The Relationship Between Birth Month and Child Health and Survival in Sub-Saharan Africa

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Abstract

Background: Most sub-Saharan African countries are not on track to achieve the fourth Millennium Development Goal: to reduce under-five mortality by two-thirds between 1990 and 2015. Under-five mortality rates (U5MR) have been declining slowly in Sub-Saharan Africa: between 1990 and 2008 the U5MR declined by only 22%. If there is a strong relationship between birth month and U5MR, then policies that help women conceive during optimal periods may help reduce U5MR. But the effectiveness of such policies will depend on whether the birth month effects are the result of structural differences in fertility patterns, or due to differences in pre and post-natal environments.

Methods: We use piecewise exponential hazard models to analyze the relationship between birth month and U5MR, in 30 SSA countries using data from the Demographic and Health Surveys. We also use logistic regression models to analyze the relationship between birth month and stunting.

Results: The birth month effects on child mortality and stunting are large and statistically significant. On average, the under-five mortality rate associated with the birth month with the highest cumulative hazard is 39% higher than the U5MR for the birth month with lowest cumulative hazard. The maximum difference in predicted probabilities of being stunted between two birth months is on average nine percentage points.

Conclusions: The birth month effects are not due to social-demographic differences in fertility patterns; in contrast, the presence of a birth month effect for stunting indicates that prenatal factors may be responsible. Studies of the effect of birth month on later life outcomes should control for the effects of birth month on child mortality, in SSA.

A physician without a knowledge of Astrology has no right to call himself a physician. (Hippocrates)

1 Introduction

Motivation

Sub-Saharan Africa (SSA) has some of largest under-five mortality rates (U5MR)[1] in the world–in 2008, there were 144 deaths per 1000 live births in SSA (You et al., 2010). SSA child mortality rates have declined slowly–between 1990 and 2008 the U5MR declined by only 22 percent (You et al., 2010). Consequently, the majority of SSA countries are not on track to achieve Millennium Development Goal 4 (MDG 4). The goal of MDG 4 is to reduce under-five mortality rate by two-thirds between 1990 and 2015 (Statistics Division of the United Nations Department of Economic and Social Affairs, 2011). It is clear that policy makers need to add new strategies to their toolkit for reducing child mortality in SSA.

Public health officials have long been aware of seasonal fluctuations in morbidity and mortality, and in response have taken measures to mediate the increases. Examples include influenza vaccination campaigns in the fall. In contrast, they have not paid much attention to another seasonal relationship: the influence of birth month on child health. In 1945, Eastman noted the lack of studies investigating the influence of birth month on child survival, and that still continues more than 65 years later. The probability of dying before age one or during childhood is not always the same for children born during different months. In many

[1]U5MR is the probability of dying before age five expressed in terms of 1000 live births.

settings, some months are associated with excess death and negative health outcomes. If there is a relationship between birth month and under-five mortality rates (U5MR) in SSA, then policies that help women conceive during optimal periods may help reduce U5MR. But the effectiveness of such policies would depend on the etiology of the birth month effect in SSA.

In the remainder of the introduction, we will review the literature of birth month effects on child health, briefly discuss the leading hypotheses behind the relationship, and finally present our research objectives.

Birth month and health

There is a well-established literature showing that birth month, or more broadly early life conditions, are predictive of health *later* in life. Numerous studies have found a relationship between birth month and later life outcomes, such as cardiovascular metabolic disease, life expectancy, female fecundity, psychiatric disorders, educational attainment, and wages (Barker et al., 2002; Bengtsson and Lindström, 2003; Curhan et al., 1996; Doblhammer and Vaupel, 2001; Gluckman et al., 2008; Huber et al., 2004; McEniry, 2011; Moore et al., 1997; Torrey et al., 1997).

In contrast, a smaller number of studies have analyzed the impact of birth month on early life outcomes such as infant and child mortality and stunting; and even fewer have focused on SSA (Breschi and Livi-Bacci, 1997; Eastman, 1945; Lokshin and Radyakin, 2012; Muñoz-Tudurí and García-Moro, 2008). Eastman (1945) found that in the United States

(1935-1937), the infant mortality rate for babies born in January was 15 percent greater than the rate for children born in August; but, given that a January baby survived the first few months of life, it then had a higher probability of surviving to age one than a baby born in August. The latter is likely due to selective survival, where the higher initial mortality levels faced by babies born in January removes the more frail infants from the population. Eastman also highlighted the role of seasonal incidence of infectious disease on the relationship between birth month and mortality. Young babies were particularly susceptible to respiratory illness which peaked during the winter months, while older infants were more susceptible to gastrointestinal illness which peaked during the summer months.

Breschi and Livi-Bacci (1997) analyzed the influence of birth month on children's survival in Europe during the second half of the 19^{th} century. The results were heterogeneous. In Belgium, the Netherlands, and the Italian regions of Savoy and Sicily, there were very small differences in infant mortality rates across birth months or seasons (the difference in infant mortality between best and worst month did not exceed 10 percent). On the other hand, in Veneto, Italy, the difference in infant mortality rates between the best and worst month was approximately 70 percent. Russia and Switzerland also had some birth seasons with excess mortality (23 and 15 percent difference between best and worst months, respectively).

Muñoz-Tudurí and García-Moro (2008) found lower infant mortality among individuals born in the spring months in a cohort of individuals born between 1800-1870 in the village of Es Mercadal on Minorca Island, Spain. The differences in survival between birth seasons were most pronounced in the first three months of life. Given that individuals born in the high risk summer months survive childhood, they were then more likely to survive into adulthood compared to individuals born in the spring. In the cohort born between 1700-1799 there were no significant differences in infant mortality by birth season, but when one disaggregated infant mortality into neonatal and post-neonatal deaths, stronger relationships emerged. Births during the summer and autumn months had significantly higher hazard of dying within the first three months of life. However, given that individuals born in summer and autumn survived the first three months, they were then significantly more likely to survive to age one. The authors explained these findings as an effect of selective survival. This also highlights the fact the relationship between birth month and mortality may not be the same across different age intervals.

Using data from the Gambian Demographic Surveillance site, Moore et al. (1997) found that birth month is associated with infectious disease mortality[2] but only for individuals older than 15 years. Given that an individual survived to age 15, the odds of dying for individuals born during the hungry season (July-October) were more than 3 times the odds of dying for individuals born during the harvest season.

Lokshin and Radyakin (2012) did not find a significant relationship between birth month and survival to age three among Indian children, but they did find statistically significant relationships between birth month and stunting. A child is considered stunted if his/her height-for-age[3] is more than two standard deviations below the mean height-for-age of the

[2]Early life conditions can also prime immune system functioning.

[3]We use length and height interchangeably although they are not the same. Typically for younger children, length measured in recumbent position is used; for older children standing height is used.

World Health Organization (WHO)'s reference population. Likewise, a child is considered severely stunted if his/her height-for-age is more than three standard deviations below the reference population. Malnutrition, infections, stress, and genetic disorders all can all lead to stunting. Height faltering is usually observed after the weaning period, and is thought to be indicative of *chronic* malnutrition and disease status, therefore does not fluctuate widely over time. However, stunting can also have its antecedents during fetal development; in those cases it is typically described as small for gestational age (SGA) (Maleta et al., 2003; McCowan et al., 1999). Lokshin and Radyakin (2012) found that children born during the monsoon months were more likely to be stunted than children born six months after the start of the monsoon. They also found that the birth month effects persisted after controlling for individual and family characteristics.

This brief review of the sparse literature on birth month and early life outcomes indicates that the birth month effect on mortality may not emerge in SSA until older ages. Furthermore, the relationship between birth month and mortality may vary over different age intervals. Finally, the relationship between birth month and mortality will likely vary across countries. There may be a birth month effect on stunting, but the magnitude of the potential effect is uncertain.

Possible explanations for birth month effects on health

Potential explanations for the birth month effect fall into three categories–seasonal heterogeneities at conception, and during the pre-natal and post natal periods. The corresponding hypotheses are that 1) births, within a year, may not be randomly distributed across the population, because, for instance, seasonal fecundability patterns[4] vary by socioeconomic status (Buckles and Hungerman, 2010); 2) individuals conceived in different months experience differential nutritional inputs and exposure to illness during the fetal period; 3) birth month is also associated with different postpartum exposures in terms of disease and nutrition (Bengtsson and Lindström, 2003; Eastman, 1945).

Differences at conception: Influence of socio-demographic characteristics

A large portion of the literature on birth month and later life outcomes assumes that births in a given month are randomly distributed across all segments of the population. This is not necessarily the case. Demographic covariates such as maternal education, birth order and spacing have long been shown to influence early child mortality and stunting (Madise et al., 1999; Mosley and Chen, 1984). It is possible that these covariates are also correlated with birth month; if so, they may be driving at least some of the relationship between birth month and health (Buckles and Hungerman, 2010; Hobcraft et al., 1985). In this way children born in different months could be different from the time of conception. Buckles and Hungerman (2010) show that for the United States, controlling for mother's socio-demographic characteristics can explain up to half of the relationship between birth month and later life outcomes.

In many sub-Sahran African countries, women of different socio-economic backgrounds do

[4]Determinants of fecundability such as monthly frequency of coitus, or monthly probability that a cycle is ovulatory may differ among different population subgroups (see Chapter 3).

not have the same birth patterns. Fluctuations in births to women of higher socio-economic-status are less seasonal (magnitude of the fluctuations are smaller) than for women of lower socio-economic status (Chapter 3). Significant differences in birth patterns also exist between individuals born to mothers of different ages and religion (Chapter 3).

Differences in prenatal conditions: Fetal origins hypothesis

Non-adaptive effects. Poor maternal conditions during critical periods of development may impair fetal growth. In other words, changes in fetal development are not necessarily adaptive, but may simply reflect developmental constraints which can later impact early child and adult health (Barker et al., 2002; Bateson et al., 2004; Lummaa, 2003). In cases where normal development may be impaired, negative effects of the phenotype change may appear early. For example, in temperate zones, rubella usually occurs seasonally, peaking in late winter and early spring, so pregnant women are at higher risk of contracting rubella during those months (World Health Organization). The pregnancy stage of women who contract rubella has significant implications on child health. If a susceptible mother contracts rubella before the 11^{th} week of her pregnancy, her child is more likely to be deaf and have congenital heart defects; infections contracted between the 11^{th} and 16^{th} weeks of pregnancy are only associated with an increased risk of deafness; in contrast, rubella infections contracted after 16 weeks are not associated with any increased risk of gestational defects (Miller et al., 1982).

Adaptive response. There is also the view that during development the fetus may adjust its physiology and metabolism (developmental plasticity)[5] as a response to cues from the mother about the external environment. The signaling from the mother occurs because of significant overlap between critical development periods (see Appendix A) and period of maternal provisioning (Kuzawa and Quinn, 2009). One of the most cited developmental responses, termed the thrifty phenotype (reduced fetal growth), is believed to be an adaptive response of the fetus to nutritional stress. It has been widely assumed that the thrifty phenotype is better suited for poor environment and that if catch-up growth takes place or if the individual becomes obese as an adult, then this mismatch between fetal and adult environments results in increased risk of metabolic syndrome and cardio-vascular diseases. From an evolutionary point of view, it is not necessarily the case that the environmental mismatch causes disease in adults, the metabolic adjustments may improve infant survival and resulting disease in adult may be a pleiotropic side effect of the phenotype change (Kuzawa and Quinn, 2009). In either case, if the response is adaptive, we may not find a birth month effect on mortality until adulthood.

Differences in postnatal conditions

A population's age-specific mortality profile may vary by birth month/season, because of the interactions between climate, disease, social-cultural behaviors influenced by seasons, and the age at which a child experiences the seasons. The latter is in part due to the interactions

[5]Developmental plasticitiy is "the ability of an organism to develop in various ways, depending on the particular environment or setting" (Gluckman et al., 2008). In other words, the same genotype under different environments may develop different phenotypes. This occurs as the result of epigenetic processes such as DNA methylation, histone modification, and micro-RNA inhibition of gene translation (Baek et al., 2008; Gluckman et al., 2008). Most epigenetic processes occur in utero (Ellison, 2010).

between waning maternal immunity and the seasonal fluctuations in disease risk (Breschi and Livi-Bacci, 1997).[6] For instance, in Italy mortality was highest among winter births "because it cumulates the high impact of the cold season on respiratory diseases right after birth with the high impact of hot summer months on digestive infections when protection of breast feeding is diminishing"(Breschi and Livi-Bacci, 1997, page 162). A child born at the peak of an infectious disease outbreak may be better protected than a child born a few months before[7] (especially in areas with low vaccination coverage), due to waning maternal immunity in the latter.

Objectives

In this chapter we describe, quantify, and analyze the relationship between birth month and child health and survival in sub-Saharan Africa using data from Demographic and Health Surveys. Specifically we aim to answer the following questions:

- Is there a relationship between birth month and under-five mortality?
- Is the relationship between birth month and neonatal, infant, and childhood mortality the same?
- Are months of higher/lower mortality risk also months associated with higher/lower probability of being stunted?
- What is the impact of controlling for individual, and family characteristics? Does it

[6] Maternal antibodies which protect infants from some infectious diseases are obtained via breast feeding (Victora et al., 1987).

[7] This of course depends on the disease. Young infants are at increased risk of dying from respiratory illness compared to older infants.

diminish the variation in mortality and development across birth months?

The following section describes the data, construction of key variables, and estimation strategies. In section 3 we present the main findings. In section 4 we discuss the results as well as policy implications. In the last section we briefly describe future work and summarize our conclusions.

2 Data and Methods

Demographic and Health Surveys

Main variables. The data used in this study come from the Demographic and Health Surveys (DHS). The DHS are nationally representative surveys of women of childbearing ages (15-49) carried out in developing countries. We have data from 30 SSA countries, with one to five surveys for each country. The DHS datasets are well suited for conducting analysis of child mortality and health. In addition to complete reproduction histories (month and year of birth of each child a woman has ever had), each woman is also asked if the child is still living. And if the child has died, the age (in completed days, months, or years) of the child's death is ascertained. Anthropometric measurements of height and weight for children under age five[8] are also taken during the survey.

Covariates. The DHS also contains a wealth of data on individual and family characteristics, which may affect the relationship between birth month and child health and survival. These include information on sex, birth order number, short preceding birth interval, ru-

[8]For a few surveys anthropometric measurements are only taken of children under the age of three.

ral/urban classification, mother's age at birth, mother's education level, and religion (Cleland and van Ginneken, 1988; Hobcraft et al., 1985; Miller et al., 1992; Mosley and Chen, 1984). There is information on ethnicity, which could impact child survival, but we do not include it in the model because we would need to standardize the variable across surveys (Gyimah, 2006).

Data Quality. One common issue with survey data is that we are restricted to births of children whose mothers have not died between the time of their birth and the interview date. There are also potential issues with misreporting of birth dates, misreporting of age at death, and event under-reporting. To account for missing birth dates, the DHS uses imputations to deal with incomplete observations (Arnold, 1990). Observations with imputed birth month and or birth year are dropped from our sample. The numbers of imputed observations ranged from less than one percent to 60 percent in some countries, but on average 12 percent of the observations were dropped. In Chapter 2, we find that the composition of the population with missing birth date data differs from that with known birth dates. The observations with imputed birth dates are more likely to be composed of older and dead children, from rural areas, and of children born of uneducated mothers ($p < 0.001$). Consequently we may be underestimating the mortality. However we do not expect that the underreporting will bias the relationship between birth month and mortality, but it could lead to underestimation of the birth month effect. For more in depth analysis of DHS birth month and year data quality please refer to Chapter 2.

We are particularly concerned with misreporting of the age at death. To limit recall bias, we limit the analyses to births in the ten years prior to the survey date. For some observations, this variable is recorded in completed days, completed months, or completed years. In creating our survival models, we utilized this detailed information to construct individual exposure time in each age interval. There is also an accompanying variable that keeps track of data quality issues, for instance whether the age at death would take place after the interview or if the age at death was imputed. Observations with missing age at death were not included in our analysis.

Estimation Strategies

Separate analyses are run for each of the 30 SSA countries.

Survival Models. Due to the discrete nature and censoring of our data, our survival analysis relies on flexible piecewise exponential hazard models (PWE) and shared frailty piecewise exponential hazard models to determine the association between birth month on mortality at different ages. The intervals over which we assume that the hazard is constant are: less than 1 month, 1 to 5 months, 6 to 11 months, 12 to 23 months, 24 to 35 months, 36 to 47 months, and 48 to 59 months. We first use a piecewise model with age intervals and birth month to generate hazards for each combination of birth month and age interval.[9] The resulting hazards are used to calculate survival probabilities as well as the under-five mortality rate (U5MR). Next we test whether the interactions between the month of birth and age interval are significant. Finally, we sequentially control for sets of individual characteristics (birth order, sex, birth interval) and maternal and family characteristics (mother's age at

[9]Stata command– streg ibn.age_intervals##ibn.birth_month, noconstant.

birth, mother's education level, rural versus urban residence), and analyze the effect on the birth month coefficients. The model with the controls for maternal characteristics is a shared frailty model, therefore we are also able to control for unobserved characteristics associated with having the same mother.[10]

We test for the effects of interactions between month of birth and age intervals because the impact between birth month and mortality at different ages may not to be the same across different months (Breschi and Livi-Bacci, 1997; Eastman, 1945; Muñoz-Tudurí and García-Moro, 2008).

Logit models. To analyze the birth month effect on stunting, we rely on anthropometric measurements taken at the time of the survey. We limit the samples to observations under the age of thee at the time of survey. We use logit models to determine the odds of being stunted controlling for birth month, sex, birth order, and age. We then control for maternal and family characteristics using a random effects logit model, with mother as the random intercept. The additional controls are mother's level of education, urban versus rural residence, and mother's age at birth. The random effects allow us to control for additional unobserved family characteristics. The equations for the logit models are in the Appendix. From the logit models, we calculate both odds ratios where the reference is the birth month associated with the highest predicted probability of being stunted.

Unlike in the survival model, this sample only includes children who are alive at the time of the survey. Consequently, the results we find for stunting could be biased by the exclusion

[10]Equations for the survival models are located in the Appendix.

of those who experience mortality, especially when child mortality is high. In the presence of heterogeneity, weaker children may die earlier if born in low survival months therefore the remaining children in low survival month may be more robust; leading to opposite birth month effects for stunting compared to survival.

3 Results

We will only report results for the months with the highest and lowest cumulative hazards which we define as worst birth month and best birth month respectively. Likewise, for the stunting results we report the birth month with highest and lowest predicted probability of being stunted, also termed worst and best birth month, respectively. Complete results can be found in the appendix.

Survival. A child's birth month has a statistically significant influence on the probability of surviving to age five in the majority of SSA countries. The birth month effects on the probability of surviving to age five (conversely the probability of dying by age five (U5MR)) are large (Table 1). On average, U5MR in the worst birth months are 39 percent higher than the U5MR in the best birth month. In Sierra Leone, Ivory Coast, and in Zimbabwe the differences were greater than 60 percent. According to the model, if all children were born during the best survival month, the overall U5MR would substantially decline.

Next we performed a likelihood ratio test to compare the fit of the model with and without interactions. The model with interactions between birth month and age interval was statistically significantly better than the model which assumes that the birth month effect is the same across different age intervals in only six countries: Burkina Faso, D.R. Congo, Ivory Coast, Niger, Nigeria, and Tanzania. In Figure 1, we plot the hazards for each age interval for the months with highest and lowest U5MR, in countries were there were significant interactions between birth month and age intervals. Therefore, in the majority of the SSA countries in our sample, the birth month effect is relatively constant across different age intervals.

In table 2, we compare the magnitude of the hazard ratio for the worst birth month compared to the best across models with different sets of controls. The three models do not include interactions between birth month and age interval–they assume proportional hazards. The hazard ratios were statistically significant in all of the models except in Togo, which we believe is due to lack of statistical power. It is also important to note that Togo had a large fraction of imputed observations which could bias our results. On average, the percent increase in the hazard ratio associated with the worst/best birth month is larger than the effect of sex, or the effect of living in an urban rather than rural setting.

Controlling for individual risk factors and maternal risk factors did not have the same effect in every country. In some countries, such as Ivory Coast, controlling for additional covariates reduces the magnitude of the hazard ratio for the worst birth month. In contrast, in Guinea and Mali, the hazard ratios increased after controlling for individual and family characteristics. Nevertheless, in the majority of the SSA countries there was very little change in the magnitude of the hazard ratio for the worst birth month compared the the best. Therefore, in general, socio-demographic differences in the seasonal distribution of births do not appear to explain much of the birth month effect on survival.

There appears to be some geographic clustering in the results. The month with the lowest or highest cumulative hazard was the same or similar in many neighboring countries (Figure 2a and 2b). For example the months with the highest survival probabilities are at the end of the year in Kenya, Uganda, and Tanzania.

Stunting. Birth month is also correlated with the odds of being stunted, in SSA. On average there was a 9 percentage point difference between the predicted probability of an average child being stunted if born in the worst versus best month (max = 14 % , min = 4 %) .[11] This birth month effect is comparable to the effect of sex and birth order on odds of being stunted.

Controlling for family and maternal characteristics resulted in an increase in the odds ratio: the odds of being stunted if born in the worst month increases compared to the odds of being stunted if born in the best month (Table 3).

There also appears to be some spatial pattern to the birth month effect on stunting (Figure 2c and 2d). For instance in Sahalien countries, the birth months associated with the lowest probability of stunting are December and November.

The relationship between birth month and survival is not necessarily the same as the relationship between birth month and stunting. In fact, in Chad and to a similar extent in Liberia, the relationships are reversed. In Benin, D.R. Congo, and in Mali, the month with the worst survival probability is the month associated with the lowest odds of being stunted

[11]Predicted probabilities estimated at the mean of sex, birth order, and age.

(Figure 2). For a little less than one third of our sample, the worst and best birth months for survival and growth are at similar times of the year.

4 Discussion

In SSA, birth month is predictive of early life outcomes. There are large and significant differences between the probability of dying by age five by birth month. There are also large and significant differences between birth months on the probability of being stunted if under age three. The birth month effects are often larger than the effects of known risk factors for child mortality and stunting. In a few countries there is some potential evidence of selective survival, as the birth month effect was reverse when comparing results for survival and stunting.

Social-demographic differences in fertility patterns do not explain the birth month effect. In many SSA countries, the birth peak occurs in months associated with high survival. This explains why family characteristics such as socio-economic status may not be mediating the relationship between birth month and health in SSA.

The presence of a birth month effect for stunting lends support to the hypothesis that prenatal factors may be responsible for the birth month effect. Specifically, in countries in which similar months were associated with both the probability of dying and being stunted, stunting is most likely to have its antecedents during fetal development or in infancy. It could be that growth is impaired to such an extent that catchup growth may not be feasible. Having birth weight and length for age during infancy would help us determine whether these birth month effects on growth were present at birth. If so, then policies aiming to reduce the prevalence of malnutrition may need to focus on pregnant women (Lokshin and Radyakin, 2012). The stunting analysis could be sensitive to model specifications; other model specifications that could be tested include the use of different cutoffs and use of continuous measure of height for age as dependent variable (Lokshin and Radyakin, 2012). It would be worthwhile to investigate whether the best and worst birth months for stunting are more similar to those, in a model of childhood survival (probability of surviving to age five given that you have survived infancy).

Future Work. We have illustrated the fact that in SSA the birth month effect is not a proxy for social differences in fertility patterns. Therefore, the birth month effect on early health most likely proxies environmental factors that influence pre or post natal nutrition or disease status or even intergenerational factors (Doblhammer and Vaupel, 2001). Our current data do not support differentiating between pre and post natal effects with our current data. Information on birth weight (a proxy for prenatal conditions) could help us answer this question: if birth weight attenuates the relationship between birth month and child development and mortality then the birth month effect is most likely due to prenatal conditions. Information on length at birth could also help us identify when fetal development may have been impaired: low length at birth indicates that fetal growth was affected before the third trimester (Maleta et al., 2003).

Geocoded data from the DHS can be used to test the impact of specific environmental factors in explaining the birth month effects. Future studies could merge the DHS with rainfall and temperature data (as in Chapter 3) and test whether seasonal malaria and malnutrition are influencing the relationship between birth month and survival and development. Kudamatsu et al. (2010) looked at the impact of weather shocks during the fetal period on the probability of dying by age one. The mechanism by which weather shock influences infant mortality is through its effect on malaria and malnutrition. But these are proxies for prenatal nutritional and disease risk at best; it would be best to have information on nutritional status and disease incidence, although they are rare. We would also want cause of death data as well as data on birth weight and length at birth.

What are the implications of our findings for studies of later life outcomes? Could selective mortality be playing a role? Our findings indicate that researchers investigating the relationship between birth month and adult health outcomes should control for the effects of infant and child mortality, especially in high U5MR settings. Controlling for child mortality may or may not influence birth month effects on adult mortality. For example, Moore et al. (2004) did not find a relationship between birth month and young adult health, after controlling for excess infant mortality for children born in the hungry season in Bangladesh.[12] In contrast, in their study of birth month and adult lifespan, Doblhammer and Vaupel (2001) found that in Denmark, mortality in early life did not impact the relationship between birth month and adult health. Instead, the birth month effect for infant mortality was similar to that for adult lifespan: babies born in spring had excess infant mortality and reduced adult lifespans. Doblhammer and Vaupel (2001)'s findings are more plausible when development changes to the fetus or infant are debilitating and not adaptive.

[12]It is possible that an effect could emerge if individuals are followed past middle age.

5 Conclusion

The majority of studies tying birth month to mortality and health have focused on later life (adult) outcomes and have occurred within a developed country context. We contribute to the literature by focusing on both mortality and stunting in sub-Saharan Africa. The breadth of this study in terms of the number of countries analyzed is also unique.

Birth month has a large and statistically significant impact on child survival and stunting. The magnitude of the birth month effect is comparable and often larger than the magnitude of the effect of other known covariates of survival and stunting. In the majority of the SSA countries the birth month effect is relatively constant across different age intervals. Controlling for socio-demographic factors did not attenuate the birth month effect on child health. There appears to be some geographic clustering in the pattern of the birth month effect indicating that environmental factors may be playing a role.

Although women of different socio-economic backgrounds do not have the same seasonal birth patterns, social differences in the seasonal distribution of births are not driving the relationship between birth month and child health and mortality in SSA. Therefore, policies that aim at decreasing the number of conceptions during months associated with excess mortality may represent an additional tool for reducing under-five mortality in SSA.[13] This also means that improving maternal education, increasing birth spacing, and other demographic correlates of under-five mortality may not reduce U5MR by as much as one would think, because seasonal factors would still be playing a role.

[13] An example may be family planning campaigns to help parents optimally time births.

Ideally we would want to identify which pre and postnatal factors lead to the birth month effect on child health and mediate the effects. But data on birth weight and length, cause of death, and time series of maternal conditions during pregnancy (disease and nutritional status) are needed.

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Appendix

Appendix A

Table 1. Stages of Prenatal and Postnatal Organ Structural Development

Sources: Benes, 1998; Dietert, 2000; Johnson, 2000; Moore, 1977; Needleman, 2000; Rice, 2000; WorldOrtho, 2002

Organ System	Early Prenatal	Mid-Late Prenatal	Postnatal
Central nervous system	3-16 weeks	17-40 weeks	Continues into adulthood
Ear	4-16 weeks	17-20 weeks	—
Heart	3-8 weeks	—	—
Immune system	8-16 weeks	17-40 weeks	Immunocompetence: 0-1+ years Immune memory: 1-18 years
Kidneys	4-16 weeks	17-40 weeks	Nephrons mature in outer cortical region, providing ability to concentrate urine
Limbs	4-8 weeks	—	—
Lungs	3-16 weeks	17-40 weeks	> 80% of alveoli are formed after birth to age 8-10
Palate	6-10 weeks	—	—
Reproductive system	7-9 weeks	10-40 weeks	Sexual maturation, breast, and cervix development: 9-16 years
Skeleton	1-12 weeks	—	Ossification continues for ~25 years
Teeth	12-16 weeks	17-24+ weeks	Primary dentition: 4 months after conception to 3 years postnatal Permanent dentition: 3 months after birth to 25 years

Source: Altshuler, K., Berg, M., Frazier, L.M., Laurenson, J., Longstreth, J., Mendez, W., and Molgaard, C.A. (2003). "Critical Periods in Development" *OCHP Paper Series on Children's Health and the Environment*, Paper 2003-2.

Appendix B: Equations for survival models:

Hazard during each age interval:

$$ln\{h(t|\mathbf{d}_{si})\} = \alpha_1 d_{1si} + \alpha_2 d_{2si} + \alpha_3 d_{3si} + \alpha_4 d_{4si} + \alpha_5 d_{5si} + \alpha_6 d_{6si} + \alpha_7 d_{7si} \tag{1}$$

Here d_{si} are dummy variables for each age interval, and α_1 to α_7 are the corresponding coefficients. When these coefficients are exponentiated they are equal to the age specific hazards.
PWE with covariates:

$$ln\{h(t|\mathbf{d}_{si}, \mathbf{x}_i)\} = ln\{h(t|d_{si}, x_i = 0)\} + \beta_2 x_2 i + ... + \beta_n x_{ni} \tag{2}$$

Here the covariates are x_{2i} to x_{ni} , and the corresponding coefficients are β_2 through β_n. The exponentiated coefficients for the covariates are hazard ratios.

PWE with covariates and shared frailty:

$$ln\{h(t|\mathbf{d}_{sij}, \mathbf{x}_{ij}, \zeta_j)\} = ln\{h(t|d_{sij}, x_i j = 0)\} + \beta_2 x_2 ij + ... + \beta_n x_{nij} + \zeta_j \tag{3}$$

Appendix C: Equations for logit models:

Model with not maternal controls

$$\begin{aligned} &\text{logit}\{Pr(stunted_i|\mathbf{month}_i, age_i, male_i, \mathbf{birthorder}_i)\} = \\ &\beta_0 + \sum_{m=1}^{11} \alpha_m month_{mi} + \alpha_{12} male_i + \beta_1 age_i + \sum_{p=2}^{4} \delta_p birthorder_{pij} + \epsilon_i \end{aligned} \tag{4}$$

where $stunted_i = 1$ if child is stunted and 0 if child is not stunted, $\mathbf{month}_i = month_{1i}, ..., month_{11i}$, and $\mathbf{birthorder}_i = parity2_2 ij, parity3_{3ij}, parity4plus_{4ij}$.

Model with random intercept for the mother

$$\begin{aligned} &\text{logit}\{Pr(stunted_{ij}|\mathbf{month}_{ij}, age_{ij}, male_{ij}, \\ &\mathbf{momage}_{ij}, primary_{ij}, secondary_{ij}, urban_{ij}, \zeta_j)\} = \\ &\beta_{0j} + \sum_{m=1}^{11} \alpha_m month_{mij} + \alpha_{12} male_{ij} + \beta_1 age_{ij} + \sum_{p=2}^{4} \delta_p birthorder_{pij} + \\ &\alpha_{13} primary_{ij} + \alpha_{14} secondary_{ij} + \alpha_{15} urban_{ij} + \sum_{p=5}^{8} \delta_p momage_{ij} + \epsilon_{ij} + \zeta_j \end{aligned} \tag{5}$$

where $\zeta_j \sim N(0, \psi)$, $\mathbf{momage}_{ij} = 20to24_{5ij}, 25to29_{6ij}, 30to34_{7ij}, 35plus_{8ij}$, and $primary_{ij} = 1$ if mother has had some primary education , $secondary_{ij} = 1$ if mother has had some secondary education.

Table 1: Highest and lowest survival probabilities to age 5 (P5) and under-five mortality rates (U5MR). Countries are listed alphabetically with years of earliest and latest survey included within the parentheses.

Country	Obs.	Best			Worst			Ratio of Worst U5MR to Best U5MR
		Month	P5	U5MR	Month	P5	U5MR	
Benin (1996-2006)	218,723	Mar	91.1	89	Aug	88.3	117	**1.31**
Burkina Faso (1993-2003)	194,384	Mar	87.6	124	Aug	84.2	158	**1.27**
Cameroon (1991-2004)	144,635	Oct	90.2	98	Aug	87.7	123	**1.26**
Chad (1996-2004)	127,892	Feb	87.2	128	Dec	81.5	185	**1.45**
Congo (2005)	46,231	Jun	91.5	85	Jan	88.7	113	**1.33**
Congo DR (2007)	85,118	Apr	90.2	98	Dec	85.5	145	**1.48**
Ivory Coast (1994-2005)	110,898	Oct	91.8	82	Feb	86.1	139	**1.70**
Ethiopia (2000-2005)	216,931	Jul	88.8	112	Dec	85.1	149	**1.33**
Ghana (1988-2008)	169,950	Oct	91.9	81	Dec	88.8	112	**1.38**
Guinea (1999-2005)	71,200	Feb and Oct	91.1	89	Jun and Apr	86.4	136	**1.53**
Kenya (1989-2009)	318,685	Oct	93.8	62	Jul	91.4	86	**1.39**
Lesotho (2004)	37,157	Mar	93.2	68	Apr	90.2	98	**1.44**
Liberia (1986-2007)	102,343	May	89.0	110	Dec	84.3	157	**1.43**
Madagascar (1992-2009)	291,159	Jan	93.4	66	Jun	91.1	89	**1.35**
Malawi (1992-2004)	258,130	Sept	87.9	121	Dec	84.7	153	**1.26**
Mali (1987-2006)	383,145	Jan and Feb	82.7	173	Nov	80.6	194	**1.12**
Mozambique (1997-2003)	152,190	May	89.5	105	Dec	84.3	157	**1.50**
Namibia (1992-2007)	133,607	Nov	94.7	53	Jun	93.2	68	**1.28**
Niger (1992-2006)	209,161	Feb	83.6	164	May	79.3	207	**1.26**
Nigeria (1990-2008)	476,763	May	87.9	121	Dec	82.7	173	**1.43**
Rwanda (1992-2005)	217,107	Jan	87.4	126	Apr	83.4	166	**1.32**
Senegal (1986-2005)	247,480	Sep	89.6	104	Aug	86.9	131	**1.26**
Sierra Leone (2008)	59,192	May	90.6	94	Aug	83.4	166	**1.77**
South Africa (1998)	58,284	May	97.3	27	Jun	93.7	63	**2.33**
Swaziland (2006-7)	29,027	Oct	93.2	68	Apr	89.8	102	**1.50**
Tanzania (1991-2008)	326,204	Jan and Nov	91.6	84	Feb	89.0	110	**1.31**
Togo (1998)	77,388	Dec	92.1	79	Feb	88.5	115	**1.46**
Uganda (1988-2006)	265,894	Dec	90.1	99	Jun	86.3	137	**1.38**
Zambia (1992-2007)	258,638	Sep	88.7	113	Jun	85.3	147	**1.30**
Zimbabwe (1988-2006)	175,546	Jul	95.3	47	Feb	92.5	75	**1.60**

Figure 1: Age specific hazard rates for best (solid navy line) and worst (dashed line) birth month by country. These hazard rates were use to calculate the survival probabilities and U5MR in table 1. This does not mean these are the lowest and highest hazard rates in each age interval. Countries are ordered alphabetically.

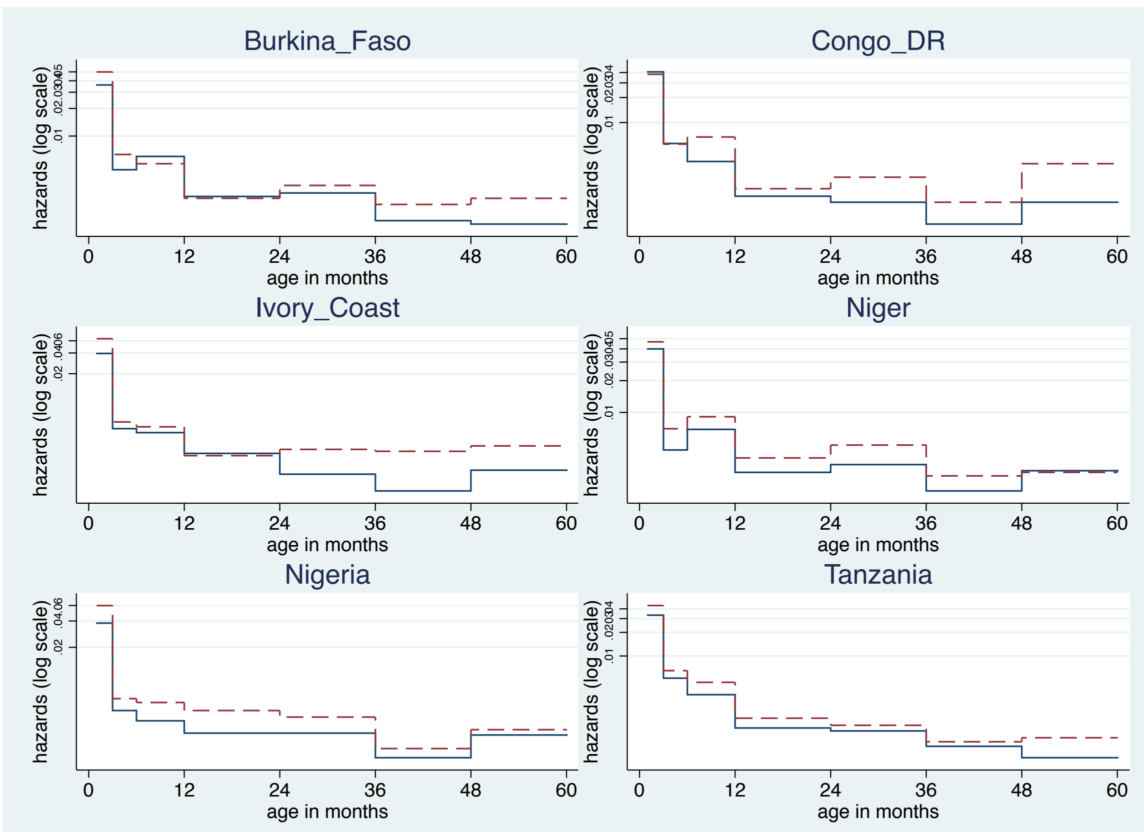


Table 2: Hazard ratios for worst birth months in three models with different sets of controls. Months in red indicate a change from Table 1.

Country	Obs.	Month	Month	Model 1 Hazard ratio		Model 2 Hazard ratio		Model 3 Hazard ratio	
Benin_1996_2006	218,723	Mar	Aug	1.282	***	1.367	***	1.380	***
Burkina_Faso_1993_2003	194,384	Mar	Aug	1.217	**	1.289	***	1.297	***
Cameroon_1991_2004	144,635	Oct	Aug	1.293	**	1.265	**	1.272	*
Chad_1996_2004	127,892	Jan	Dec	1.396	***	1.530	***	1.583	***
Congo_2005	46,231	Sep	Jan	1.472	*	1.455	*	1.378	+
Congo_DR_2007	85,118	May	Dec	1.340	**	1.403	**	1.511	***
Ivory_Coast_1994_2005	110,898	Oct	Feb	1.549	***	1.392	**	1.370	**
Ethiopia_2000_2005	216,931	Jul	Dec	1.287	***	1.299	***	1.309	***
Ghana_1988_2008	169,950	Oct	Dec	1.396	***	1.380	**	1.389	**
Guinea_1999_2005	71,200	Feb and Oct	Jun and Apr	1.634	***	1.775	***	1.776	***
Kenya_1989_2009	318,685	Oct	Jul	1.350	***	1.327	***	1.338	***
Lesotho_2004	37,157	Mar	Apr	1.624	*	1.645	*	1.703	*
Liberia_1986_2007	102,343	May	Dec	1.429	***	1.448	***	1.374	***
Madagascar_1992_2009	291,159	Jan	Jun	1.221	**	1.252	**	1.258	**
Malawi_1992_2004	258,130	Sep	Dec	1.242	***	1.258	***	1.255	***
Mali_1987_2006	383,145	Jan and Feb	Nov	1.122	**	1.252	***	1.237	***
Mozambique_1997_2003	152,190	May	Dec	1.456	***	1.526	***	1.507	***
Namibia_1992_2007	133,607	Nov	Jun	1.299	*	1.274	+	1.322	*
Niger_1992_2006	209,161	Feb	May	1.337	***	1.360	***	1.374	***
Nigeria_1990_2008	476,763	May	Dec	1.539	***	1.547	***	1.582	***
Rwanda_1992_2005	217,107	Jan	Apr	1.313	***	1.345	***	1.361	***
Senegal_1986_2005	247,480	Sep	Aug	1.242	***	1.221	**	1.194	**
Sierra_Leone_2008	59,192	May	Aug	1.810	***	1.768	***	1.787	***
South_Africa_1998	58,284	May	Jun	2.189	***	2.194	***	2.197	**
Swaziland_2006_7	29,027	Sep	Apr	1.549	+	1.562	*	1.571	+
Tanzania_1991_2008	326,204	Jan and Nov	Feb	1.329	***	1.261	***	1.247	***
Togo_1998	77,388	Dec and May	Feb	1.359	*	1.280	+	1.262	
Uganda_1988_2006	265,894	Dec	Jun	1.365	***	1.362	***	1.371	***
Zambia_1992_2007	258,638	Sep	Jun	1.287	***	1.261	***	1.277	***
Zimbabwe_1988_2006	175,546	Jul	Feb	1.620	***	1.592	***	1.626	***
age interval, birth month				X		X		X	
sex, birth order, birth interval						X		X	
mom age at birth, education, urban								X	
shared frailty								X	

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table 3: Predicted probability of being stunted if born in birth months correlated with lowest and highest stunting rates. We also present the odds ratio (worst versus best) of being stunted in model with and without maternal controls. The odds ratio increases after controlling for maternal characteristics. Countries are listed alphabetically with years of earliest and latest survey included within the parentheses.

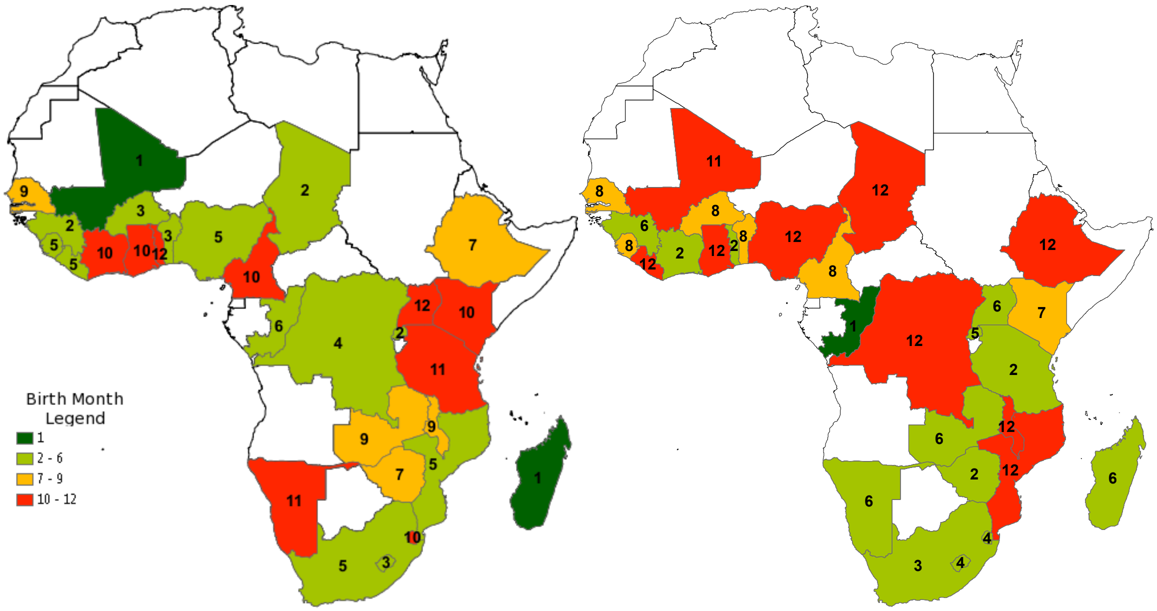
			Best		Worst		Model 1 Odds Ratio	Model 2 Odds Ratio
Country	**Obs.**	**Groups**	**Month**	**Pred Prob**	**Month**	**Pred Prob**	**Worst/Best month**	**Worst/Best month**
Benin (1996-2006)	13,796	12,648	August	23%	January	33%	1.613 ***	2.106 ***
Burkina Faso (1993-2003)	11,206	10,629	November	22%	February	31%	1.583 ***	1.976 ***
Cameroon (1991-2004)	8,270	7,331	April	12%	August	19%	1.675 ***	2.186 ***
Chad (1996-2004)	6,647	6,028	December	23%	February	35%	1.829 ***	2.042 ***
Congo (2005)	2,746	2,523	July	12%	February (Jan)	25%	2.353 ***	3.415 ***
Congo DR (2007)	4,774	4,145	December	7%	August	18%	2.833 ***	3.78 ***
Ivory Coast (1994-2005)	6,348	5,858	August	12%	April	18%	1.613 **	2.182 **
Ethiopia (2000-2005)	10,715	9,895	June	22%	December	32%	1.685 ***	2.245 ***
Ghana (1988-2008)	9,692	8,911	September	18%	January	25%	1.548 ***	1.858 ***
Guinea (1999-2005)	5,861	5,488	December	12%	August	23%	2.27 ***	4.026 ***
Kenya (1989-2009)	17,274	15,016	December	16%	July	22%	1.472 ***	1.788 ***
Lesotho (2004)	2,106	1,989	October	9%	June	21%	2.621 **	3.053 **
Liberia (1986-2007)	5,797	5,174	November	7%	June	15%	2.338 ***	3.478 ***
Madagascar (1992-2009)	16,020	14,149	October	26%	March	33%	1.46 ***	1.636 ***
Malawi (1992-2004)	15,413	13,971	July	29%	January	43%	1.824 ***	2.306 ***
Mali (1987-2006)	20,777	18,825	December	21%	July	29%	1.475 ***	1.658 ***
Mozambique (1997-2003)	8,968	8,308	July	26%	January	39%	1.812 ***	2.266 ***
Namibia (1992-2007)	7,742	7,063	September	16%	March	23%	1.597 ***	1.864 ***
Niger (1992-2006)	12,472	11,231	Jan (March)	21%	June	34%	1.941 ***	2.623 ***
Nigeria (1990-2008)	25,036	22,547	April	23%	January	26%	1.237 **	1.268 ***
Rwanda (1992-2005)	12,212	10,703	June	23%	October	32%	1.557 ***	1.908 ***
Senegal (1986-2005)	15,492	13,818	December	4%	April	8%	1.937 ***	2.248 ***
Sierra_Leone_2008	3,117	2,879	April	6%	Jan	13%	2.495 ***	4.307 **
Swaziland (2006-7)	1,574	1,449	December	15%	January	21%	1.526	1.922
Tanzania (1991-2008)	19,307	17,240	Sep	20%	February	32%	1.797 ***	2.519 ***
Togo (1998)	5,120	4,743	November	18%	July	27%	1.745 **	2.184 ***
Uganda (1988-2006)	15,369	13,079	October	22%	April	25%	1.32 *	1.333 *
Zambia (1992-2007)	14,837	13,259	October	32%	June	38%	1.311 **	1.486 ***
Zimbabwe (1988-2006)	8,888	8,271	August	17%	February	27%	1.844 ***	2.787 ***
Controls								
sex, age, birth order				X		X	X	X
urban, education, mom age								X
random effects								X

*** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Note: Since stunting is a chronic measure of health, we do not control for the month in which the survey was administered. Survey month is more likely to impact measures of wasting. South Africa is omitted because height for age data was not collected.

Figure 2: Map illustrating best and worst birth months associated with mortality and stunting.

(a) Birth month with lowest cumulative hazards (b) Birth month with highest cumulative hazards



(c) Best birth month for stunting (d) Worst birth month for stunting