the demand for female agricultural labor. There is a strong seasonality of labor demand for the rural population: rural markets depend heavily on the agricultural cycle, and therefore the opportunity cost of a woman's time varies during the year. Her ability to work during the high-demand months is important for household income.

I hypothesize that the interaction between these two seasonal sources is an important determinant of child well-being. For some rural families, months with higher potential income coincide with those of higher expected infant survival. In this case, parents face a stark trade-off between their newborn's odds of survival and the well-being of the existing family members. In other areas, the months do not coincide. In these cases we expect that, on average, parents will be guided by the simultaneous benefits of infant health and minimal income-loss to have children at the safest times.

I develop a model to illustrate this phenomenon and test its implications, taking advantage of both cross-section and time variation. Studying decisions on birth-month using nationally representative household survey data, I find that the magnitude of the trade-off between newborn health and family income affects the extent to which parents maximize child survival across countries and regions. I also show that families who are less dependent on maternal labor respond less to this trade-off, as do those in places where rural wages have become less seasonal. In both cases, the trade-off is lower and considerations of infant welfare are more likely to win out.

[4] The data are from the Demographic and Health Surveys, which are described in greater detail below.

In terms of how effectively parents execute their choices, one would expect those with access to better planning technology to be more responsive to the level of the trade-off, since they can time births more precisely. I show that, indeed, the response to the trade-off level varies positively with contraceptive availability. Finally, since urban families have a much smoother labor market throughout the year, I compare urban and rural households. As expected, the gap between them in chosen expected survival widens as the level of the trade-off increases.

My results have several distinct implications. First, the existence of a strong trade-off between infant health and family income can create a poverty trap in which the poor knowingly invest less in their children's future human capital, thereby creating adults who are so poor that the trade-off between child health and family consumption remains stark. Second, family planning campaigns can have benefits beyond helping control family size, birth spacing, and exposure to sexually transmitted diseases: they can also help families optimally time births and thus assist them in raising healthier children. Finally, in places where the trade-off is extreme, the greatest help may be in programs that help families smooth consumption, such as access to credit and economic diversification. Contraception will only increase these families' abilities to have children at less safe times, whereas agricultural policies could ease their choice between income and children's health. Taken together, these findings suggest that it is important to consider the degree of trade-off when determining which set of policies to implement in a given setting.

Section 2 provides background information on the seasonality of infant mortality and rural labor markets in Sub-Saharan Africa. I outline a simple model of fertility timing and obtain predictions about how parents should respond when they face family consumption versus child-investment trade-offs (Section 3). In Section 4, I construct measures of the healthiness of each birth-month in each area. Section 5 describes how countries and regions are classified according to the level of the trade-off that families face. The predictions from the model are tested, and the main results are discussed in Section 6. Section 7 discusses the implications of the results for the value of life. Section 8 concludes.

2 Infant Mortality and Labor Markets

2.1 Infant Mortality

Infant mortality in Sub-Saharan Africa is high: today, more than ten percent of children born live die before reaching the age of one. Figure 1 compares infant mortality rates across regions of the world. Infant mortality rates in Africa are substantially higher than for the rest of the world. In many countries, the causes of infant mortality—including infections, diarrhea, measles, premature births, and poor maternal health—can be linked to seasonal variation. For example, Figure 2 depicts the infant survival rates for Mozambique by month of birth. The rates bottom out below 87 percent in July and peak in December at nearly 92 percent, implying a five-point swing in the probability of survival to age of one.

Diseases are a partial source of this variation. Malaria and parasitic diseases, for instance, become a bigger threat during rainy seasons when it is damp and organisms can grow more quickly. In some countries, malaria flourishes only during the rainy season, when it particularly threatens pregnant mothers and newborns, whose immunity to it is weakened and non-existent, respectively. In other countries, malaria is endemic throughout the year and illnesses like measles and polio, typical of the drier months, create seasonal variation in health. In short, the diseases that create seasonality in health differ across countries. Figure 3 shows the differences in malaria seasonality in the African continent. In some countries, the duration of malaria transmission lasts only several months, while in others it occurs year-round. There is also a third group of countries that are malaria free.

In addition to disease, variations in infant mortality may be linked to the fact that rural households typically have highly seasonal income streams. Food insecurity is typically lowest immediately after the harvest and highest before the new harvest. Calorie deficits in lean periods generate lower birthweight babies, who are less likely to survive (Prentice et al., 1987).

This seasonal variation in mortality is observable to the families it affects. While the effects of season of birth on long-term outcomes (such as female fertility or adult mortality) may be difficult to notice, 38 percent of deaths that occur before the age of five happen during the first month of life (Lawn et al., 2005), and the environmental conditions in Africa that cause this variation in birth-month desirability have not changed much for centuries. It is reasonable to expect that knowledge of which months are the best months for infants and mothers has been handed down from generation to generation.

2.2 Labor Markets and Fertility

Women in Sub-Saharan Africa are usually responsible for managing cereal crops (Adepoju and Oppong, 1994), which are dependent on rainfall. The demand for female labor thus peaks during the rainy season. After the harvest and before the rains begin, demand for female labor is low: the cereal crops are not growing and the tasks typical of these months (like clearing the fields) are performed by men.[5]

Eighty percent of Sub-Saharan African women earn most of their income from agricultural work (Kwesiga, 1998). Female family members' ability to work during these months of high agricultural demand is therefore essential to a household's income. Since most families have little or no access to credit for consumption smoothing and because most live close to subsistence, shortfalls in income translate directly into painful consumption shortfalls. Childbearing reduces a woman's productivity for months: advanced pregnancy hardens physical work, breastfeeding prevents long, uninterrupted hours in the fields, and traditional taboos stigmatize a mother's appearance outside the home during the period immediately following a birth.[6]

Aggregate data suggest that the average woman recognizes these variations in infant-healthiness prognoses and labor opportunity costs throughout the year. Figure 4 shows that births tend to be concentrated in months with an estimated higher probability of survival. This is only suggestive evidence, since underreporting of infants who die before the age of one could drive some of the observed relationship. Figure 5 shows that

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[5] In many African countries, men are given the more dangerous and physically demanding tasks. This accounts for the division of labor.

[6] These taboos serve the purpose of helping new mothers recover after delivery (Page and Lesthaeghe, 1981).

births also tend to be less common during harvest season, implying some displacement of births away from the busiest months of the year.

There is a substantial body of research relating separately agricultural cycles and weather with births.[7] In addition, studies show that seasonality in births is a pervasive phenomenon, that individual countries have very stable seasonal patterns, and that these patterns differ between counties.[8] This paper contributes to and expands on the existing research by estimating how elastic the timing of births is to seasonal variation in healthiness and labor demand. I also explore the related topic of accounting for the degree to which a birth is planned in these populations; this helps to isolate biological explanations.

The only other paper, to my knowledge, that attempts to explain seasonal birth variation using measures of both opportunity cost and infant health is Pitt and Sigle (1997). Their study is limited to the rural Senegalese population, where no trade-off between the two exists. They conclude, as I do for Senegal, that both forces go in the same direction: when demand for female labor is down, the chance of infant survival is up.

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[7] For example, German peasants and the rural Egypt population are studied by Nurge (1970) and Levy (1986), respectively. They both find that families attempt to avoid births in periods of peak labor demand.

[8] See Lam and Miron (1991) for a detailed discussion.

3 A Fertility Timing Model

In this section, I model the household's decision of *when* to have a child during the year. I make two central assumptions: (1) households want to have a child, and (2) households want to plan the season of birth.[9]

Parents choose the month of birth, *m*, in order to maximize their utility. This depends exclusively on two arguments: survival of the newborn, *S(m)*, and family consumption, *C(m)*:

$$U(m) = S^{\gamma}(m)\, C^{1-\gamma}(m)$$

For simplicity, I assume that there are only two months in the year: $m = \{1, 2\}$.

To capture the infant mortality and labor market seasonality present in Sub-Saharan African countries, both survival and consumption are considered as a function of time of birth. Survival can be either high (S_H) or low (S_L). I normalize for all countries the first month ($m = 1$) to imply high survival probability, and the second month ($m = 2$) to imply low survival probability:

$$S(m) = \begin{cases} S_H & if \quad m = 1 \\ S_L & if \quad m = 2 \end{cases}$$

Family consumption during the year depends on the time of birth through the maternal labor market. As discussed above, Sub-Saharan African families live near subsistence level. They possess few savings and have limited access to credit markets. I assume that

[9] I assume a unitary family decision model. The results hold in the case of women making decisions independently on their productivity and fertility.

consumption in a particular year depends exclusively on family income for that year, which is the combination of maternal wages and earnings from other family members:[10]

$$C(m) = L_2 w_1 + L_2 \; w_2 + y$$

where L_m is the labor supplied by the mother in each month and it is a function of her child's month of birth, w_m is the wage earned in month m, and y is the annual income from other family members, which I assume for the moment to be independent of fertility decisions.

Mothers have only one indivisible unit of time in each period. They can either use it in the labor market to earn wages, or have a child and spend their time in childbearing activities. I abstract from labor-leisure considerations. Maternal labor supply in each month is:

$$L_1 = \begin{cases} 1 & if \quad m = 2 \\ 0 & if \quad m = 1 \end{cases} \qquad \text{and} \qquad L_2 = \begin{cases} 1 & if \quad m = 1 \\ 0 & if \quad m = 2 \end{cases}$$

Parents optimize by comparing the utility of giving birth in month 1:

$$U(m = 1) = S_H^{\gamma} (w_2 + y)^{1-\gamma}$$

relative to the utility of giving birth in month 2:

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[10] Families cannot smooth consumption across years because of the lack of savings and credit markets. However, it is reasonable to assume that they can, at least partially, smooth consumption during the year. Basically, individuals earn most of their income in a short period of time and then consume it throughout the year.

$$U(m=2) = S_L^{\gamma}(w_1 + y)^{1-\gamma}$$

They choose to give birth at *m=1* if

$$\left(\frac{S_H}{S_L}\right)^{\gamma} \geq \left(\frac{w_1 + y}{w_2 + y}\right)^{1-\gamma}$$

and will otherwise decide to give birth at *m=2*. We can rewrite the above expression as:

$$\left(\frac{S_H}{S_L}\right)^{\gamma} \geq \left(\frac{\bar{y} - w_2}{\bar{y} - w_1}\right)^{1-\gamma} \tag{1}$$

where $\bar{y} \equiv w_1 + w_2 + y$ denotes the potential annual family income.

The left side in inequality *(1)* represents the ratio of survival of being born in month 1 relative to month 2. This ratio is, by definition, always greater than one. The right side in *(1)* is the ratio of the income loss from giving birth in the second month and the income loss from giving birth in the first month. This can be greater than, equal to, or smaller than one depending on the relation between wages in the two periods.

The relation between w_1 and w_2 is crucial to the family's decisions, and depends on where they live. Heterogeneity between countries results from the fact that, in some countries, the months of high survival rate coincide with high wages, while in others the high survival period is at the time of low wages. When wages in the second month are higher than in the first ($w_1 < w_2$), the marginal product of labor is higher at the time of the year that expected survival is low (S_L). The loss from not working in month 2 is therefore greater than from not working in month 1, and the ratio on the right side in equation *(1)* is smaller than 1. In this case, parents face no trade-off. Both survival and family consumption are maximized by giving birth at $m = 1$.

On the other hand, when $w_1 > w_2$, the opportunity cost to give birth is highest when expected survival is high ($m = 1$). In this case, families have to choose between maximizing survival or consumption. The optimal choice will depend on how strong seasonal mortality and labor demand are and parent's relative preferences between consumption and infant survival.

Heterogeneity within countries derives from the difference between the urban and rural labor markets. I assume that only the labor market of the rural population, which depends on agriculture, is seasonal. That is, urban populations face constant wages throughout the year, $w_1 = w_2$.

The above setup leads to several implications that I later test with the household data:[11]

- *Prediction 1*: As the level of trade-off increases across countries (or regions), rural families choose, on average, lower survival months. The more the healthiest months coincide with high labor demand, the less likely parents are to maximize infant survival.
- *Prediction 2*: Parent are *less* responsive to the trade-off as the fraction of total household income that comes from maternal labor decreases $\left(\frac{w_1 + w_2}{\bar{y}}\right)$ and as

[11] Some of these predictions are implied from a richer version of the model. The intuition behind it is the same as in the simple version developed in this section.

the amount that other family income (y) can increase when maternal labor is reduced increases.[12]

- *Prediction 3*: As seasonality in wages becomes smaller, the trade-off is reduced and families make better decisions regarding children's health.
- *Prediction 4*: If birth-month is chosen with some error, the availability of better family planning should increase the observed response to the trade-off between newborn health and family income.
- *Prediction 5*: If urban wages are constant throughout the year, the gap between urban and rural survival maximization increases with the level of rural trade-off.

4 Estimation: Seasonal Infant Mortality

4.1 Estimation Strategy

Simple monthly averages in infant mortality may be misleading. Therefore, to test predictions of the model, I must first isolate variations in infant mortality that arise exclusively from changes in exogenous factors within the year, and abstract from potential behavioral changes that can affect the probability of a newborn's survival.

There are two reasons why simply computing the monthly survival average can be misleading. First, maternal behavior may vary during the year – mothers may be less attentive to children during the months when they are busiest, for example. Second, families with different characteristics (for example, the level of wealth) that affect

[12] I bound together these two effects because the results in Section 6 can be driven by either one.

survival of their newborns might disproportionately give birth in certain months. Thus, some of the observed seasonality might be due to family selection.

I solve the first problem by estimating infant survival using only exogenous seasonal variation as explanatory variables: rainfall precipitation and food availability.[13] Data on the average monthly rainfall precipitation comes from the Global Precipitation Climatology Project (GPCP) database.[14] I use the information provided by the Food and Agriculture Organization of the United Nations (FAO) to indicate which months during the year are characterized by food insecurity in a country. The lean, or low calorie, season occurs when food stocks from the previous year's harvest have run out before the new ones have been harvested.

To get around the potential family selection problem, I take advantage of the rich information in the birth records of the Demographic and Health Surveys (DHS).[15] For most of the countries in my sample more than one survey exists. I merge all surveys available to create the sample of births for each particular country. The Reproduction module, which is administered to all women interviewed, contains their entire birth history. It has data on the month and year of the birth, gender, birth order, number of

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[13] Average monthly temperature is another potential variable but it does not seem to predict changes in survival probabilities. The main regression results are unaffected by the inclusion of this variable.

[14] The GPCP dataset extends from 1979 to 2003 and combines actual weather station rainfall measures with satellite information on the density of cold cloud cover. Rainfall estimates are derived at 2.5 latitude and longitude degree intervals. I average the information for the 25 years available and for the nodes within the country to construct the average monthly-country rainfall precipitation.

[15] The DHS are nationally representative samples of households, where all women in the household between the ages of 15 and 49 are interviewed. Along with individual and household characteristics like education, spouse's education, urban/rural status, and income measures, information is also gathered on female reproduction history. See the Appendix for a complete list of surveys used.

births, whether the child is still alive at the time of the survey, and, if the child is dead, the age at which he or she died. No information on the biological father is included.

Using this detailed birth information, I compare differences in the probability of survival to the age of one among siblings from the same mother. I relate these differences to birth months. That is, for each birth record in the sample of a mother who had more than one birth since 1960, I generate a variable indicating whether the child survived more than 12 months. Using a linear probability model, I regress the survival binary variable on a set of explanatory variables, measures of rainfall and food availability, and, most importantly, the mother fixed effects.[16]

I run the following regression for each country individually (as I have discussed above, the effect of rainfall and food availability differ across countries). The unit of observation in the analysis is a birth *i*, at month *m*, to mother *j*:

$$\begin{aligned}\Pr(Survival)_{i,m,j} = \;& \beta_0 + \beta_1 Gender_{i,m,j} + \beta_2 Order_{i,m,j} + \beta_3 Age_{i,m,j} + \gamma_j \; Mother_j + \\ & \beta_4 Rain_m + \beta_5 \frac{1}{2}\sum_{t=1}^{2} Rain_{m-t} + \beta_6 \frac{1}{2}\sum_{t=1}^{2} Rain_{m+t} + \\ & \beta_7 Lean_m + \beta_8 \frac{1}{2}\sum_{t=1}^{2} Lean_{m-t} + \beta_9 \frac{1}{2}\sum_{t=1}^{2} Lean_{m+t} + u_{i,m,j}\end{aligned} \tag{2}$$

where *Gender* is the sex of the newborn, *Order* is the birth order within the mother's offspring, *Age* represents age of the mother at time of birth, *Mother* is the mother fixed

[16] If families who are more susceptible to *seasonal* infant mortality give birth disproportionately in particular months, we may still over- or underestimate the effect of exogenous factors on infant health. In particular, if highly affected families concentrate more births in worse (better) months, seasonal infant mortality would be overestimated (underestimated). Empirically, the distribution of births is uncorrelated with observable family characteristics like education and incomes.

effects, $Rain_t$ is the country's average monthly precipitation at time t, and $Lean_t$ is a binary variable indicating whether the month t is prone to be a food-insecure month.

The regression includes current, lag, and lead measures of rainfall and food availability. I include the lag measures to control for factors affecting the mother's health during the last months of pregnancy, which influences fetus' health and the probability of infant death. I distinguish the month of birth from the following two months. The first month of life is the most critical for an infant. Survival starting in the second month strongly depends on the nutritional and immunological qualities of breastfeeding.

After running each country-specific regression, I generate the expected monthly survival using the predicted coefficients net of mother fixed effects:

$$\begin{aligned}\hat{E}(Survival)_{m,c} \quad = \quad & \hat{\beta}_{4,c} Rain_{m,c} + \hat{\beta}_{5,c} \frac{1}{2}\sum_{t=1}^{2} Rain_{m-t,c} + \hat{\beta}_{6,c} \frac{1}{2}\sum_{t=1}^{2} Rain_{m+t,c} + \\ & \hat{\beta}_{7,c} Lean_{m,c} + \hat{\beta}_{8,c} \frac{1}{2}\sum_{t=1}^{2} Lean_{m-t,c} + \hat{\beta}_{9,c} \frac{1}{2}\sum_{t=1}^{2} Lean_{m+t,c}\end{aligned}$$

Finally, I construct a measure that captures the loss in expected infant survival from not being born in the best month. I compare months relative to the highest possible survival month in each country. A higher difference in expected survival implies higher *Loss*, which is my dependent variable in my tests of the model. *Loss* measures how much parents are giving up in terms of expected infant survival:[17]

$$Loss\, E(Survival)_{m,c} = \max(Survival)_c - \hat{E}(Survival)_{m,c} \tag{3}$$

[17] Parents maximize survival by reducing the loss.

As an alternative approach, I regress the probability of survival on a set of month indicator variables. This estimation does not make any assumptions about the sources of variation in infant health. The coefficients potentially capture exogenous factors other than rainfall and food seasonality that affect infant mortality. The month effects also capture potential behavioral changes in the care of the child. As we will see in section 6, using monthly indicators does not significantly change the results.

Using this alternative strategy, I regress the probability of survival to the age of one on the set of month indicator variables and the mother fixed effects:

$$\Pr(Survival)_{i,m,j} = \sum_{t=1}^{12} \alpha_t m_t + \gamma_j Mother_j + u_{i,m,j} \tag{4}$$

where m_t is an indicator of being born in month t. I then construct the expected survival for each month-region combination using only the information from the set of binary variables in equation *(4)*.

$$\hat{E}(Survival)_{m,c} = \sum_{t=1}^{12} \hat{\alpha}_{t,c} m_t \tag{5}$$

My alternative measure of *Loss* is computed using equation *(3)*.

It worth noting that there are at least two reasons why the seasonal infant survival might be biased given the data used in this paper, regardless of which specification I employ. First, the surveys rely on a woman's recollection of the dates of all her live births. Children who have died, especially shortly after birth, are more likely to be misreported or just not reported at all. In both cases, seasonal infant mortality is underestimated. Second, the surveys do not provide information on births from women who have died. Maternal mortality is highest in Sub-Saharan Africa. The UN estimates that 920 women died for every 100,000 live births in year 2000. Children whose mothers die have lower survival chances. If maternal mortality follows the same pattern as infant mortality, then the estimated effect is underestimated by not having information on birth histories of deceased mothers.

4.2 Results

The average infant mortality across countries in my sample is 11 percent. I find the lowest rates in southern countries (Namibia, Zimbabwe, and South Africa) with average estimates below 7 percent for the period 1960-2002, and the highest in Liberia, Mali, and Guinea with 20, 16, and 15 percent respectively.[18]

After running regression *(2)* I test for the presence of seasonality in infant survival. The null hypothesis of no seasonality is rejected at standard levels in all but four countries.[19] On average, the difference between the peaks and troughs in estimated expected survival is 3 percentage points. This implies that for the average country mortality ranges between 9 and 12 percent, simply as a result of changes in exogenous seasonal factors. The difference between peaks and troughs is on average higher (almost 4 percentage points) when using specification *(5)*. Both measures are, however, highly correlated (0.94). This suggests that changes in maternal behavior do not play a major role in seasonal survival. Instead, weather and food play the key roles.

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[18] These estimates are similar to the numbers reported by UNICEF.

[19] The exceptions are Ivory Coast, Gabon, Rwanda and Sudan. Gabon and Rwanda are near the Equator, where conditions remain essentially constant through the year. Sudan is the biggest country in Africa, so a country average might not be very representative measure.

The effect of rainfall on infant health varies from country to country. For example, in the Ethiopia-Kenya-Tanzania-Zambia belt, where malaria transmission is highly seasonal (See Figure 3), higher precipitation around the time of birth is associated with higher infant mortality. The effect of rainfall on survival is opposite for neighboring countries whose geography imply different duration of the malaria transmission season. In Burkina Faso, months with higher rainfall precipitation are also associated with a higher number of deaths, while in Guinea and Togo they are associated with higher survival rates. Note, from the map in the figure, that Burkina Faso lies in a temporal transmission area while Guinea and Togo lie in the permanent transmission zone.

I also find that food insecurity plays a particularly important role in Sahelian countries like Senegal, Mali, and Burkina Faso. Existing evidence from this region shows that the average birth during the hungry season is usually 200 to 300 grams below normal, and that the prevalence of low birthweight babies doubles in those months (Moore et al., 1997).

As an illustration, Figure 6 shows the relation between infant mortality and exogenous factors for three countries in the sample. In Tanzania (Figure 6a) infant mortality and rainfall are positively correlated while in South Africa (Figure 6b) they are negatively correlated. One main difference between these two countries is that Tanzania has a strong seasonal pattern of malaria, and South Africa is practically malaria free. In Burundi (Figure 6c), over the first 10 months of the year, rainfall and mortality are negatively correlated. In November and December, there is an "unexpected" increase in mortality coinciding with the food-insecure part of the year.

5 Estimation: Level of Trade-off

The model in Section 3 shows that the "birth-month" decision depends on family and residence-specific circumstances. In particular, the decision depends on the relationship between the labor market and infant survival seasonality. In this section, I determine the extent of the trade-off rural families face between maximizing children's health and maximizing family income.

Using information on the cereal crop calendars, I identify high and low labor-demand periods to compare wages for rural populations within the year. The Food and Agricultural Organization (FAO) reports agricultural seasons at the African regional level; I complement this information with more detailed country-specific variations from the Famine Early Warning Systems Network where available.

I compare, for each country and region, the average survival during the dry season (after the harvest is done and before planting begins), when female labor demand is low, with the average survival outside the dry season, when female labor demand is high. This determines the magnitude of the trade-off that families face:

$$TradeOff_c = \hat{E}(Survival \mid high\, L^D)_{m,c} - \hat{E}(Survival \mid low\, L^D)_{m,c} \tag{6}$$

Countries or regions where the expected survival is higher during the low labor demand part of the year are the ones that correspond to $w_1 < w_2$ in the model, and thus face no trade-off between maximizing infant survival and family consumption. On the other hand, countries where expected survival is higher during the high labor demand period face this trade-off, coinciding with the situation of $w_1 > w_2$ in the model. A higher *TradeOff* value is thus a country with more conflict between income and survival.

According to the classification above, 118 regions have a negative *TradeOff* and 112 have a positive one. The mean *TradeOff* is approximately zero ($0.9e^{-5}$), the values ranging from -0.075 to +0.09. Eighty percent of the distribution is concentrated between –0.029 and +0.025. This implies a difference in expected survival of 2.5 and 3 percentage points between the two seasons. Figure 7 plots the histogram for the entire distribution.

Figure 8 shows how the distribution of births is correlated with infant survival for two countries. The rural population in Tanzania (Figure 8a) does not face a trade-off, and they concentrate births when survival is higher. On the other hand, the rural population in South Africa (Figure 8b) faces a trade-off, and their allocation of births during the year is smoother and, on the surface, does not appear to respond to infant survival.

6 Estimation: Predictions of the Model

In this section I compare family behavior in choosing month of birth (and, therefore, choosing expected survival) across countries and regions, within countries, and across time to test the five predictions obtained from the model in Section 3: (1) Families who live in areas with a larger trade-off choose birth months that are worse for infant survival, *(2)*, *(3)* and *(5)* families facing less of a tradeoff – those less dependent on female wages or whose labor demand is less seasonal – choose lower-mortality months, and *(4)* access to family planning exacerbates these effects by helping families target desired birth-months more accurately.

I construct my sample of births using information in the DHS births records, merging data on live deliveries from 50 different surveys belonging to 28 countries and

232 regions. The total sample includes 366,419 births between 1980 and 2003; the rural population accounts for 67.51 percent of this total. Descriptive statistics are in Table 1. For comparative purposes, the sample is split between births occurring in countries with no trade-off (negative *TradeOff*) in column *(2)* and countries with trade-off (positive *TradeOff*) in column *(3)*. The statistics for the full sample are reported in the first column. Urbanization, maternal and paternal education, family size, usage and availability of modern contraceptive, average infant survival, and poverty ratios are similar in magnitude across the two groups. Thus, the level of trade-off is not correlated with other variables that could affect fertility decisions.

For each birth, I assign the constructed measure of loss in expected survival by the specific month and place of birth (equation (*3*)). This constitutes the dependent variable in the regressions. This variable captures the loss in expected survival from not choosing the best possible month for a given place of birth. As discussed in Section 4, I have estimated infant survival in two different ways: using exogenous variation across months and using monthly indicator variables. I run all regressions in this section using *Loss E(survival)* and *TradeOff,* each constructed from a different version of infant survival. *Version 1* refers to the results obtained when estimating infant survival with exogenous factors, and *Version 2* refers to estimates derived from monthly binary variables.

6.1 The Response of Rural Families to the Trade-Off

The model first predicts that parents choose months of birth with lower expected survival as *TradeOff* increases. Using the sub-sample of rural births, I regress the expected loss in infant survival on family and birth characteristics, and the country level of the trade-off:

$$Loss\ E(Survival)_{i,m,c} = \beta_0 + \beta_1 TradeOff_c + X_{i.m.c}'\gamma + u_{i,m,c} \tag{7}$$

where X is a control matrix that includes child and family information (gender, parents' education, income proxies, birth order, and family size). By construction, the *TradeOff* variable varies at the country level, so I cannot control for fixed differences across countries. For the same reason, robust standard errors are used in all specifications.

The model predicts that as the magnitude of the trade-off increases, parents reduce expected survival. If this prediction is true, we would expect $\beta_1 > 0$. Table 2 presents these results. The coefficient for the country trade-off level is positive and significant at the one-percent level for both versions of the regression. As the level of the trade-off of the country increases, families choose months of births that are, on average, worse for the health of their newborns. That is, parents are sensitive to the trade-off and compromise their newborn's survival probability in favor of family consumption.

The coefficient estimates for the *TradeOff* variable are fairly similar for the two specifications: 0.58 (*Version 1*) and 0.47 (*Version 2*). The standard deviation for *TradeOff* is 0.018 and 0.019, and for *Loss in Expected Survival* is 0.018 and 0.022 for *Version 1* and *2*, respectively. This implies that a 1.5 standard deviation higher trade-off increases the loss in infant survival by between 50 and 60 percent of a deviation: an increase of 1.5 percentage points in infant mortality.[20,21] This is a substantial effect on the average infant mortality of 11 percent.

As I will discuss later, I can only estimate differences in infant mortality using monthly indicator variables at the regional level (*Version 2*). However this should not be a problem since both versions deliver similar results in all regressions. To avoid unnecessary repetition, while I report both versions of the regressions in the tables, I will only hereafter discuss the results from exogenous estimates (*Version 1*).

6.2 Maternal Wages and Other Family Income

The second prediction of the model states, in summary, that there is a positive correlation between a family's dependence on maternal income and its sensitivity to the trade-off. The smaller the fraction of income coming from maternal labor and/or the more other family income can increase when maternal labor is reduced, the less a family will

[20] The dependent variable (*Loss E(Survival)*) and the main exogenous variable (*TradeOff*) are both constructed using estimates of seasonal infant survival. Higher seasonality in infant survival should induce higher average loss. If the level of the trade-off is either positively or negatively correlated with seasonality, left- and right-hand variables will be correlated. I check for this possibility by standardizing the loss in expected survival so each country has mean zero and variance equal to one. All results in the paper hold when using this new variable.

[21] Seasonal infant survival is calculated using the entire rural population, and the average estimate is assigned to all children born in the same month. However, not all families are likely to be affected by exogenous factors with the same intensity. In particular, family income might determine the acuteness. If income distribution within a country is correlated with the level of trade-off, results in regression *(7)* would be bias. Specifically, if the fraction of families more likely to be affected is positively (negatively) correlated with the level of trade-off, β_1 is overestimated (underestimated). The ratio of people living below the poverty line is uncorrelated with the trade-off (-0.08) suggesting that the above might not be a concern.

respond to the trade-off. I test for this implication by examining variation in the number of working-age children families have at the time of the new birth.

Africa has a high incidence of child labor. For the average country in my sample, it is estimated that approximately 34.6 percent of children between 10 and 14 years old are involved in economic activity (ILO, 1996).[22] Child labor is an overwhelmingly rural phenomenon, where it is a major contribution to family income: as many as 70 percent of all child laborers are involved in agricultural production (ILO, 1998).

For families in rural areas, older children can substitute for pregnant mothers. The family income loss from mothers not working during the high labor demand months is lower, and expected survival can be increased. Alternatively, if children are already working, we can interpret that the maternal wage will be a smaller fraction of the family's total income. As a result, the reduction in consumption for each household member becomes smaller when mothers cannot work, and parents can target healthier months for their newborns.

For each child in my sample, I calculate the number of siblings in the 10-14 age range at the time of his/her birth[23] and compare how family composition affects the response of households within countries to the trade-off:

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[22] Estimates available for Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Cote d'Ivoire, Ethiopia, Ghana, Guinea, Kenya, Madagascar, Malawi, Mali, Mozambique, Niger, Nigeria, Senegal, Tanzania, Uganda, Zambia, and Zimbabwe for year 1995.

[23] I construct this measure using information on siblings' year of birth and whether they are alive. I restrict the sample to ages 10 to 14. Older children are more likely to have left the household and may not contribute to family income. Results are robust to the use slightly different age groups.

$$Loss\ E(Survival)_{i,m,c} = \beta_0 + \beta_1 Siblings_{i,m,c} + \beta_2 (Siblings * TradeOff)_{i,m,c} + X'\gamma + \delta_c\ Country_c + u_{i,m,c} \quad (8)$$

where *Siblings* is the number of siblings 10 to 14 years old at the time of birth, *Country* are country-fixed effects, and the remaining variables are as described above.

A higher number of children should be associated with lower reaction to the trade-off, $\beta_2<0$, if the model's predictions are correct. The results from regression *(8)* are in Table 3. The first row contains the estimate for the interaction term (β_2). The coefficient is negative and significantly different from zero at five percent level. Parents make healthier choices for their newborns when there are older siblings in the household in this particular age range.[24] The point estimate is equal to -0.033, implying that the presence of an older sibling at time of birth reduces the effect of the trade-off by around six percent. Consistent with model, having other members of the family to contribute makes the cost of the mother's not working smaller, allowing parents to make better choices regarding the health of their newborn.

The level effect of number of siblings on *Loss*, β_1, is significant at the five percent level, but the magnitude is approximately zero ($2.05e^{-4}$).

6.3 Irrigation

Rural wages become less seasonal with the introduction of irrigation systems that allow women to undertake gardening activities during the dry months. I obtained data from the World Development Indicators on the percentage of cropland that is irrigated in countries in my sample. This information is gathered on an annual basis, which allows me to study

[24] The presence of children younger than 10 has no significant effect on chosen month of birth.

family behavior across time. As the percentage of irrigated land increases in a country, parents should become freer to choose months with higher expected survival (third prediction of the model). That is, irrigation reduces the trade-off.

The percentage of irrigated land may be correlated with country wealth. I therefore I control in the regression for the per capita GDP and its interaction with the trade-off level:

$$\begin{aligned} Loss\ E(Survival)_{i,m,c,y} = \quad & \beta_0 + \beta_1 Irrigation_{c,y} + \beta_2 (Irrigation * TradeOff)_{i,m,c,y} + \\ & \beta_3 GDP_{c,y} + \beta_4 (GDP * TradeOff)_{i,m,c,y} + \\ & X'\gamma + \delta_c\ Country_c + \delta_y Year_y + u_{i,m,c,y} \end{aligned} \tag{9}$$

where the *Irrigation* represents the percentage of cropland that it is irrigated for country *c* in year *y*, *GDP* is the country per capita income, and *Year* and *Country* are the respective fixed effects.

The results, presented in Table 4, show that the introduction of irrigation- holding per capita GDP constant- disproportionately benefits countries with higher ex-ante trade-off by allowing their families to choose better birth months for the health of their children. The coefficient estimate for this effect (β_2) has the expected sign and is significant at the one percent level. If we compare the magnitude results in Table 2, we can see that the size of these new estimates is large. A two-percentage points increase in national irrigation would offset the entire effect of the trade-off, holding per capita income constant.

One reason for this implausibly large result could be the presence of non-linearities in the effect of irrigation. Only about one percent of the land is irrigated for the median country-year in the sample, and less than ten percent of the observations have more than nine percent of cropland irrigated. Irrigation may have a larger effect at these extremely low levels.

It is worth noting that per capita GDP has a similar effect. The richer the country becomes, the lower the reaction to the earnings versus health trade-off is (β_4<0). The point estimate (row three) is equal to 0.582, implying that an increase of $800 in per capita income eliminates the effect of the trade-off on infant survival. As countries become richer, families are less damaged by wage losses. I do not include this effect with the predictions of the model because wealth has potential implications for the seasonality of infant mortality. In particular, we would expect parents to have more control over environmental changes responsible for seasonal mortality as they become richer. If this were true, they would have less incentive to target low mortality months, rendering the predictions from the theory ambiguous. Empirically, however, the first effect dominates.[25] The level effect for both *Irrigation* (β_1) and *GDP per capita* (β_3) are small and not significantly different from zero.

6.4 Modern Contraceptive Availability

Parents with access to modern contraceptive methods should appear more responsive to the level of trade-off because they can time births more effectively. Using information from the surveys on whether the mother has ever used contraceptive methods, I separate the sample of rural births into two groups:

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[25] Alternatively, we could think that parents do not adapt fast to changes in the intensity of seasonal mortality.

$$
\begin{aligned}
Loss\ E(Survival)_{i,m,c} = \quad & \beta_0 + \beta_1 Use_{i,m,c} + \beta_2 (Use * TradeOff)_{i,m,c} + \\
& X'\gamma + \delta_c\ Country_c + u_{i,m,c}
\end{aligned}
\tag{10}
$$

where *Use* is an indicator variable equal to one if the mother has ever used modern contraceptive methods.

If the prediction of the model is correct we should find that $\beta_2 > 0$: parents in rural areas who have access to a better planning technology reduce expected survival more than parents who do not as the level of trade-off increases. Table 5 shows these results. The first row corresponds to the interaction term (β_2). Contraceptive availability does accentuate the response to the level of trade-off. The point estimate is positive and significantly different from zero. The magnitude of the coefficient is small, implying that an increase of 1.5 standard deviations in family trade-off makes contraceptive users reduce expected survival over contraceptive non-users by 0.2 percentage points. The level effect of using modern contraceptive methods (β_1) is small and not significantly different from zero.

This small effect could imply that traditional contraceptive methods are widely used and sufficiently effective that modern technology does not increase accuracy much. It is more likely, however, that the OLS results are biased for several reasons. First, the use of contraceptive methods has costs (monetary and otherwise). We should expect that the families who will benefit more from planning the seasonality of births are the ones more likely to pay for it. In this case, the estimates in Table 5 would be consistent with families responding to the trade-off but would be uninformative about the effect of making family planning more accessible. The point estimates would be upward biased.

A second problem with the OLS estimates is that, as the level of contraceptive use in a country varies, the marginal family who uses them also changes. There is a composition effect in the sample of women who plan births. In particular, we can think that, as contraceptive availability increases, the costs of using them are reduced so that families who benefit less will start using them to plan. In this case, it is not clear how the bias would affect the results. Moreover, cross-country evidence does not show any relation between the trade-off that rural families face and the level of contraceptive use.

Third, I use only a proxy for planned births but not the actual level of planning involved in a particular birth. The information I have to construct the variable *Use* tells me whether a woman has ever used modern contraceptive methods, but there is no indication of the frequency or efficacy of usage. This measurement error would bias the coefficient estimates towards zero.

Finally, other problems might arise if the planning of births is correlated with other factors that could affect the fertility distribution. Seasonal migration and monthly variation in marriage (or first unions in general) could be correlated with individual characteristics, including willingness and capability to plan births.

6.5 Modern Contraceptive Availability – Instrumental Variables

In order to correct for these potential biases and have a better interpretation of the coefficients, I re-estimate regression *(10)* instrumenting for contraceptive usage. I use two different instruments from the DHS questionnaires. I construct the first instrument from information on whether the mother "knows where to find male condoms." I code it as a binary variable equal to one if the woman reports a place where she knows male condoms to be available, and zero otherwise. This represents whether the modern technology for planning births is accessible. One could argue, of course, that individuals gather information on things they are interested in, and women who desire to plan their births will have better knowledge of where to find condoms. Alternatively, I construct a second instrument that indicates if the woman in the sample has ever heard of family planning in the media (television, radio, or newspapers), a variable that is more likely to be exogenous to a woman's desire for planning births.

Table 5 presents the results from regression *(10)* using two stage least squares. The first two columns show the coefficients from using the first instrument, the third and fourth columns from using the second one. In the first stage, both instruments appear to be strongly correlated with the use of contraceptive methods. In the second stage, the point estimates for the specification using knowledge of where to get male condoms are slightly higher. Note that for both instruments the magnitudes of the coefficients are very similar to the ones found in Table 2. These results are suggestive that better contraceptive technology has a strong effect in helping time births better, allowing parents to respond more to the level of trade-off.

6.6 Urban vs. Rural Families

Labor demand is not seasonal for women living in the cities. Therefore, urban families are not subject to the earnings versus infant-health trade-off. We should find that, as the severity of the trade-off in a country increases, the gap between urban and rural infant survival maximization also increases. This is the fifth prediction of the model.

The level of contraceptive use in urban areas is much higher than in rural ones. Therefore, comparing average family behavior between the two groups would be misleading. Instead, I compare the difference between contraceptive users in urban and rural areas (using contraceptive non-users as a control group) as the trade-off level changes. The regression specification becomes:

$$\begin{aligned} Loss\ E(Survival)_{i,m,c} \quad = \quad & \beta_0 + \beta_1 Rural + \beta_2 Use_{i,m,c} + \beta_3 (Rural * Use)_{i,m,c} + \\ & \beta_4 (Use * TradeOff)_{i,m,c} + \beta_5 (Rural * TradeOff)_{i,m,c} + \\ & \beta_6 (Use * Rural * TradeOff)_{i,m,c} + X'\gamma + \delta\ Country_c + u_{i,m,c} \end{aligned} \qquad (11)$$

where *Rural* is an indicator of whether the family lives in a rural area and the rest of variables are as described above.

The coefficient of interest is β_6, which indicates the difference in infant survival maximization between urban and rural families as the trade-off level changes. From the model, we expect it to be positive. Urban wages are constant throughout the year, implying that urban families are not subject to any trade-off. If rural families increase survival maximization as the trade-off decreases, then the gap between urban and rural in survival maximization should increase with the level of the trade-off.

I estimate equation *(13)* both with OLS and 2SLS[26]. Table 6 shows the results. The first row reports the coefficient for the triple interaction, β_6. The point estimates are positive and statistically different from zero at the one-percent level. The difference in response to the trade-off between urban and rural households using 2SLS is comparable to the estimates in Table 5.

[26] The marginal woman who uses modern contraceptive methods most likely differs across urban and rural areas. This concern adds to the existing reasons discussed in section 6.4 for using the instrumental variables approach in this context.

6.7 Regional Results

A country might not be the appropriate unit of analysis to study seasonal infant health, because of within-country variation in seasonal factors and mortality. To complement this country-level variation, I also obtain estimates across regions within countries. The DHS contains information on the region of residence. The definitions of regions sometimes change, however, between surveys of the same country. In these cases, I have used the most recent survey file. Proceeding in this way, I construct a sample with 232 regions from 28 countries. These new estimates have the advantage of capturing regional differences, but have two disadvantages: first, the samples sizes are much smaller, and second, there is a lack of information on exogenous seasonal changes.

I do not have regional measures of rainfall that can be matched to the DHS nor information on differences within countries for food-insecure months. For this reason, I can only obtain estimates of monthly infant survival from using the monthly binary indicators. This corresponds to *Version 2* in the country-level regressions. Country estimates are, however, similar for both versions.

I re-estimate equation *(7)* using regional variation in the level of trade-off. Table 8 shows that, as the level of the trade-off increases across regions, rural families who plan births maximize expected infant survival less. This is true whether the regression controls for country-fixed effects or not. The point estimates are between 40 and 60 percent of the cross-level results. This smaller effect obtained might be the result of an increase in measurement error in estimating the variables. Smaller sample sizes are used to estimate seasonal infant mortality, which may bias toward zero the point estimates.

7 Implications for the Value of Life

This section discusses whether the results obtained from empirical analysis are consistent with the assertion that parents understand the implications for newborn survival and income loss from choosing one birth-month over another. If parental decisions are fully informed, they can be used to determine the value parents place on an infant's life. In this case, we can interpret the results in Table 2 as the equilibrium choices between infant survival and the mother's earnings.

The empirical estimates indicate that parents give up approximately 1.5 percentage points of survival when they face a high level of trade-off. To obtain a measure of the value parents place on infant life, we compare this number with the amount of money they are earning in return for the sacrifice in expected child survival. The average GDP *per worker* for countries in my sample is \$4,038.[27] This measure may exceed annual female agricultural earnings for several reasons. First, rural wages are usually lower than urban pay, so a national average overstates rural earnings. Second, there are gender differences in wages. Finally, we need to account for how much work-time is lost because of infant delivery. Because these three points are difficult to address, results in this sections should be taken as suggestive.

To construct an estimate of female agricultural earnings, I assume that the ratio of female-to-male earnings is 0.8, and that the ratio of rural-to-urban wages is 0.6. This yields annual female agricultural earnings of \$1,934. I further assume that a woman loses

[27] This is the average across countries in the sample in income per worker (PPP adjusted) for year 1990 (PWT, 2005). Worker for this variable is usually a census definition based of economically active population.

between a quarter and a half of her annual earnings if she gives birth during the high labor demand period. Following the existing literature,[28] I compute the value of statistical life by comparing the 1.5 percentage point change in infant survival with the change in family earnings, and extrapolate this over the affected population to generate the population's average willingness willing to pay to avoid one statistical mortality. I estimate that parents' value of statistical life of their newborns in Sub-Saharan Africa is between $32,304 and $64,608, or between 18.6 and 37 years of *per capita* income. To the extent that these are plausible values,[29] they suggest that family decisions on birth-month are informed and support the idea that parents are aware of the trade-off and respond optimally to it.

8 Conclusion

Families in rural Africa appear to respond rationally to environmental constraints. First, they attempt, when possible, to maximize infant survival by choosing those months of birth that have higher survival rates. Second, they try to time deliveries to occur when the opportunity cost of women's time is lower. When these two objectives are in conflict, they face a trade-off between infant health and family earnings.

Using variation across regions and countries, within countries, and across time, I have shown that parents significantly sacrifice the expected survival chances of a newborn when the trade-off between infant health and earnings is high. An increase of

[28] See Viscusi and Aldy (2003) for a review of the estimates on the value of statistical life.

[29] The existing value of statistical life literature is primarily focused on developed countries and no estimates exist for any African populations. There is therefore no means of comparison by which to gauge whether these are reasonable estimates or not.

1.5 standard deviations in the level of the trade-off faced by the family is associated with an increase in expected mortality of 1.5 percentage points. This is equal to 38 percent of the total seasonal infant mortality fluctuation for the average country, and roughly equal to 14 percent of the total average infant mortality. These numbers are consistent with the idea that parents understand the consequences of choosing on birth month over another. Compared with potential income loss from delivery in high labor demand months, they imply reasonable values for the statistical life of their newborns.

Family planning is a useful way to improve infant survival by timing births during the year. This new role for contraceptive usage should be emphasized alongside the more traditional functions it plays in family reduction and birth spacing. However, helping families plan their births will only reduce infant mortality in those cases where families choose the more propitious months to give birth. For this to happen, agricultural and financial policies that focus on smoothing labor market seasonality are necessary. Increasing the resources devoted to family planning will not save lives, more likely the contrary, until the demand for female labor becomes more evenly distributed throughout the year. The introduction of irrigation and promotion of alternative activities for agricultural laborers should be stressed, to minimize the harsh trade-off the families face.

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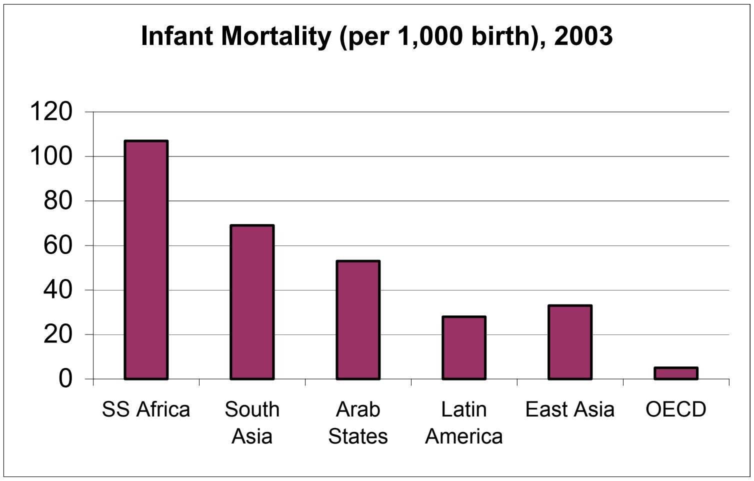
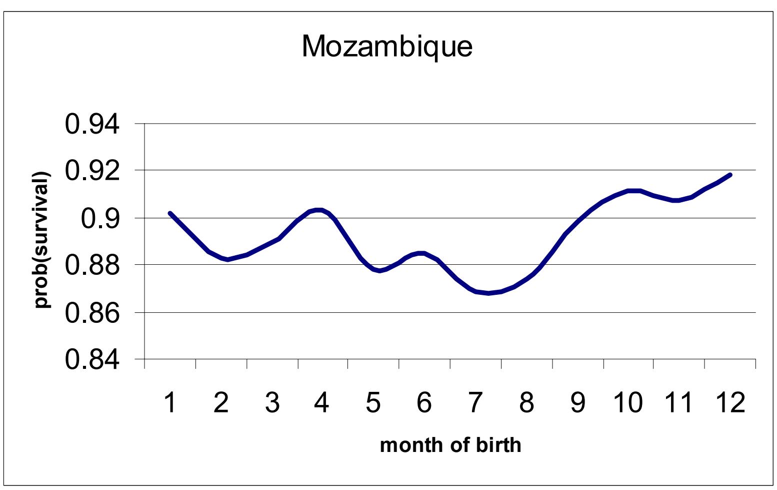
Figure 1: Infant Mortality by Region of the World



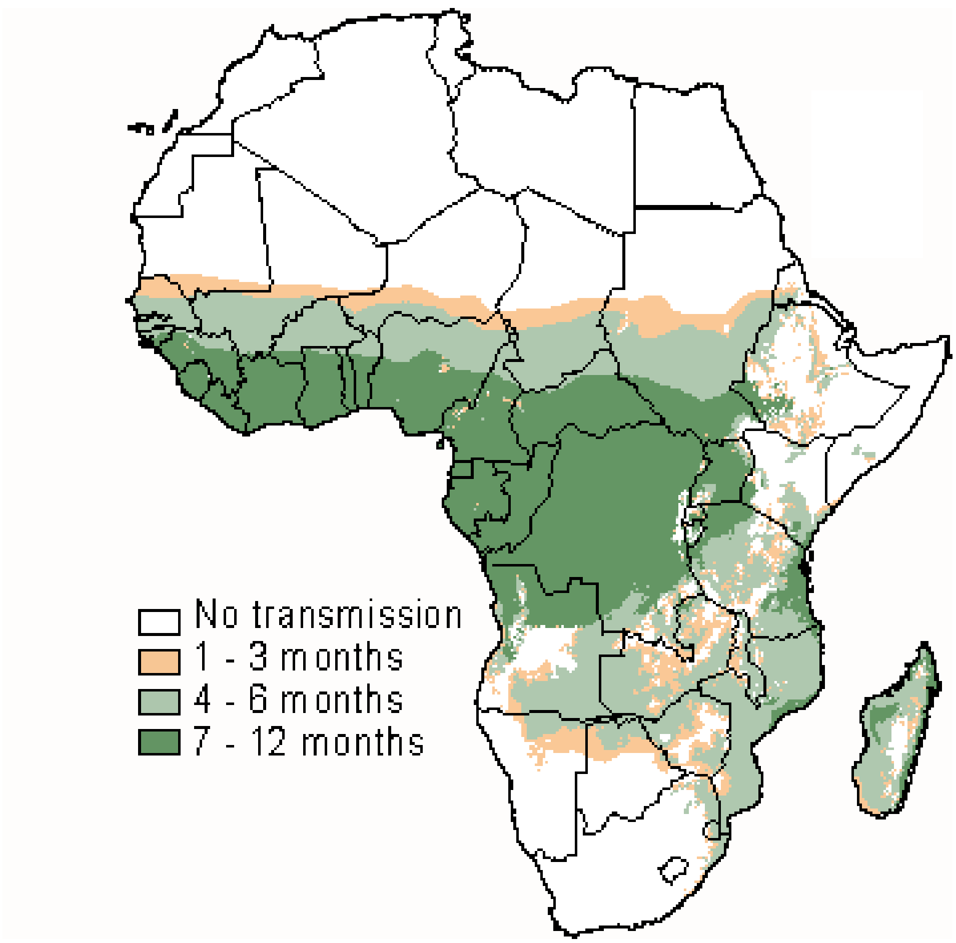
Source: Human Development Indicators, 2003. Variable indicates the number of children who died before the age of 1 per 1,000 live births.

Figure 2: Seasonal Infant Survival



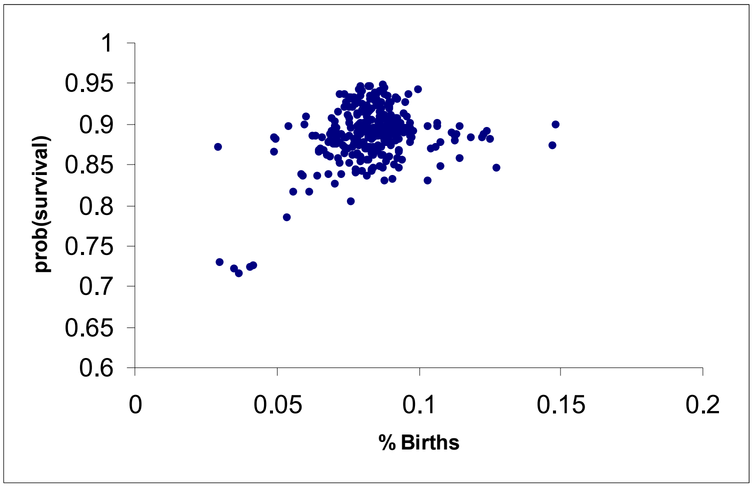
Source: Author's estimation using DHS data.

Figure 3: Seasonality in Malaria Transmission



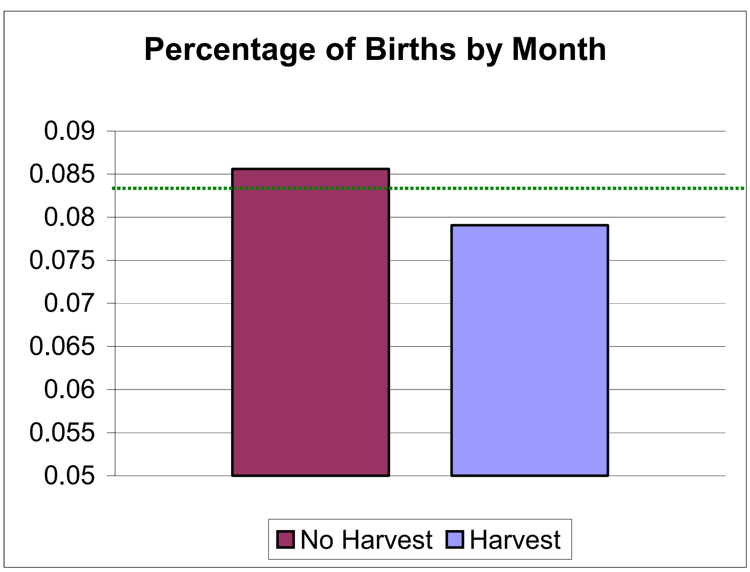
Source: MARA/ARMA (Mapping Malaria Risk in Africa / Atlas du Risque de la Malaria en Afrique). Map generated from theoretical models based from long-term climate data. It represents suitability of climatic factors and potential duration of the malaria transmission season in the average year.

Figure 4: Birth Distribution and Probability of Survival



Source: Author's estimates using DHS data. Each point represents a month-country observation.

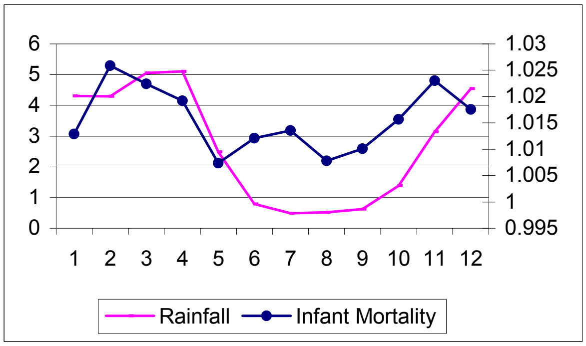
Figure 5: Distribution of Births and Labor Market



Source: Author's estimates using DHS and FAO data. The "percentage of births by month" represents the percentage of annual births that the average month during the *Harvest* and *No Harvest* periods has. Both measures are compared with the percentage of births that a month would have if births were equally distributed throughout the year.

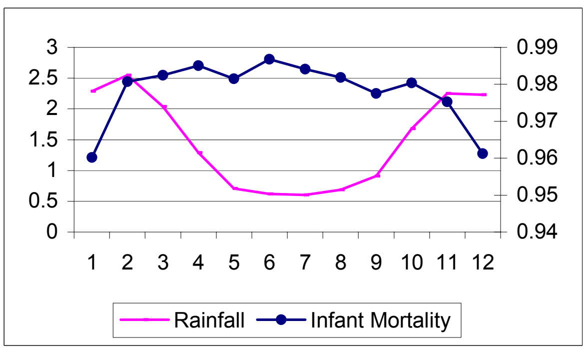
Figure 6: Infant Mortality and Exogenous Factors

Figure 6a: Tanzania – More rainfall, higher mortality



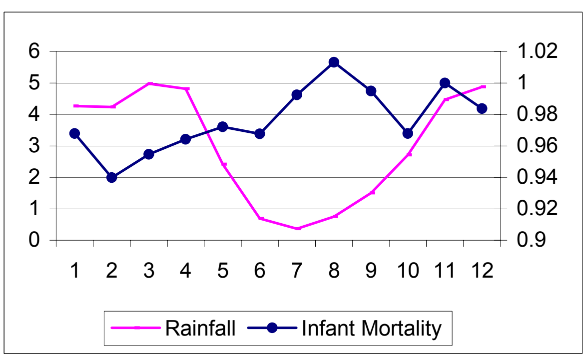
Source: Author's estimation using DHS and GPCP data.

Figure 6b: South Africa – More rainfall, lower mortality



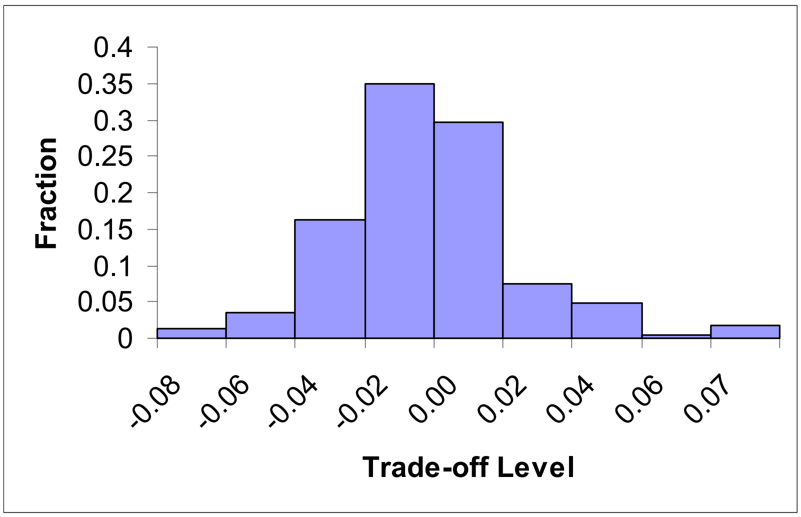
Source: Author's estimation using DHS and GPCP data.

Figure 6c: Burundi – More rainfall, lower mortality, and effect of hungry season



Source: Author's estimation using DHS, GPCP, and FAO data. November and December are typically food-insecure months, which seems to increase infant mortality.

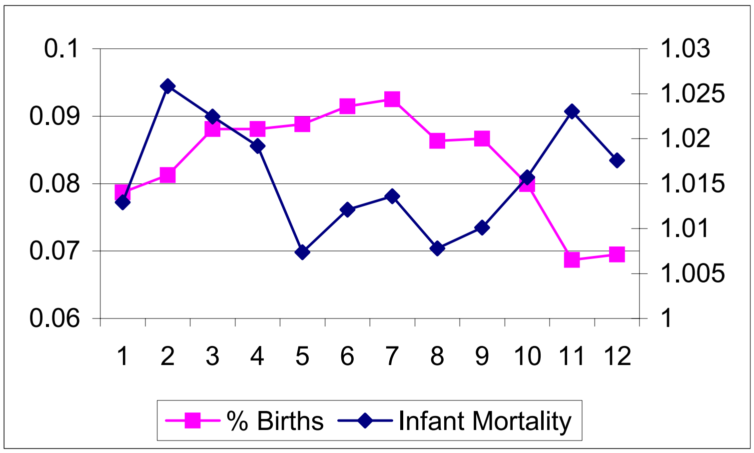
Figure 7: Distribution of Trade-off levels



Source: Author's estimation using DHS, GPCP and FAO data.

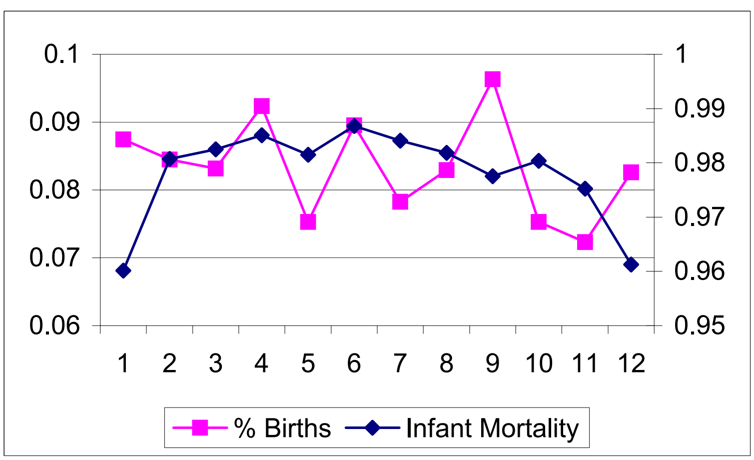
Figure 8: Infant Mortality and Seasonal Distribution of Births

Figure 8a: Tanzania – No trade-off



Source: Author's estimation using DHS, GPCP and FAO data.

Figure 8b: South Africa – Trade-off



Source: Author's estimation using DHS, GPCP and FAO data.

Table 1: Descriptive Statistics of Births

	(1) Full sample	(2) Trade-off < 0	(3) Trade-off > 0
% Rural births	67.27	67.74	66.86
% Male births	50.59	50.27	50.86
% Mothers with no education	46.24	47.41	45.23
% Mothers with primary education	33.24	35.92	30.92
% Spouses with no education	39.02	40.24	37.96
% Spouses with primary education	29.74	32.20	27.60
% Births in families with > 4 births	27.08	27.61	26.62
Average Infant Survival	90.86	90.26	91.38
% Ever used modern contraceptive	30.99	29.16	32.57
% Knowledge contraceptive source	60.83	60.43	61.17
% Heard family planning	42.13	40.43	43.61
Poverty ratio	72.17	73.21	71.26
# Observation	366,419	170,119	196,300

Source: Author's estimation from the DHS sample used. Poverty ratio is the fraction of people living with less than $2 a day according to the World Bank.

Table 2: Do rural populations respond to the trade-off?

Least Squares Regression – Dependent variable: *Loss E(survival)*$_{i,m,c}$

	(1) Version 1	(2) Version 2
Country Trade-Off	0.582	0.472
	[0.068]***	[0.106]***
Birth Characteristics	Yes	Yes
Parental Education	Yes	Yes
Income Proxies	Yes	Yes
Country Fixed Effects	No	No
N	247,383	247,383
R-squared	0.23	0.15

Notes – Robust standard errors are in brackets. Errors clustered at country level. In Version 1 the probability of survival is estimated using exogenous seasonal variation. In Version 2 the probability of survival is estimated using monthly dummy variables. Birth characteristics are gender, birth order, and maternal total number of births. Mother and father's education is in single years. Income proxies include household asset ownership variables (phone, television, radio, car, electricity, and refrigerator).

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

Table 3: Effects of Working-Age Children in the Household

Least Squares Regression – Dependent variable: *Loss E(survival)*$_{i,m,c}$

	(1) Version 1	(2) Version 2
(# Siblings 10-14 yrs) * Trade-Off	-0.033	-0.064
	[0.016]**	[0.015]***
# Siblings 10-14 yrs.	2.07e-04	4.19e-04
	[9.88e-05]**	[1.89e-04]**
Birth Characteristics	Yes	Yes
Parental Education	Yes	Yes
Income Proxies	Yes	Yes
Country Fixed Effects	Yes	Yes
N	247,383	247,383
R-squared	0.31	0.27

Notes – Robust standard errors are in brackets. Errors clustered at country level. In Version 1 the probability of survival is estimated using exogenous seasonal variation. In Version 2 the probability of survival is estimated using monthly dummy variables. Irrigation is percentage of cropland irrigated in the country. Birth characteristics are gender, birth order, and maternal total number of births. Mother and father's education is in single years. Income proxies include household asset ownership variables (phone, television, radio, car, electricity, and refrigerator).

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

Table 4: Effects of Smoother Seasonal Labor

Least Squares Regression – Dependent variable: *Loss E(survival)*$_{i,m,c}$

	(1) Version 1	(2) Version 2
Irrigation * Trade-Off	-0.380	-0.402
	[0.077]***	[0.071]***
Irrigation	-7.43e-04	-3.67e-04
	[5.72e-04]	[2.76e-04]
GDP per capita * Trade-Off	-7.46e-04	-8.19e-04
	[3.81e-04]**	[3.45e-04]**
GDP per capita	1.05e-06	1.43e-06
	[2.16e-0.6]	[2.16e-0.6]
Birth Characteristics	Yes	Yes
Parental Education	Yes	Yes
Income Proxies	Yes	Yes
Country Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
N	247,383	247,383
R-squared	0.33	0.30

Notes – Robust standard errors are in brackets. Errors clustered at country level. In Version 1 the probability of survival is estimated using exogenous seasonal variation. In Version 2 the probability of survival is estimated using monthly dummy variables. Irrigation is percentage of cropland irrigated in the country. Birth characteristics are gender, birth order, and maternal total number of births. Mother and father's education is in single years. Income proxies include household asset ownership variables (phone, television, radio, car, electricity, and refrigerator).

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

Table 5: Effects of Access to Contraceptive Methods

Least Squares Regression – Dependent variable: *Loss E(survival)*$_{i,m,c}$

	(1) Version 1	(2) Version 2
(Contraceptive Use * Trade-Off)	0.063	0.057
	[0.020]***	[0.024]**
Contraceptive Use	-1.58e-04	-1.95e-03
	[1.69e-04]	[7.54e-03]
Birth Characteristics	Yes	Yes
Parental Education	Yes	Yes
Income Proxies	Yes	Yes
Country Fixed Effects	Yes	Yes
N	247,383	247,383
R-squared	0.31	0.27

Notes – Robust standard errors are in brackets. Errors clustered at country level. In Version 1 the probability of survival is estimated using exogenous seasonal variation. In Version 2 the probability of survival is estimated using monthly dummy variables. Birth characteristics are gender, birth order, and maternal total number of births. Mother and father's education is in single years. Income proxies include household asset ownership variables (phone, television, radio, car, electricity, and refrigerator).

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

Table 6: Effects of Access to Contraceptive Methods – 2SLS

2SLS Regression – Dependent variable: *Loss E(survival)*$_{i,m,c}$

	IV: Knowledge of contraceptive source		IV: Heard of Family Planning	
	(1) Version 1	(2) Version 2	(3) Version 1	(4) Version 2
(Contraceptive Use *	0.662	0.595	0.403	0.416
Trade-Off)	[0.116]***	[0.078]***	[0.096]***	[0.166]**
Contraceptive Use	-1.21e-04	5.52e-05	1.60e-03	1.81e-03
	[1.12e-03]	[1.27e-03]	[1.74e-03]	[1.83e-03]
Birth Characteristics	Yes	Yes	Yes	Yes
Parental Education	Yes	Yes	Yes	Yes
Income Proxies	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
First Stage (p –value)	< 0.005	< 0.005	< 0.005	< 0.005
N	221,971	221,971	247,383	247,383
R-squared	0.30	0.28	0.32	0.28

Notes – Robust standard errors are in brackets. Errors clustered at country level. In Version 1 the probability of survival is estimated using exogenous seasonal variation. In Version 2 the probability of survival is estimated using monthly dummy variables. Instrument 1: Knowledge on source of male condoms; Instrument 2: Heard of family planning in the media (television, radio or newspapers). Birth characteristics are gender, birth order, and maternal total number of births. Mother and father's education is in single years. Income proxies include household asset ownership variables (phone, television, radio, car, electricity, and refrigerator).

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

Table 7: Do rural and urban families react differently to the trade-off?

Dependent variable: *Loss E(survival)*$_{i,m,c}$

	OLS		2SLS Both Instruments	
	(1) Version 1	(2) Version 2	(3) Version 1	(4) Version 2
(Contraceptive Use * Rural	0.088	0.106	0.439	0.483
* Trade-Off)	[0.018]***	[0.009]***	[0.058]***	[0.054]***
Contraceptive Use	-2.58e-04	-3.47e-04	4.88e-04	2.01e-04
	[2.06e-04]	[2.29e-04]	[1.25e-03]	[1.16e-03]
Rural	3.28e-04	4.16e-04	-8.86e-05	-4.54e-04
	[3.87e-04]	[4.46e-04]	[3.77e-04]	[5.55e-03]
Interaction Terms	Yes	Yes	Yes	Yes
Birth Characteristics	Yes	Yes	Yes	Yes
Parental Education	Yes	Yes	Yes	Yes
Income Proxies	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
First Stage (p – value)			< 0.005	< 0.005
N	366,419	366,419	325,362	325,362
R-squared	0.34	0.29	0.33	0.31

Notes – Robust standard errors are in brackets. Errors clustered at country level. In Version 1 the probability of survival is estimated using exogenous seasonal variation. In Version 2 the probability of survival is estimated using monthly dummy variables. Birth characteristics are gender, birth order, and maternal total number of births. Mother and father's education is in single years. Income proxies include household asset ownership variables (phone, television, radio, car, electricity, and refrigerator). * Significant at 10%; ** Significant at 5%; *** Significant at 1%

Table 8: Do rural populations respond to the trade-off? – Regional Evidence

Least Squares Regression – Dependent variable: *Loss E(survival)*$_{i,m,c}$

	(1)	(2)
Region Trade-Off	0.291	0.182
	[0.051]***	[0.070]**
Birth Characteristics	Yes	Yes
Parental Education	Yes	Yes
Income Proxies	Yes	Yes
Country Fixed Effects	No	Yes
N	105,543	105,543
R-squared	0.07	0.21

Notes – Robust standard errors are in brackets. Errors clustered at region level. Probability of survival is estimated using monthly dummy variables (version 2). Birth characteristics are gender, birth order, and maternal total number of births. Mother and father education's is in single years. Income proxies include household asset ownership variables (phone, television, radio, car, electricity, and refrigerator).

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

Appendix: List of DHS surveys

Country (Survey Year)

Burkina Faso (1992/1993)
Burkina Faso (1998/1999)
Burkina Faso (2003)

Benin (1996)
Benin (2001)

Central African Rep. (1994/1995)

Cote d'Ivoire (1994)
Cote d'Ivoire (1998/1999)

Cameroon (1991)
Cameroon (1998)

Ethiopia (2000)

Gabon (2000)

Ghana (1993)
Ghana (1998)
Ghana (2003)

Guinea (1999)

Kenya (1993)
Kenya (1998)
Kenya (2003)

Comoros (1996)

Liberia (1986)

Madagascar (1992)
Madagascar (1997)

Mali (1995/1996)
Mali (2001)

Malawi (1992)
Malawi (2000)

Mozambique (1997)

Nigeria (1990)
Nigeria (1999)
Nigeria (2003)

Niger (1992)
Niger (1998)

Namibia (1992)
Namibia (2000)

Rwanda (1992)
Rwanda (2000)

Sudan (1990)

Senegal (1986)
Senegal (1992/1993)
Senegal (1997)

Chad (1996/1997)

Togo (1998)

Tanzania (1992)
Tanzania (1996)
Tanzania (1999)

Uganda (1995)
Uganda (2000/2001)

South Africa (1998)

Zambia (1992)
Zambia (1996)
Zambia (2001/2002)

Zimbabwe (1994)
Zimbabwe (1999)