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# Nutrition, information, and household behaviour: experimental evidence from Malawi

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# Nutrition, Information, and Household Behavior:

# Experimental Evidence from Malawi

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## Abstract

Incorrect knowledge of the health production function may lead to inefficient household choices, and thereby to the production of suboptimal levels of health. This paper studies the effects of a randomized intervention in rural Malawi which, over a six-month period, provided mothers of young infants with information on child nutrition without supplying any monetary or in-kind resources. A simple model first investigates theoretically how nutrition and other household choices including labor supply may change in response to the improved nutrition knowledge observed in the intervention areas. We then show empirically that, in line with this model, the intervention improved child nutrition, household consumption and consequently health. These increases are funded by an increase in male labor supply. We consider and rule out alternative explanations behind these findings. This paper is the first to establish that non-health choices, particularly parental labor supply, are affected by parents' knowledge of the child health production function.

**Keywords:** Infant Health, Health Information, Labor Supply, Cluster Randomized Control Trial

**JEL classification:** D10, I15, I18, O12, O15

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## 1. Introduction

Since Becker's (1965) seminal article, economists have long recognized that many goods are not directly bought in the market, but are produced at home using a combination of market and non-market goods. The home production framework has been particularly fruitful in studying the production of health, in particular child health (Grossman 1972, Rosenzweig and Schultz 1983, Gronau 1986 and 1997). An important implication of such models is that households make choices given their knowledge of the (child) health production function. Consequently, deficiencies in knowledge lead to suboptimal household choices and thereby distorted levels of child health. Establishing empirically the consequences of deficiencies in knowledge on household behavior has, however, been challenging because knowledge is endogenous and is usually either unobserved or proxied by education which also affects child health through other channels including earnings.

In this paper, we overcome this challenge by exogenously improving mothers' knowledge of the child health production function through a cluster randomized trial in rural Malawi, which, in solely providing information on child nutrition to mothers, yields a clean source of identification. Our contribution is twofold. First we assess whether the intervention improved child nutrition and consequently health. Second, drawing on a simple theoretical model, we investigate how other household choices change to accommodate the improved knowledge of the production function. In so doing, we establish empirically that non-health choices, particularly parental labor supply, are affected by parents' knowledge of the child health production function. This finding is a key contribution of the paper.

In the context we study, rural Malawi, mothers have many misconceptions about child nutrition. To take some examples, it is common practice to give porridge diluted with unsterilized water to infants as young as one week; the high nutritional value of groundnuts, widely available in the area, is not well-known; and widespread misplaced beliefs include that eggs are harmful for infants as old as 9 months, and that the broth of a soup contains more nutrients than the meat or vegetables therein. This evidence suggests that important changes can be expected if these misconceptions are corrected. Moreover, the fact that mothers are the main care-givers of young children, and that Malawi is a predominantly matrilineal society, means that targeting mothers is likely to be an effective way of improving children's health.

The intervention we study delivered information in an intense manner: trained local women visited mothers in their homes once before the birth of their child and four times afterwards, and provided information on early child nutrition on a one-to-one basis. Moreover, the fact that the intervention had been running for at least 3 years when outcome data were collected, allows for a sufficient time-frame for practices to change. This lapse also allows us to measure medium-term impacts, which is important since interventions often perform much better in the short- rather than medium-term (Banerjee et al. 2008 and Hanna et al. 2012).

Consistent with improvements in knowledge, we find evidence of improvements in infants' diets and household food consumption, particularly of protein-rich foods and of fruit and vegetables. Clearly, permanent increases in consumption must go hand-in-hand with increases in labor supply (unlike responses to shocks); otherwise households will not be able to afford such increased consumption. Indeed, we find strong evidence to suggest that these improvements are funded by increases in the labor supply of adult males. Overall, the findings are consistent with households learning that some relatively costly foods are more nutritious than they previously believed, and adjusting their labor supply so as to facilitate increases in their children's intake of them. Indeed, we show that households adjust their behavior on several margins including child diet inputs and adult labor supply, making their response more complex than simply changing the composition of consumption while keeping total consumption constant.

We find that improving knowledge of child nutrition improves children's physical growth, particularly height, a widely used indicator of long-term nutritional status. This finding is particularly important for policy: malnutrition is a severe and prevalent problem in developing countries where around one third of children below the age of five are stunted in growth (de Onis *et al.* 2000) and almost half of all child mortality is associated with malnutrition (Pelletier *et al*. 1995). Moreover, malnutrition in infanthood not only decreases welfare, but is also linked to poor cognitive and educational performance and low productivity later on in life.[5]

The paper pays careful attention to the important issue of inference in cluster randomized trials when the number of clusters is small. It is well known that in this situation, standard statistical formulae for clustered standard errors based on asymptotic theory (cluster-correlated Huber-White estimator) provide downward biased standard error estimates (Donald and Lang 2001, Wooldrige 2004, Duflo *et al.* 2004, Cameron *et al.* 2008). We use two leading methods for inference in this case - randomization inference (Fisher 1935, Rosenbaum 2002) and wild-bootstrap cluster-t (Cameron *et al.* 2008). Furthermore, we assess their performance in our data using Monte Carlo experiments, and find that both methods

[5] For long-term consequences of poor health or nutritional status in infanthood on long-term outcomes see, among others, Behrman 1996, Strauss and Thomas 1998, Glewwe *et al.* 2001, Alderman *et al*. 2001, Behrman and Rosenzweig 2004, Schultz 2005, Van den Berg *et al.* 2006, Hoddinott *et al.* 2008, Maluccio *et al.* 2009, Banerjee *et al.* 2010, Currie *et al.* 2009, Van den Berg *et al.* 2009, Maccini and Yang 2009, Currie 2010, Van den Berg *et al.* 2010, Lindeboom *et al.* 2010, Almond and Currie 2011, Barham 2012.

perform relatively well. This is the first empirical paper to present the performance of these two methods side-by-side. This is of clear interest for many empirical applications, given the strong and ever-increasing trend of cluster randomized trials with a small number of clusters.

Our work fits into at least three strands of the literature. The first is the growing literature assessing the effectiveness of providing health information on behavior (Dupas, 2011a).[6] The evidence on this is mixed. On the positive side, Madajewicz *et al.* (2007) and Jalan and Somanathan (2008) find that the provision of specific information - such as the arsenic or fecal concentration of water- affects associated practices; Dupas (2011b) shows that teenage girls change their sexual behavior in response to information on the risks of contracting HIV. Other studies, however, find no impacts of providing health information on associated practices and behaviors. Kamali et al. (2003), Kremer and Miguel (2007) and Luo *et al.* (2012) find that health education does not change health behaviors relating to HIV in Uganda, deworming in Kenya and anemia in China.

This paper departs from these studies not only by considering a broader and more multifaceted type of information (ways to improve child nutrition), but also by studying the responses of households on a wider range of household margins - with a particular focus on labor supply - than those directly targeted by the intervention. In doing so, this is one of the first papers to investigate how individual and household behaviors not directly related to the topic of an information campaign adjust in response to it.

Second, our paper also contributes to the literature evaluating the effects of interventions that provide nutrition information on child health. Morrow *et al.* (1999) and Haider *et al.* (2000)

[6] For the case of education, see for instance Jensen (2010).

have studied effects of similar interventions on feeding practices only (specifically exclusive breastfeeding) within small scale randomized controlled trials in Mexico and Bangladesh respectively. Further, a set of mostly non-experimental studies has investigated the effects of similar interventions on health outcomes, finding improvements in child weight-for-age, an indicator of medium-term health status (Alderman 2007, Linnemayr and Alderman 2011, Galasso and Umapathi 2009). This paper builds on this literature by considering the effects on child health, health practices, and other margins of household behavior, all identified through a randomized controlled trial.

Finally, our paper relates to the literature investigating the causal effects of parental education on child health. Much of this literature relates to developed countries and provides mixed evidence. Currie and Moretti (2003) and McCrary and Royer (2011) find respectively, decreased incidence of low birthweight and modest effects on child health of increased maternal schooling in the US, while Lindeboom *et al.* (2009) find little evidence that parental schooling improves child health in the UK. For developing countries, we are only aware of Breierova and Duflo (2004) and Chou *et al.* (2010) who find that parental schooling decreases infant mortality in Indonesia and Taiwan respectively. However, it is difficult to disentangle whether the effect of education is working through changes in knowledge of the child production function, or through increased income and hence access to more and better quality care. Related to this, Thomas *et al.* (1991) and Glewwe (1999) find that almost all of the impact of maternal education on child's height in Brazil and Morocco can be explained by indicators of access to information and health knowledge.

The rest of the paper is structured as follows. Section 2 provides some background information on rural Malawi and describes the experimental design and data, section 3 describes the theoretical framework, while section 4 sets out the empirical model. Our main results are presented in section 5. Section 6 rules out alternative potential explanations behind our findings, while section 7 concludes.

## 2. Background and Intervention

### 2.1 Background

Malnutrition in the early years (0-5) has important, potentially devastating, short- and long-run effects. It leaves children vulnerable to other illnesses and diseases, threatening their very survival (Bhutta *et al*. 2008) and affects longer term outcomes such as schooling, adult health and productivity (Glewwe *et al.* 2001, Maluccio *et al.* 2009). It is one of the major public health and development challenges facing Malawi, one of the poorest countries in Sub-Saharan Africa. The Malawi Demographic and Health Survey (DHS) Report for 2004 indicates an under-five mortality rate of 133 per 1000, and under-nutrition is an important factor driving this: Pelletier *et al*. (1994) estimate that 34% of all deaths that occur before age 5 in Malawi are related to malnutrition (moderate or severe). Moreover, 48% of Malawian children aged younger than 5 years suffer from chronic malnutrition, a rate that is the second highest in sub-Saharan Africa.

Poor feeding practices are at least partly responsible for these extreme malnutrition indicators. Over half of all infants below 6 months of age are given food and/or unsterilized water (DHS, 2004), which can lead to gastrointestinal infections and growth faltering (Haider *et al.* 1996, Kalanda *et al.* 2006) and is contrary to World Health Organization (WHO) recommendation of exclusive breastfeeding for the first six months of an infant's life. Furthermore, porridge diluted with unsterilized water is often given in large quantities to infants as young as one week (Kerr *et al.* 2007). In terms of nutrition for infants above 6 months of age, their diets - rich in staples such as maize flour - frequently lack the necessary diversity of foods to provide sufficient amounts of energy, proteins, iron, calcium, zinc, vitamins and folate: indeed in our sample, 25% of children aged 6-60 months did not consume any proteins over the three days prior to the survey, with a further 30% having consumed just one source of protein. Poor nutritional practices are likely to be related to a lack of knowledge: for instance, only 15% of mothers in our sample knew how to best cook fish combined with the local staple so as to maximize nutritional value.

It is against this background that, in 2002, a research and development project called MaiMwana (Chichewa for "Mother and Child") was set up in Mchinji District, in the Central region of Malawi.[7] Its aim was to design, implement and evaluate effective, sustainable and scalable interventions to improve the health of mothers and infants. Mchinji is a primarily rural district, with subsistence agriculture being the main economic activity. The most commonly cultivated crops are maize, groundnuts and tobacco. The dominant ethnic group in the district is the Chewa (over 90% in our data). Socio-economic conditions are comparable to or poorer than the average for Malawi (in parentheses in what follows), with literacy rates of just over 60% (64%), piped water access for 10% (20%) of households, and electricity access for just 2% (7%) of households.[8]

[7]MaiMwana is a Malawian trust established as a collaboration between the Department of Pediatrics, Kamuzu Central Hospital, the Mchinji District Hospital and the UCL Centre for International Health and Development. See http://www.maimwana.malawi.net/MaiMwana/Home.html

[8] Source: Malawi Population and Housing Census, 2008.

## 2.2 The Intervention

In 2005, MaiMwana established an infant feeding counseling intervention in Mchinji District (still ongoing), to impart information and advice on infant feeding to the mothers of babies aged less than six months.[9] The intervention thus targets the very first years of life, a critical period for growth and development during which nutritional interventions are likely to be most beneficial (Shroeder *et al.* 1995, Shrimpton *et al*. 2001, Victora *et al*. 2010). The information is provided by trained female volunteers ("peer counselors" hereon) nominated by local leaders. In practice, peer counselors are literate local women aged 23-50 years with breastfeeding experience.[10]

Each peer counselor covers an average population of 1,000 individuals, identifying all pregnant women within this population and visiting them five times in their homes: once before giving birth (3rd trimester of pregnancy) and four times afterwards (baby's age 1 week, 1 month, 3 months, 5 months). Although all pregnant women are eligible for the intervention and participation is free, in practice around 60% of them are visited by the peer counselors.

In terms of the content of the visits, exclusive breastfeeding is strongly encouraged in all visits starting from the very first. Information on weaning is provided from when the baby is 1 month old (visits 3-5) and includes suggestions of suitable locally available nutritious foods, the importance of a varied diet (particularly, the inclusion of protein and

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[9] Though the intervention is predominantly focused on nutrition, it also touches on other issues such as birth preparedness, HIV testing and counseling, vaccinations, and family planning. See subsection 6.3 for a discussion of how these aspects of the intervention relate to our results.

[10] Peer counselors receive an initial 5 day and annual refresher training, and attend monthly meetings. They are not paid, but receive a bicycle, meeting allowances, registers, calendars and supervision forms. They are supervised by 24 government health surveillance assistants and 3 MaiMwana officers.

micronutrient-rich foods, including eggs) and instructions on how to prepare foods so as to conserve nutrients and ease digestion (for instance to mash vegetables rather than liquidize them; to pound fish before cooking it). Peer counselors were provided with a manual to remind them of the content relevant for each visit, and simple picture books to aid in explaining concepts.

Lewycka *et al.* (2013) find that the intervention reduces infant mortality by between 18-36%, probably due to the increase in exclusive breastfeeding. Our paper addresses a different question using a different data source collected specifically to do so: first, whether the intervention affected consumption, nutritional practices and child nutrition to the age of around 5 years, and second, what are the underlying mechanisms behind the observed effects.

### 2.2.1 Experimental Design

The evaluation is based on a cluster randomized controlled trial designed as follows (see Lewycka *et al*. 2010, Lewycka 2011, Lewycka *et al.* 2013). Mchinji District was divided into 48 clusters by combining enumeration areas of the 1998 Malawi Population and Housing Census.[11] This was done in a systematic way, based on the contiguity of enumeration areas and respecting boundaries of Village Development Committees (VDCs)[12], such that each cluster contained approximately 8,000 individuals. Within each cluster, the 3,000 individuals (equating to 14 villages on average) living closest to the *geographical* centre of the cluster

[11]The District Administrative Centre was excluded because it is relatively more urbanized and less comparable to the rest of the District.

[12]This is an administrative area in Malawi, grouping together a number of villages and headed by a Group Village Headman.

were chosen to be included in the study.[13] The study population therefore comprises of individuals living closest to the geographical centre of the clusters and was selected in this way in order to limit contamination between neighboring clusters by creating a natural buffer area. 12 clusters were randomly selected to receive the infant feeding counseling intervention, with an average of three peer counselors covering each cluster. A further 12 serve as controls.[14]

### 2.2.2 Evaluation Sample Description

A census of women of reproductive age was conducted by MaiMwana in all of the clusters in 2004, before the intervention started ("baseline census" from hereon) in July 2005.[15] Approximately 3.5 years into the intervention, which is still in place, we drew a random sample from the baseline census in order to conduct the first follow-up survey.[16] Specifically,

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[13] The geographic centre was chosen to be the most central village in the cluster as shown on a cartographic map from the National Statistical Office, Malawi, and whose existence was corroborated with the District Commissioner's records. See Lewycka (2011), pp. 122 for more details.

[14] Another 24 clusters were randomly assigned to receive a participatory women's group intervention, whereby women of reproductive age were encouraged to form groups to meet regularly to resolve issues relating to pregnancy, child birth and neo-natal health. Child nutrition was not a primary focus of this intervention and so we exclude these clusters from this analysis (see instead Rosato *et al.* 2006, Rosato *et al.* 2009 and Lewycka *et al.* 2013). MaiMwana Project also improved health facilities across the District, which benefitted both intervention and control clusters equally.

[15] Further details on this baseline census can be found in Lewycka *et al.* (2010). We take the intervention start date to be July 2005, the date by which the first 6-month cycle had been fully completed, in line with Lewycka *et al.* (2013). .

[16]Data collection was carried out by MaiMwana in collaboration with the authors of this paper. Data were collected in Nov 2008-March 2009 (Oct 2009-Jan 2010) at first (second) follow-up. To ensure that results were not driven by seasonality, field teams collected data in intervention and control clusters at the same time. Data

in 2008 we drew a random sample of 104 women of reproductive age (17-43), regardless of their child bearing status[17], from each of the 24 clusters, leaving us with a target sample of 2,496 women. The baseline census contains some socio-economic and demographic characteristics of these women and their households, as shown in Table 1. Women are on average 24.5 years old, just over 61% of them are married, over 70% have some primary schooling but just 6% have some secondary schooling, and 66% reported agriculture as their main economic activity. Households are predominantly agricultural and poverty is high, as indicated by the housing materials and assets. The table also shows that the randomization worked well with the sample well-balanced across intervention and control clusters at baseline given that only 1 out of 25 variables turns out to be unbalanced.[18]

[TABLE 1 HERE]

We assess the impact of the intervention over three and a half years after it began. While this has the benefit of allowing us to assess the effect of the intervention in the medium rather than short term, it also increases the risk of attrition. We succeeded in interviewing around two thirds of the sample drawn for the first follow-up survey: 65% in intervention clusters

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were collected using Personal Digital Assistants (PDAs) with in-built consistency checks, which we believe resulted in improved accuracy relative to paper questionnaires. The data are available for download at http://www.esds.ac.uk/ (study 6996).

[17]This was done to avoid any potential bias arising from endogenous fertility decisions in response to the intervention. This turns out not to be an important concern, as we show in section 6.2.

[18]Other welfare programs were operating in the District at the same time as this intervention. The potentially most important is the Mchinji Social Cash Transfer, providing cash transfers to the poorest 10% of households in the district. At the time of our surveys, the intervention was in the pilot stage and only 2.5% of households in our sample (distributed evenly between intervention and control clusters) report having received it.

and 67% in control clusters. Apart from the time lapse between baseline and the first follow-up, two additional factors contributed to the attrition. First, the district of Mchinji is particularly challenging for the collection of panel data because respondents are known to report "ghost members" - fictitious household members - with the intention of increasing future official aid/transfers which may depend positively on household size (see Miller and Stoka 2012 for "ghost members" and Giné, Goldberg and Yang 2012 for problems relating to personal identification in Malawi). Hence, it is possible that some women listed in the baseline census were in fact "ghost members" and so could not be found by the field team in 2008. Second, an unexpected sharp drop of the British Pound against the Malawi Kwacha resulted in fewer resources to track women who had moved.

The right hand panel of Table 1 shows that the balance on baseline characteristics is maintained in the sample of women who were found ("interviewed sample"). A small imbalance is detected on just 1 variable at the 10% level, suggesting that attrition between baseline and the first follow-up was not significantly different between intervention and control clusters. While it is reassuring that attrition is not significantly different between intervention and control clusters in terms of observed variables, it could nonetheless be the case that there is differential attrition in terms of unobserved variables. To deal with such concerns, in section 6.4 we consider attrition in detail, allowing for differential attrition in both observed and unobserved variables, and show that our conclusions are robust to this.

We conducted a second follow-up survey on these women one year later, in 2009-10, tracking and successfully interviewing 91% of the women interviewed at first follow-up: 92.5% and 90% in intervention and control areas respectively. Though not displayed, the balance for this sample is very similar to that displayed in the last three columns of Table 1, with the addition of a small imbalance in marital status.

The surveys contain detailed information on household consumption; consumption of liquids and solids for each child in the household (≤6 years); breastfeeding practices (≤2 years); health for all individuals in the household, reported by main respondent; weights and heights of children (≤6 years); education (≥6 years) and labor supply (≥6 years); and the main respondent's knowledge about child nutrition.

## 3. Conceptual Framework

In order to understand how information of the type provided by the intervention might affect household decisions, we present a simple theoretical model in which households care about adult consumption and leisure, and about the health of their child, which is a function of the child's consumption. We assume for simplicity that households have 1 adult and 1 child. The adult chooses simultaneously the amounts to spend on child consumption, C, adult consumption, $A$, and leisure $L$ (or labor supply, $T$-$L$, since $T$ is total time endowment of the adult). The household's optimization problem is therefore:

$$\max_{\{C,A,L\}} \quad U(A,L) + G(H) \qquad (1)$$

$$st: \quad pA + C \leq w(T - L) \qquad (2)$$

$$H = h(\theta C) \qquad (3)$$

where $U(.,.)$ captures the utility from adult consumption and leisure, $G(.)$ captures the utility from child health, $p$ is the price of adult consumption relative to child consumption, and $w$ is the wage per unit of time. The child health production function, $h(\theta C)$, depends on the child's consumption, C, and θ, which is a parameter reflecting the household's efficiency in child health production: for a given amount of child consumption, C, a larger θ corresponds to better child health.[19] In this framework, we think of the intervention as raising the value of θ, by directly increasing knowledge about child nutrition.

As standard, we assume that *U(.,.),G(.),* and *h(.)* are increasing and strictly concave in their arguments and that the second order condition to attain an interior maximum is satisfied.[20,21] After differentiating the first order conditions with respect to θ (see Appendix A) we find that $\frac{dC}{d\theta}$ is positive if and only if:

$$\theta C[(G'')(h')^2 + h''G'] + G'h' > 0 \qquad (4)$$

Condition (4) is satisfied when $\mathrm{K}(\theta\mathrm{C}) \equiv \mathrm{G}(\mathrm{h}(\theta\mathrm{C}))$ is not too concave, and in particular when the concavity of $\mathrm{K}(\theta\mathrm{C})$, as measured by the elasticity of $\mathrm{K}^{'}(\theta\mathrm{C})$, is less than one.[22] A commonly used function that would satisfy this condition globally is $\mathrm{K}(\theta\mathrm{C}) = (\theta\mathrm{C})^{\alpha}$, with α<1. However, it is worth stressing that for $\frac{dC}{d\theta} > 0$ to hold, condition (4) need not hold for all

[19]We use a static, unitary model to draw out the key behavioral responses to the intervention in the simplest way. See Chiappori (1997) and Blundell *et al.* (2005), among others, for work that incorporates labor supply, household production and/or children within a collective framework. See Grossman (1972) for dynamic considerations of a health production function.

[20] The assumption that U(.,.) and G(.) are separable allows us to abstract from the signs and magnitudes of the cross-partial derivatives of the household utility function with respect to A and H, as well as H and L. Given that the empirical literature has not shed light on these cross-partial derivatives, allowing for such non-separabilities would complicate the model without improving its predictive power.

[21] We assume that the household cannot borrow, which is consistent with well-known credit constraints in developing countries, as discussed for instance in Dupas (2011a).

[22] Note that condition (4) can be rewritten as $-\theta\mathrm{C}\frac{\mathrm{K}''(\theta\mathrm{C})}{\mathrm{K}'(\theta\mathrm{C})} < 1$ in which the left hand side is the elasticity of $\mathrm{K}'(\theta\mathrm{C})$. This type of condition normally arises in models with additive utility and hence it is natural that it appears here. For instance, note that the condition would imply a restriction in the coefficient of relative risk aversion would K() be the Bernoulli utility function in a model with uncertainty.

values of *$\theta C$:* it is enough that it holds locally at the optimum. This allows us to establish the first proposition:

**Proposition 1.** *If condition (4) is satisfied, providing information on child nutrition increases child consumption:* $\frac{dC}{d\theta} > 0$.

It is optimal to accommodate this increase in child consumption along the other two margins available to the household: decreasing adult consumption and decreasing leisure. This is because the concavity of the utility function implies that utility decreases less by simultaneously reducing $L$ and $A$ than by reducing only one margin. Due to the decrease in leisure, total household consumption increases (the increase in child consumption more than offsets the decrease in adult consumption).[23] Appendix A establishes these results summarized in Proposition 2:

**Proposition 2:** *If condition (4) is satisfied and leisure and adult consumption are complements, ($U_{LA} > 0$) or substitutes ($U_{LA} < 0$), but satisfying $wU_{LA} - pU_{LL} > 0$, then providing information leads to: (i) a decrease in leisure, L, (ii) an increase in household consumption, pA+C, (iii) a decrease in adult consumption, A.*

It is worth highlighting that complementarity between leisure and adult consumption ($U_{LA} > 0$) is sufficient but not necessary for this result to hold.[24] The same result will be

[23] Our simple model abstracts from differential labor supply responses of the mother and the father. In a two parent model, one could imagine that additional time devoted to the acquisition and preparation of more nutritious foods might be to the detriment of mother's labor supply and/or leisure. However, if male and female wages are the same, it would still be the case that total household labor supply increases with the father more than offsetting any potential reduction in mother's labor supply. If male wages are higher than female wages, the results would hold in terms of earnings rather than labor supply.

[24] $U_{LA} > 0$ is also sufficient for the second order conditions to hold.

obtained when leisure and adult consumption are substitutes, as long as $U_{LA}$ is not too large in absolute value (see Appendix A). Note that the literature has not reached a consensus on whether consumption and leisure are complements or substitutes; with early work by Heckman (1974) favoring the latter while Mortensen (1977) favors the former.

Therefore, under assumptions which we believe to be not too restrictive, receiving information on child nutrition should increase both child and household consumption, decrease adult consumption and increase adult labor supply. We now turn to testing these propositions using the data and experimental set-up described in Section 2.

## 4. Empirical Framework

### 4.1 Estimation and Inference

The randomized experiment provides a clean and credible source of identification to test the propositions emerging from the theoretical framework above. To do so, we estimate OLS regressions of the form

$$Y_{ict} = \alpha + \beta_1 T_c + X_{ict}\beta_2 + Z_{c0}\beta_3 + \mu_t + u_{ict}, \quad t=1,2 \qquad (5)$$

where $Y_{ict}$ includes outcomes for unit $i$ (household or individual, depending on the outcome of interest) living in cluster $c$ at time $t$ (=1, 2 for first and second follow-ups, 2008-09 and 2009-10, respectively).[25] In line with the model, the dimensions of household behavior likely to be affected include household and child consumption, labor supply, and child health[26]; $T_c$

[25] For binary outcomes, results using Probit models are very similar and are not reported.

[26] Adult consumption also may be affected but, unfortunately, no good measure of adult-specific goods is available in our data.

is a dummy variable which equals 1 if the main respondent of our survey was, at the time of the baseline in 2004, living in a cluster that later received the intervention; $X_{ict}$ is a vector of household/individual-level variables measured at time t including a quadratic polynomial in age and gender; $Z_{c0}$ is a vector of cluster-level variables measured at baseline such as proportions of women with Chewa ethnicity, and proportions with primary or secondary schooling. $\mu_t$ is a vector of month-survey year dummies indicating the month of the interview, and $u_{ict}$ is an error term which is uncorrelated with the error term of others living in other clusters ($E[u_{ict}u_{jwq}] = 0$ for $i \neq j, c \neq w$), but which may be correlated in an unrestricted way with that of others living in the same cluster, independently of the time period ($E[u_{ict}u_{jcq}] \neq 0$). Note that this correlation structure allows for the error term for individuals/households in the same cluster to be correlated over time, and also for the presence of spillovers within but not across clusters, which is reasonable for our case given the presence of large buffer areas in place between study areas in adjacent clusters, as discussed in section 2.2.1.

The treatment indicator, $T_c$, is defined on the basis of the cluster of residence of the main respondent in the 2004 baseline census, regardless of whether she received the peer counselor's visit. Therefore, we identify an intention-to-treat parameter. Defining $T_c$ on the basis of baseline residence avoids two biases: the first potentially arising from peer counselors choosing to visit some mothers and not others (and *vice versa*, with some mothers choosing not to receive the visits), which would render actual participation endogenous; the second bias might occur if women have migrated to intervention clusters from control clusters so as to benefit from the intervention.

In terms of inference, standard statistical formulae for clustered standard errors based on asymptotic theory (cluster-correlated Huber-White estimator) provide downward biased standard error estimates if the number of clusters is small thus over-rejecting the null hypothesis of no effect (Donald and Lang 2001, Wooldrige 2004, Duflo *et al.* 2004, and Cameron *et al.* 2008). This is a potential issue here, as there are just 24 clusters. The literature has put forward two approaches to obtain valid p-values for the null hypothesis of no effect: wild cluster bootstrap-t (Cameron *et al.* 2008) and randomization inference (Fisher 1935, Rosenbaum 2002).[27]

To implement randomization inference, we follow Small *et al.* (2008) to take into account the covariates. This is done by regressing the outcome variable on all covariates, except for $T_c$, and applying the randomization inference procedure to the residuals from this regression. The test statistic is as follows:

$$\sum_{c:T_c=1} \frac{\hat{v}_{ict}}{N_1} - \sum_{c:T_c=0} \frac{\hat{v}_{ict}}{N_0}$$

where $\hat{v}_{ict}$ is the residual of the first-stage regression for household *i* in cluster *c* at time *t*, $N_1$ is the number of households in treated clusters and $N_0$ is the number of households in control clusters. Randomization inference constructs the distribution for the test statistic for every possible permutation of the randomization across clusters.[28] In practice, given the large number of possible permutations (2,704,156 in our case), it is not possible to compute the test statistic for every possible permutation of the randomization allocation. We instead use

[27] See Cohen and Dupas (2010) and Bloom et al (2013) for recent applications of randomization inference in economics, and Lucas (2010) and Busso et al (2013) for application of the wild cluster bootstrap-t.

[28] Randomization inference is non-parametric and exploits the randomization, rather than asymptotic results, for inference. A disadvantage, however, is that inference is conducted on a sharp null hypothesis of no effect for any unit in the data, rather than the more interesting hypothesis of null average effect.

100,000 randomly selected permutations to construct the distribution. The p-value is then constructed based on the proportion of test statistic values that are greater than the actual test statistic value.

In each of the estimation tables, we report clustered standard errors computed using the cluster correlated Huber-White estimator, as well as the p-values of tests of the null that the coefficient is zero computed using both wild-bootstrap cluster-t procedure and randomization inference. Moreover, in section 5.3, we present the results of a Monte Carlo exercise in which we compare the test size for these two approaches with the nominal test size, within data generating processes that incorporate the main features of our data (number of clusters, number of observations and intra-cluster correlation).

### 4.2 Internal Validity

Although the identification of the treatment effect relies on the randomization, one potential source of bias arises from the fact that the intervention reduced infant mortality in intervention areas (Lewycka *et al*. 2013). However, this is only likely to be relevant for outcomes relating to children's health, where this differential mortality might alter the (unobserved) distribution of health endowments of children in our sample. Under the assumption that weaker children are the ones more likely to survive as a result of the intervention (an intuitive and common assumption known as "the selection effect" - see Deaton 2007, Bozzoli *et al.* 2009 among others), this would imply that the average child health endowment is relatively poorer in intervention areas. Consequently, we may be *underestimating* the effect of the intervention on children's health. Another potential source of bias is that if the intervention affected fertility, this could alter the composition of children in intervention and control clusters.[29] However, as we show in section 6.2, the intervention does not appear to have affected either fertility or family planning, suggesting that this is not an issue in our context.

Finally, an important potential source of bias in our sample arises from the attrition encountered between the baseline and first follow-up surveys, which was greater than initially expected. In section 6.4, we provide several pieces of evidence that alleviate concerns that our results are biased due to attrition.

### 4.3 Outcomes

In line with the theoretical model, our outcomes of interest span six domains: health knowledge, child and household consumption, labor supply, and child health and morbidity. We pool data from the 2008-09 and 2009-10 follow-up surveys for the analysis. Statistics pertaining to the outcomes described in this section are provided in section 5. Detail on the various measures within each domain is provided in Appendix C. However, two points are worth highlighting here: first, child consumption is measured from maternal reports of the foods consumed by each child. Second, special care was taken to measure household consumption, rather than household expenditures. This is important in this context, since a large proportion of consumption is self-produced, rather than purchased from a market.

Within each domain, we have several outcome measures, meaning that we end up with 30 outcome variables. To limit the problem caused by multiple inference (the probability of rejecting a test is increasing in the number of tests carried out), we aggregate the multiple

[29]This is not a problem when we compare household or adult level outcomes since the sample is drawn on from a census of women of reproductive age, independent of their fertility.

outcome measures within a domain into a summary index, following Anderson (2008). The index is a weighted mean of the standardized values of the outcome variables (with outcome variables re-defined so that higher values imply a better/more desirable outcome), with the weights calculated to maximize the amount of information captured in the index by giving less weight to outcomes that are highly correlated with each other. Another benefit of averaging across outcomes is that power is increased by reducing measurement error. In Table E1 of the Appendix E, we report the outcomes that we use to compute the index associated to each specific domain.

By using a summary index, our results provide a statistical test for whether the intervention has a "general effect" on each of the six main domains being tested which is robust to concerns about multiple inference (Kling *et al.* 2007; Romano and Wolf 2005, Liebman *et al.* 2004). However, because it is not possible to assess the magnitude of the effect from the results using the index, we also report the results on individual outcome variables.

## 5. Results

In this section, we first show the impacts on all six composite indices, in Table 2. The subsequent tables (Tables 3-8) display the more detailed results for the impacts on the sub-component of each index, for those indices which show an overall statistically significant effect[30]. Note that for ease of reading, each of Tables 3-8 reproduces the summary index from Table 2, in its first column. In each table, we show the Huber-White clustered standard errors, wild cluster bootstrap-t p-value, randomization inference p-value and intra-cluster coefficient.

[30] Tables E2-E5 of Appendix E displays results for the sub-components of those indices that do not show a statistically significant effects of the intervention.

### 5.1 Overall Findings

Table 2 displays intervention impacts on all six composite indices, as described in section 4.3. For child level outcomes, we estimate the impacts on children born after the intervention began in July 2005, as these are the ones whose mothers were eligible to be visited by the peer counselor. This means that we consider impacts for children aged up to 4.5 years at the time of the second follow-up survey. Furthermore, since the intervention was on-going at the time of our surveys, we estimate impacts separately for children aged less than 6 months (whose mothers were potentially being visited by the counselors at the time of the survey) and those aged above 6 months. For household and adult outcomes, we consider impacts on our entire sample, regardless of whether or not the household was directly exposed to the intervention; and of the household's fertility choices.

The key rationale underlying the intervention is that households are inefficient producers of child nutrition because they do not have the correct knowledge. In other words, the nutrition production function that households optimize over is "distorted". In line with this, the first column of Table 2 reports that the intervention improved mothers' knowledge of child nutrition (captured in section 3 by an increase in the parameter $\theta$). These improvements in knowledge translated into improved child consumption for both children aged less than 6 months and those aged over 6 months (columns 2 and 3 in Table 2).[31] The positive impacts on the latter group imply that positive impacts of the intervention were retained even once the peer counselor stopped visiting the household.

Though the intervention provides no monetary or in-kind resources, the household model in section 3 predicts that household food consumption should increase. In line with this, column

[31] Note child-specific consumption is measured at second follow-up only.

4 of Table 2 shows that the intervention increases total household food consumption, measured using the composite index, at 5% significance. This increased household consumption is funded by improvements in adult labor supply, particularly that of males (column 5). Female labor supply is unchanged by the intervention (column 6). This increase in labor supply is a clear prediction of the theoretical model (proposition 2), and is also intuitive, as the increase in consumption needs to be funded. Moreover, as we will see when disaggregating by the sub-components of the index, this is a margin with considerable scope to increase labor supply.

A key question of policy interest is whether the observed adjustments on various margins of household behavior (increased consumption and labor supply) improved child health. Column 8 shows that these changes in behavior translate into improved child physical growth for children aged above 6 months. Similarly, column 7 indicates an improvement, albeit not statistically significant, in physical growth for younger children. No significant effects are found on child morbidity.[32] Note though that given the substantial infant mortality reductions found by Lewycka *et al.* 2013, and under the assumption that weaker children are the ones more likely to survive as a result of the intervention, the reported effects likely *under-estimate* the true effect of the intervention on child health.

While the composite indices allow us to assess the general impact of the intervention of each domain, their magnitudes cannot be interpreted, as the weighing used to build the index distorts the scale. To shed more light on the magnitude of the effects, we next report and

[32]Table E4 in Appendix E shows that the prevalence of diarrhea decreases for children below 6 months, consistent with the earlier result that intake of water and non-maternal milk decreases for this group of children.

discuss findings for individual outcomes for those composite indices with a statistically significant effect of the intervention.

## 5.2 Nutritional knowledge, consumption and labor supply

The intervention resulted in improvements in the main respondent's knowledge of child nutrition. The index aggregates together the correct responses to 7 questions (reproduced in Appendix D). Columns 2-8 of Table 3 report the impact of the intervention in terms of the proportion of respondents who correctly answered each of the 7 questions. The results show that the knowledge improvements are concentrated on breastfeeding practices when infants are ill, and on knowledge of food preparation practices. We note that the intra-cluster correlation coefficient is very high for most components of the index, which makes it particularly difficult to find statistically significant differences.[33]

[TABLE 3 HERE]

Improvements in child consumption were detected both for children below and above 6 months. For the former group, we see from Table 4 that the improvement comes from a reduction in both water intake and non-maternal milk. Table 5 shows that improvements for the latter group are driven by substantially higher consumption of beans (which are protein-rich) in the three days prior to the interview. The intakes of meat and eggs (also protein rich)

[33] Note that the number of observations is smaller than for other household level variables. Since we ask different knowledge questions in the first and second follow-ups, we do not pool the data from both waves and rather use the responses from both waves simultaneously to build the index so as to maximize its informational content.

are also positive, although not statistically significant, probably because of the reduced sample size (child food intake was only collected in the second follow-up survey).

[TABLES 4 AND 5 HERE]

We saw from Table 2 that the intervention resulted in improvements in overall household food consumption. Columns 2 – 5 of Table 6 show that the improvement is due to an increase in consumption of proteins, and of fruit and vegetables. Focusing on proteins, which are particularly important for child growth, we decompose the effect on the extensive and intensive margin (calculations available upon request). Around 26% of households do not report consuming any protein-rich foods in the 7 days prior to our survey; hence there is a clear opportunity for improvement in the extensive margin. Indeed, the extensive margin is responsible for 1/3 of the consumption increase. The increase in the intensive margin corresponds to 210g of meat/poultry extra and 640g beans extra per child per month. To put these quantities in perspective, a toddler will usually have 50 grams of beans in a portion, together with some vegetables and carbohydrates.

[TABLE 6 HERE]

A number of factors are likely to explain this substantial increase in food consumption: first, the time span of the intervention is sufficiently long (it had been already up and running for over 3.5 years by the time consumption was first measured); second, the intervention was intensive and involved up to 5 one-to-one home visits; third, preliminary results available upon request indicate spill-over effects to children not directly targeted by the intervention: the diets of older siblings of the directly exposed children also benefited from the nutrition information spread in the treated communities. Fourth, as we have seen from the labor supply results in Table 2, there was scope to increase labor supply to fund the increased consumption.

Table 2 also showed that male labor supply increased as a result of the intervention. Looking at the sub-components of the index - probability of any work, probability of having at least two jobs, and the number of hours worked - Table 7 reports positive effects of the intervention on all three, though only statistically significant for the probability of having at least two jobs. However, it should be noted that the intra-cluster correlation for the number of hours worked is much higher than for the probability of having at least two jobs (0.10 vs. 0.036), which greatly reduces our power to find a significant effect of the intervention on the former.

[TABLE 7 HERE]

The finding that the intervention increases male labor supply is consistent with it being a margin with considerable scope for increase. Indeed, previous research in Malawi has shown that labor supply is upward sloping rather than fixed (Michaelowa et al. 2010; Goldberg 2013). In the data that we use, only 12% of males in control clusters have a second job, most of them on non-agricultural self-employment activities.[34] Moreover, there is considerable entry into and exit from secondary jobs: among those with (without) a secondary job at first follow-up, 33% (7%) have one by the time of the second follow-up, a year later. While an extensive literature has documented increases in labor supply in response to increases in

[34] Over half of these second jobs involve employment in own/family business, a quarter involve work on the family farm, and the rest involve work as an employee in public/private sector (~20%) or on someone else's farm (<5%).

uncertainty and income shocks in developing countries (Saha 1994, Kochar 1999, Rose 2001, Lamb 2003, Kijima 2006, Ito and Takashi 2009), this is the first paper to document that labor supply responds to changes in the perceived child health production function.

This increase in labor supply was a clear prediction of the theoretical model (proposition 2). However, beyond the model, there are important features of Malawian society that are likely to be contributing to the finding that male labor supply increases. In particular, the main ethnic group in the Mchinji District - the Chewa - is a matrilocal and matrilineal group, meaning that men usually move to their wives' villages on marriage, and that wealth (predominantly land) is often held by women and passed on through the matriline (Phiri 1983, Sear 2008). As a consequence, women have more power and authority than in patrilineal societies common across most of Africa and South Asia (Reniers 2003). Indicative of this empowerment, all three measures of labor supply - work participation, the likelihood of having two jobs and hours worked - are strikingly similar for males and females (last rows of Table 7 and Table E2).[35] Finally, mothers are generally the main caregivers of children. Thus, the finding that male labor supply increases in response to mother receiving information on child nutrition is in line with the cultural background in this setting (mothers having enough power so as to persuade the father to work more).

### 5.2 Child Health

Table 2 documented improvements in child physical growth for children older than 6 months. Looking at the sub-components of the physical growth index in Table 8, we see that the

[35]This has been documented by others for the Malawian context including Goldberg (2013) and 2004 DHS (pages 34-36, Malawi DHS 2004 Report). In the also matrilineal Khasi society (India), women and men have similar labor supply profiles (Gneezy, Leonard, and List 2009).

improvement in growth is due to an increase in the average height-for-age z-score by 0.27 of a standard deviation of the WHO norm.[36] This is an important increase, and corresponds in magnitude to 65% of the average effect size obtained with the direct provision of food in food-insecure populations (Bhutta et al. 2008).

[TABLE 8 HERE]

Clearly, we cannot disentangle whether the improvement in physical growth is due to the reduction in the intake of liquids other than breast milk when the child was less than 6 months, or to the improvement in child food intake after age 6 months, or a combination of both. Our key message of the paper is that households responded to the information provided by increasing consumption and working more, to improve child health, which is the first such finding in this literature.

### 5.3 Monte Carlo on inference methods

As previously discussed, two leading methods have been proposed to carry out inference when the number of clusters is small: wild cluster bootstrap-t and randomization inference. However, there is limited evidence on how these two methods compare and in what situations they perform well. For instance, Cameron, Gelbach and Miller (2008) present some Monte Carlo simulations showing the performance of the wild cluster bootstrap-t and a range of other methods but randomization inference. However, their design differs from ours in terms of sample size and intra-cluster correlation, which are presumably important drivers of the size of bias in the Huber-White clustered standard errors. Here, we present the results of

[36] As is common with anthropometric data from developing countries, the SD of the height-for-age z-score in our sample is larger than in the WHO Reference Population (in our case the SD is 1.5 instead of 1), and so this increase corresponds to a 18% of a SD increase using the SD for our sample.

Monte Carlo experiments specifically designed to be informative about our main regressions (those of Table 2).

We present Monte Carlo results for 9 different Data Generating Processes (DGPs), each corresponding to a column of Table 2 (except for less than six months anthropometrics for which the Monte Carlos could not be performed due to an intra-cluster correlation of zero, once covariates were accounted for). Each DGP uses the same sample and covariates as in Table 2, and are parameterized to replicate the same correlations between the outcome variable and the covariates (except for the intervention variable) as in Table 2 (more details on the design of the Monte Carlo experiments are provided in the Appendix B). The effect of the binary intervention variable, $T_c$, is set at zero for all units. That is, the DGP is such that null hypothesis of no intervention effect, both on average and for every unit, is true. Each Monte Carlo experiment includes a cluster level random effect constructed such that the intra-cluster correlation of the simulated data matches that in the actual data.

For each of the DGPs discussed above, Table 9 show the test size associated with testing the null hypothesis of no effect with 5% significance. The first row shows the test size when we use cluster-correlated Huber-White standard errors to form the t-statistic. As expected, the test sizes are considerably larger than 0.05 and hence the test clearly over-rejects the null. Randomization inference provides test sizes that are generally statistically close to the nominal test size, and if anything slightly below it. The results of the wild-t bootstrap procedure are also quite close to the nominal size, but slightly above it for some cases (although not by much). Because one inference procedure yield test sizes slightly above the nominal size and the other one slightly below, it is reassuring that we obtain very similar p-values for the different outcome variables across Tables 2-8.  These results are informative for other researchers not only because it extends the characteristics of the Data Generating Processes in which these procedures are shown to work, but also because it compares hand by hand the two leading approaches when carrying out inference under a small number of clusters, which, to our knowledge has not been done so far.

[TABLE 9 HERE]

## 6. Alternative Explanations

We have argued, using the model of section 3, that consumption and labor supply increase because the productivity of child consumption (in terms of child health) increased as a result of the intervention. Here we consider four alternative explanations for our findings. The first is that increases in adult labor supply are driven by improvements in adult health that are somehow generated by the intervention; second, the intervention decreased fertility in intervention clusters, potentially yielding an increase in child quality and thus health and nutrition; third, information provided on issues other than child nutrition could have generated the observed improvements in child health; and fourth, the high attrition rates encountered between the baseline and first follow-up. We discuss each in turn and provide evidence to rule them out as explanations for the observed findings.

### 6.1 Adult Health

Whilst it is possible that increases in adult labor supply are driven by improvements in adult health that are somehow generated by the intervention, we believe this to be unlikely since the advice provided is targeted specifically at children's nutrition, which is unlikely to yield commensurate improvements in adult health – as Table 10 attests to.[37]

[TABLE 10 HERE]

### 6.2 Fertility and Family Planning

A second explanation for the increased parental investment into child nutrition and improved child health is that the intervention decreased fertility in intervention clusters, potentially yielding an increase in child quality (Becker and Tomes, 1976). A reduction in fertility could be generated through two channels: first, indirectly, by reducing infant mortality and as a result inducing households to reduce their demand for children; or second, directly, through the family planning component of the intervention.

To investigate these potential fertility effects, we examine the effect of the intervention on the use of modern family planning methods, as well as the number of children born to women in our sample since the intervention started as reported in the MaiMwana Health Surveillance System.[38] Results are displayed in Table 11. The coefficients are small and far from significant at conventional levels, despite the low levels of intra-cluster correlation. The lack of effects on family planning is consistent with conversations with program officials, who

[37] The non-significant effects on the sub-components of the health indices are shown in Table E5 of Appendix E.

[38] The MaiMwana Health Surveillance System interviews the mothers of all children born in the 24 clusters since 2005 at 1 month and 7 months of age (see Lewycka *et al.* 2013 for more details). This source therefore provides a more complete picture of births in the study areas than cross-sectional surveys. Nevertheless, there may still be selection from differential mortality of infants in the first month life as a result of the intervention.

indicated that this component was not effective because counselors were uncomfortable discussing this issue; it is also consistent with results of Lewycka *et al.* (2013).

[TABLE 11 HERE]

### 6.3 Other aspects of the intervention

As is often the case with public health programs, the intervention provided information on issues other than infant feeding practices which could also have influenced child health: encouragement of vaccination of infants, promotion of HIV testing, and information on hygiene practices. Though these additional aspects of the intervention could improve child health, it is much more difficult to believe that they could increase household food consumption and labor supply, which are the key findings of this paper.

Lewycka *et al.* (2013) find that BCG vaccination rates increased due to the intervention, but polio vaccination rates actually decreased, and there was no change in pentavalent vaccination rates. Moreover, vaccination rates in the control clusters are high and differences between intervention and control (even if statistically significant) are small (e.g. 98% vs. 95% for BCG). Furthermore, Lewycka *et al.* (2013) find no significant effect of the intervention on antenatal HIV counseling and testing.[39] This is not all that surprising, since the intervention only encouraged women to get tested for HIV, and did not provide any resources or incentives to overcome the two main constraints in this setting - direct costs of getting tested (e.g. costs of travelling to usually distant clinics) and stigma effects of getting tested -

[39] Interestingly, they find that HIV testing rates increased substantially over the intervention period (2005-2008) in both intervention and control clusters, which may be a consequence of government policy mandating HIV testing of pregnant women.

both of which are shown to be important in this context by Thornton (2008) and Ngatia (2011) respectively. Finally, our finding that the intervention did not reduce the prevalence of diarrhea for children aged between 6 and 53 months and adults (Table E4) suggests that the component on hygiene information probably had limited success.

For these reasons, we believe that the main factor driving the results reported in Section 5 is the information provided on child nutrition, rather than any other aspects of the intervention.

### 6.4 Attrition

One concern is that our results may be biased due to attrition between the baseline census (2004) and the two follow-up surveys (2008-09, 2009-10). Although attrition is related to observables (Table E6 of Appendix E), they key is that it is the same in treatment and control (follow-up rates of 65% and 67% in intervention and control clusters respectively). Moreover we showed in Table 1 that both the sample drawn and the sample successfully interviewed are well-balanced along observed characteristics. However a concern might remain that attrition induced differences in unobserved variables, potentially biasing our findings.

In particular, our estimates on child physical growth (Table 8) could be biased upwards if households with *worse* health endowments were more likely to attrit from intervention than from control clusters. However, when we repeat the analysis in Table 8 for older children living in intervention clusters (born before July 2005, hence whose mothers were not eligible to receive the counselors' visits when they were young infants), we find that their health status is worse (though not significantly so) in intervention than in control clusters. This provides suggestive evidence that those who attrited from intervention clusters are, if anything, relatively healthier than those attriting from control clusters (results available upon request).

We also address the issue of attrition directly using a Heckman selection model (Heckman, 1979). A first stage Probit model estimates the probability that a sampled woman (and therefore her household) was successfully interviewed as a function of the intervention and characteristics of the assigned interviewer at first follow-up (given that the majority of attrition occurred between baseline and first follow up). Estimates from the first stage yield an inverse-Mills Ratio, which enters as an additional regressor in the second stage - equation (5) augmented with the inverse Mills Ratio - thereby correcting for selection due to attrition.

The interviewer characteristics provide a source of exogenous variation in the first stage (see for instance Zabel 1998, Fitzgerald *et al.* 1998). Specifically, we use the number of children aged 0-3 in the interviewer's household and the size of the interviewer's plot of land, both of which proxy for the ease and intensity with which interviewers were able to track respondents. Individuals with young children may be more intrinsically motivated to take part in a study on child health, and/or they may know many other community members with young children; interviewers with a larger plot of land have a higher opportunity cost of time. Both of these factors turn out to be jointly strong predictors of whether or not a woman is interviewed (p-value of joint significance $<0.01$). A key identification assumption is that interviewer characteristics are uncorrelated with respondents' characteristics and outcomes. We believe this assumption to be reasonable in this context.[40]

[40]A concern noted by Thomas *et al.* (2012) is that good interviewers may be assigned to the most difficult clusters. In our case this concern is not relevant due to the process through which interviewers were allocated to clusters. Clusters were paired so as to include an intervention and a control cluster in the pairing. Among

Table 12 reports the estimates of the program effects for two outcomes, household consumption and main respondent's labor supply.[41] As can be seen, the selection corrected estimates (middle panel) are very close in magnitude to the OLS estimates reported earlier (repeated here in the top panel), thereby providing additional evidence that our results are not driven by attrition bias.

[TABLE 12 HERE]

## 7. Conclusion

In this paper, we use exogenous variation in mothers' knowledge of the child health production function induced by a cluster randomized intervention in Malawi, to establish empirically that improving knowledge of the child health production function influences a broad range of household behaviors.

We first establish empirically that the intervention improved mothers' knowledge on nutrition. Using a simple theoretical model, we show that households should react to this improved knowledge by increasing consumption (both child and household) and increasing adult labor supply. In line with the predictions of the model, our empirical results show that households act on improved nutrition-related information not only by changing the

potential interviewers residing in either of the two clusters, the best was selected as an interviewer to cover the pair of clusters (and hence the interviewer was not allocated to the area from a central pool). The fact that there was just 1 interviewer per pair of clusters makes it very unlikely that chosen interviewers were representative of the population of the cluster.

[41]The baseline census does not include information on men or individual children, so we do not know who attrited.

composition of consumption but also by increasing total food consumption, which yields improvements in child height. Hence, in line with basic economic theory, labor supply increases to fund the increase in consumption (especially as the intervention did not provide any monetary or in-kind resources). This finding of a non-health outcome, labor supply, being linked to how parents perceive the child health production function, is a novel finding and a key contribution to this literature.

The paper conducts very careful inference, using the two leading approaches for inference in studies with small numbers of clusters - randomization inference and wild cluster bootstrap-t. This is the first paper to show the performance of both methods alongside each other. We show that both perform quite well in our data, with a slight tendency for randomization inference to either do very well or slightly under-reject (and the converse for wild-bootstrap cluster-t).

We hypothesize that two issues might have contributed to the success of the intervention. First, the provision of information was not merely a one-off event in the intervention areas, but a sustained activity, still in place, that serves to spread information and to remind households of the importance of child nutrition on an ongoing basis. This may also explain why households adjusted on non-health margins to adhere to advice provided by this nutrition intervention and may shed light on why some health information campaigns have been successful, while others have failed. Second, the main ethnic group in rural Malawi, the Chewa, is a matrilineal one, in which women are likely to have more bargaining power and authority within the household than women in patrilineal societies common in much of the rest of Africa and South Asia. This higher female empowerment might indicate that women are in a good position to implement the recommendations given by the counselors as well as to encourage fathers to work more. It is not clear whether such responses may emerge in other settings and we see this as an area worthy of further investigation.

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# Tables

**Table 1: Baseline Sample Balance**

| | Full Sample | | | Interviewed Sample | | |
|---|---|---|---|---|---|---|
| | **Control Group** | **Difference: Treatment - Control** | **p-value** | **Control Group** | **Difference: Treatment - Control** | **p-value** |
| **Woman's Characteristics** | | | | | | |
| Married (dv = 1) | 0.615 | -0.021 | 0.386 | 0.661 | -0.034 | 0.184 |
| Some Primary Schooling or Higher | 0.707 | 0.033 | 0.402 | 0.682 | 0.040 | 0.340 |
| Some Secondary Schooling or Higher | 0.066 | 0.010 | 0.535 | 0.060 | -0.007 | 0.545 |
| Age (years) | 24.571 | -0.180 | 0.637 | 25.492 | -0.429 | 0.376 |
| Chewa | 0.948 | -0.044 | 0.330 | 0.957 | -0.050 | 0.246 |
| Christian | 0.977 | 0.006 | 0.476 | 0.979 | 0.008 | 0.336 |
| Farmer | 0.661 | -0.075 | 0.108 | 0.688 | -0.060 | 0.128 |
| Student | 0.236 | 0.015 | 0.438 | 0.204 | 0.022 | 0.274 |
| Small Business/Rural Artisan | 0.036 | 0.030 | 0.129 | 0.037 | 0.024 | 0.220 |
| | | | | | | |
| **Household Characteristics** | | | | | | |
| Agricultural household | 0.995 | -0.005 | 0.471 | 0.995 | 0.002 | 0.591 |
| Main Flooring Material: Dirt, sand or dung | 0.913 | -0.041 | 0.232 | 0.916 | -0.027 | 0.474 |
| Main roofing Material: Natural Material | 0.853 | -0.018 | 0.697 | 0.857 | -0.004 | 0.891 |
| HH Members Work on Own Agricultural Land | 0.942 | -0.057 | 0.124 | 0.950 | -0.056 | 0.120 |
| Piped water | 0.011 | 0.040 | 0.314 | 0.009 | 0.032 | 0.340 |
| Traditional pit toilet (dv = 1) | 0.772 | 0.054 | 0.218 | 0.791 | 0.054 | 0.182 |
| # of hh members | 5.771 | 0.066 | 0.817 | 5.848 | 0.132 | 0.863 |
| # of sleeping rooms | 2.116 | 0.199 | 0.038* | 2.152 | 0.166 | 0.128 |
| HH has electricity | 0.002 | 0.007 | 0.166 | 0.002 | 0.004 | 0.338 |
| HH has radio | 0.630 | 0.030 | 0.408 | 0.641 | 0.015 | 0.709 |
| HH has bicycle | 0.509 | 0.015 | 0.643 | 0.512 | 0.008 | 0.843 |
| HH has motorcycle | 0.008 | 0.001 | 0.925 | 0.007 | 0.002 | 0.779 |
| HH has car | 0.006 | -0.002 | 0.612 | 0.007 | -0.003 | 0.298 |
| HH has paraffin lamp | 0.925 | 0.032 | 0.262 | 0.926 | 0.036 | 0.178 |
| HH has oxcart | 0.058 | -0.015 | 0.204 | 0.059 | -0.022 | 0.090+ |
| N | 1248 | 1248 | | 846 | 814 | |

Notes to Table: + indicates significant at the 10% level, * indicates significant at the 5% level. p-values reported here are computed using the wild cluster bootstrap-t procedure as in Cameron *et al.* 2008, explained in section 4.1. Full Sample includes all women (and their households) originally drawn to be part of the 2008-09 survey. Interviewed Sample includes women (and their households) actually interviewed in 2008-09 (and used in the analysis).

**Table 2: Effects on the summary indices**

| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] | [9] | [10] |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Main Respondent's Knowledge on Nutrition** | **Child Food Consumption** | | **Household Food Consumption** | **Labor Supply** | | **Child Physical Growth** | | **Child Morbidity (reversed)** | |
| | | **< 6 months** | **> 6 months** | | **Adult Males** | **Adult Females** | **< 6 months** | **> 6 months** | **< 6 months** | **> 6 months** |
| $T_z$ | 0.169+ | 0.250* | 0.143+ | 0.218* | 0.262+ | 0.018 | 0.066 | 0.102* | 0.058 | -0.013 |
| Standard Error | [0.086] | [0.098] | [0.074] | [0.082] | [0.131] | [0.165] | [0.056] | [0.036] | [0.070] | [0.102] |
| Wild Cluster Bootstrap p-value | {0.058} | {0.016} | {0.076} | {0.018} | {0.086} | {0.955} | {0.293} | {0.022} | {0.438} | {0.861} |
| Randomization Inference p-value | {0.065} | {0.028} | {0.099} | {0.037} | {0.062} | {0.903} | {0.366} | {0.035} | {0.509} | {0.920} |
| Observations | 1512 | 151 | 1280 | 3200 | 3642 | 4138 | 312 | 2175 | 376 | 2356 |
| R-squared | 0.107 | 0.214 | 0.099 | 0.063 | 0.183 | 0.136 | 0.062 | 0.026 | 0.059 | 0.053 |
| IntraCluster Correlation | 0.169 | 0.041 | 0.085 | 0.087 | 0.146 | 0.140 | 0.019 | 0.021 | 0.021 | 0.150 |
| Mean Control Areas | -0.040 | -0.109 | -0.054 | -0.099 | -0.135 | -0.050 | 0.245 | 0.266 | -0.034 | 0.022 |

Notes to Table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the cluster (at which treatment was assigned); wild cluster bootstrap-t p-values and randomization inference p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. All regressions include controls for cluster-level education and Chewa ethnicity in 2004 and dummies for the month of interview. All regressions other than that in column 4 includes controls for age and age-squared. Outcome variables are summary indices of variables relating to that domain of outcomes. They are constructed as described in section 4.4. Higher values of the index in columns 9 and 10 indicate less morbidity. The component variables for each index are outlined in Table A2 in the appendix. Sample in columns 1 and 4 includes all households in our sample, sample in columns 2, 3 and 7-10 include children born after the intervention began in July 2005, and so who were aged between 0-53 months at the time of interview. Sample in columns 5 and 6 includes all males and females aged 15-65 years in our sample.

**Table 3: Components of Knowledge Index**

| | Summary Index | Breastfeeding when infant has diarrhoea | Are biscuits or groundnuts/soya more nutritious for kids aged 6 months-3 yrs? | From what age should solid foods be given infants? | How should an HIV positive woman feed her baby? | Is nsima or porridge more nutritious for an infant aged > 6 months? | What is the best way of cooking fish with porridge for an infant aged > 6 months? | Should eggs be given to an infant aged > 9 months? |
|---|---|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
| $T_z$ | 0.169+ | 0.253+ | -0.052 | 0.037 | 0.138 | -0.101 | 0.067** | 0.104 |
| Standard Error | [0.086] | [0.115] | [0.041] | [0.026] | [0.150] | [0.078] | [0.019] | [0.069] |
| Wild Cluster Bootstrap p-value | {0.058} | {0.084} | {0.290} | {0.166} | {0.444} | {0.210} | {0.002} | {0.186} |
| Randomization Inference p-value | {0.065} | {0.028} | {0.222} | {0.292} | {0.399} | {0.179} | {0.008} | {0.192} |
| Observations | 1512 | 1512 | 1512 | 1512 | 1512 | 1512 | 1512 | 1512 |
| R-squared | 0.11 | 0.10 | 0.05 | 0.04 | 0.04 | 0.07 | 0.04 | 0.02 |
| IntraCluster Correlation | 0.169 | 0.277 | 0.082 | 0.049 | 0.408 | 0.183 | 0.057 | 0.107 |
| Mean, Control | -0.04 | 0.217 | 0.938 | 0.88 | 0.393 | 0.857 | 0.026 | 0.719 |

Notes to Table: All regressions include controls for age, age-squared, cluster-level education and Chewa ethnicity in 2004 and dummies for the month of interview.Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the the cluster (at which treatment was assigned); wild cluster bootstrap-t and randomization inference p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. Sample contains all households in our sample with a female main respondent. "Summary Index" aggregates the measures in columns 2-8 using the method described in section 4.3. The variables in columns 2-8 are dummy variables equal to 1 if the respondent answered correctly. Questions in columns 2-6 and column 8 were multiple choice questions where respondents chose 1 correct answer from 3-5 options. Question in column 7 was an open-ended question, with interviewers marking correctly answered options.

**Table 4: Intake of Liquids by Children Aged < 6 months.**

| | [1] | [2] | [3] |
|---|---|---|---|
| | **Summary Index** | **Water** | **Milk other than maternal** |
| $T_z$ | 0.250* | -0.144+ | -0.082* |
| Standard Error | [0.098] | [0.081] | [0.034] |
| Wild Cluster Bootstrap p-value | {0.016} | {0.106} | {0.020} |
| Randomization Inference p-value | {0.028} | {0.077} | {0.112} |
| Observations | 151 | 359 | 151 |
| R-squared | 0.214 | 0.249 | 0.087 |
| IntraCluster Correlation | 0.0405 | 0.024 | 0.060 |
| Mean, Control | -0.109 | 0.488 | 0.101 |

Notes to Table: All regressions include controls for age, age-squared, gender, cluster-level education and Chewa ethnicity in 2004 and dummies for the month of interview. Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the the cluster (at which treatment was assigned); wild cluster bootstrap-t and randomization inference p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. Sample includes children aged less than 6 months. "Summary Index" aggregates the measures in columns 1-2 using the method described in section 4.3. "Water" is an indicator for whether the child had any water in the 3 days prior to the survey, "Milk other than maternal" is an indicator (measured in second follow up only) for whether the child had milk other than breastmilk in the 3 days prior to the survey.

**Table 5: Effects on Child Food Consumption (>6 months)**

| | Summary Index | Any beans | Any meat | Any fish | Any eggs | Any vegetables | Any fruit | Any nsima | Any porridge |
|---|---|---|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] | [9] |
| $T_z$ | 0.143+ | 0.225** | 0.091 | 0.007 | 0.026 | -0.010 | -0.011 | 0.025 | 0.094 |
| Standard Error | [0.074] | [0.056] | [0.096] | [0.098] | [0.052] | [0.020] | [0.057] | [0.015] | [0.064] |
| Wild Cluster Bootstrap p-value | {0.076} | {0.006} | {0.563} | {0.927} | {0.637} | {0.643} | {0.825} | {0.134} | {0.246} |
| Randomization Inference p-value | {0.099} | {0.007} | {0.279} | {0.947} | {0.624} | {0.627} | {0.869} | {0.142} | {0.261} |
| Observations | 1280 | 1288 | 1287 | 1289 | 1288 | 1,291 | 1,288 | 1,290 | 1,294 |
| R-squared | 0.10 | 0.07 | 0.02 | 0.01 | 0.011 | 0.141 | 0.153 | 0.143 | 0.035 |
| IntraCluster Correlation | 0.085 | 0.113 | 0.085 | 0.111 | 0.0502 | 0.0181 | 0.0923 | 0 | 0.136 |
| Mean, Control | -0.0541 | 0.258 | 0.291 | 0.463 | 0.164 | 0.959 | 0.7 | 0.93 | 0.8 |

Notes to Table: All regressions include controls for age, age-squared, gender, cluster-level Chewa ethnicity and education in 2004 and dummies for the month of interview. Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the the cluster (at which treatment was assigned); wild cluster bootstrap-t and randomization inference p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. Sample contains all children born after July 2005, and who were aged between 6 and 53 months at time of survey. Data on child solid intake collected at second follow up only. "Summary Index" aggregates the measures in columns 2-9 using the method described in section 4.3. The variables in columns 2-9 are dummy variables equal to 1 if the corresponding food was consumed by the child in the 3 days prior to the survey.

**Table 6: Household Consumption**

| | [1] | [2] | [3] | [4] | [5] |
|---|---|---|---|---|---|
| | | **Per Capita Monthly Food Consumption for:** | | | |
| | **Summary Index** | **Cereals** | **Proteins** | **Fruit and Vegetables** | **Other Foods** |
| $T_z$ | 0.218* | -9.878 | 128.359* | 269.819+ | 60.453 |
| Standard Error | [0.082] | [52.450] | [54.798] | [108.600] | [33.561] |
| Wild Cluster Bootstrap p-value | {0.018} | {0.931} | {0.022} | {0.060} | {0.150} |
| Randomization Inference p-value | {0.037} | {0.952} | {0.016} | {0.042} | {0.020} |
| Observations | 3200 | 3205 | 3202 | 3204 | 3204 |
| R-squared | 0.063 | 0.118 | 0.02 | 0.195 | 0.024 |
| IntraCluster Correlation | 0.087 | 0.074 | 0.042 | 0.172 | 0.053 |
| Mean Control Areas | -0.10 | 606.00 | 349.80 | 679.70 | 149.70 |

Notes to Table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the cluster (at which treatment was assigned); wild cluster bootstrap-t and randomization inference p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. All regressions include controls for age, age-squared, cluster-level education and Chewa ethnicity in 2004 and dummies for the month of interview. Coefficients in columns 2-6 are in terms of Malawi Kwacha. (The average exchange rate to the US Dollar was approx. 140MK = 1 US$ at the time of the surveys). "Food Index" is an index of the food items in cols. 2-5, constructed as described in section 4.3. "Cereals" includes consumption of rice, maize flour and bread, "Proteins" includes consumption of milk, eggs, meat, fish and pulses, "Fruit and Vegetables" includes consumption of green maize, cassava, green leaves, tomatoes, onions, pumpkins, potatoes, bananas, masuku, mango, ground nuts and other fruits and vegetables, "Other Foods" includes cooking oil, sugar, salt, alcohol and other foods.

**Table 7: Effects on Labor Supply**

| | Male Adults | | | |
|---|---|---|---|---|
| | [1] | [2] | [3] | [4] |
| | **Summary Index** | **Works** | **Has at least 2 jobs** | **Weekly Hours Worked** |
| $T_z$ | 0.262+ | 0.096 | 0.072* | 4.31 |
| Standard Error | [0.131] | [0.078] | [0.028] | [2.918] |
| Wild Cluster Bootstrap p-value | {0.074} | {0.303} | {0.020} | {0.230} |
| Randomization Inference p-value | {0.062} | {0.251} | {0.057} | {0.202} |
| Observations | 3642 | 3961 | 3958 | 3642 |
| R-squared | 0.183 | 0.17 | 0.05 | 0.16 |
| IntraCluster Correlation | 0.146 | 0.208 | 0.036 | 0.100 |
| Mean, Control | -0.135 | 0.836 | 0.122 | 25.740 |

Notes to Table: All regressions include controls for age, age-squared, cluster-level education and Chewa ethnicity in 2004 and dummies for the month of interview. Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the the cluster (at which treatment was assigned; wild cluster bootstrap-t and randomization inference p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. Sample includes all males aged 15-65 years. "Summary Index" contains the variables in columns 2-4 and is computed using the method described in section 4.3. "Works" in an indicator of whether individual had an income-generating activity at the time of the survey, "Has at least 2 jobs" is an indicator for whether individual has 2 income generating activities, "Weekly Hours worked" give the total hours worked in the week prior to the survey on both income generating activities.

**Table 8: Intervention Effects on Child Physical Growth, Children aged > 6 months**

| | [1] | [2] | [3] | [4] |
|---|---|---|---|---|
| | **Summary Index** | **Height for Age** | **Healthy weight for age** | **Healthy weight for height** |
| $T_z$ | 0.102* | 0.271* | 0.030 | 0.048 |
| Standard Error | [0.036] | [0.102] | [0.019] | [0.027] |
| Wild Cluster Bootstrap p-value | {0.022} | {0.022} | {0.150} | {0.132} |
| Randomization Inference p-value | {0.035} | {0.055} | {0.312} | {0.147} |
| | | | | |
| Observations | 2175 | 2192 | 2265 | 2217 |
| R-squared | 0.026 | 0.046 | 0.024 | 0.029 |
| IntraCluster Correlation | 0.021 | 0.022 | 0.018 | 0.017 |
| Average, Control | 0.266 | -2.338 | 0.817 | 0.845 |

Notes to Table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the the cluster (at which treatment was assigned); wild cluster bootstrap-t p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. All regressions include controls for age, age-squared, gender, dummies for the month of interview and cluster-level education and Chewa ethnicity in 2004. Sample includes children born after July 2005 and who were aged between 6 and 53 months at time of measurement. "Summary Index" contains the variables in columns 2-4 and is computed using the method described in section 4.3. "Height-for-Age"is a standardised z-score relative to the WHO reference population, "Healthy weight for age" is a dummy variable =1 if child's weight-for-age z-score is not more than 2 std deviations above or below the WHO reference population and "Healthy weight for height" is a dummy variable =1 if child's weight-for-height z-score is within 2 std deviations of the WHO reference population.

**Table 9: Test size obtained from Monte Carlo experiments**

| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] | [9] | [10] |
|---|---|---|---|---|---|---|---|---|---|---|
| Test size ↓ | **Main Respondent's Knowledge on Nutrition** | **Child Food Intake** | | **Household Food Consumption** | **Labor Supply** | | **Child Physical Growth** | | **Child Morbidity (reversed)** | |
| | | **< 6 months** | **> 6 months** | | **Adult Males** | **Adult Females** | **< 6 months** | **> 6 months** | **< 6 months** | **> 6 months** |
| **Method** | | | | | | | | | | |
| Huber-White Clustered Standard Errors | 0.093* | 0.088* | 0.072* | 0.078* | 0.081* | 0.085* | n/a | 0.086* | 0.108* | 0.084* |
| Wild Cluster Bootstrap-t | 0.048 | 0.061 | 0.061* | 0.065 | 0.055 | 0.047 | n/a | 0.070* | 0.073* | 0.051 |
| Randomization Inference | 0.039 | 0.046 | 0.052 | 0.034* | 0.05 | 0.041 | n/a | 0.047 | 0.037 | 0.047 |
| | | | | | | | | | | |
| IntraCluster Correlation in Data | 0.169 | 0.041 | 0.033 | 0.087 | 0.146 | 0.140 | 0.019[a] | 0.020 | 0.021 | 0.150 |

Notes to Table: Table reports test sizes from Monte Carlo simulations conducted using the 3 different inference methods above. Simulations conducted according to the procedure described in Appendix B. Nominal test size for each simulation is set at 0.05. * Indicates statistically different test size from 0.05 at the 5% level of significance. [a] For the outcome "Improvements in Child Physical Growth" for children aged < 6 months, the intra-cluster correlation for the outcome variable once the effects of covariates are removed was 0 and thus we did not conduct the Monte Carlo simulations for this outcome. Higher values of the index in the last two columns indicate less morbidity.

**Table 10: Effects on Adult Health**

| | [1] | [2] |
|---|---|---|
| | **Summary Index** | **Summary Index** |
| | **Males** | **Females** |
| $T_z$ | -0.007 | -0.020 |
| Standard Error | [0.044] | [0.038] |
| Wild Cluster Bootstrap p-value | {0.873} | {0.693} |
| Randomization Inference p-value | {0.899} | {0.685} |
| | | |
| Observations | 3726 | 4226 |
| R-squared | 0.022 | 0.040 |
| IntraCluster Correlation | 0.073 | 0.063 |
| Mean, Control | 0.004 | 0.012 |

Notes to Table: All regressions include controls for age, age-squared, gender, cluster-level education and Chewa ethnicity in 2004 and dummies for the month of interview. Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the cluster (at which treatment was assigned); wild cluster bootstrap-t and randomization inference p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. Summary Index calculated based on 8 outcome measures outlined in Table B2 using the method described in section 4.3.

**Table 11: Intervention Effects on Family Planning and Fertility**

| | [1] | [2] |
|---|---|---|
| | **Use of any modern family planning method** | **Number of children since July 2005** |
| $T_z$ | 0.023 | -0.049 |
| Standard Error | [0.052] | [0.040] |
| Wild Cluster Bootstrap p-value | {0.667} | {0.300} |
| Randomisation Inference p-value | {0.652} | {0.525} |
| | | |
| Observations | 2809 | 1655 |
| R-squared | 0.065 | 0.089 |
| IntraCluster Correlation | 0.036 | 0.014 |
| Mean, Control | 0.378 | 0.583 |

Notes to Table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the cluster (at which treatment was assigned); wild cluster bootstrap-t p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. All regressions includes controls for age, age-squared, and (family planning regression only) for cluster-level Chewa ethnicity and education in 2004 and dummies for the month of interview. "Number of children since July 2005" is the number of children born to the main respondent and surveyed at age 1 month since July 2005; Column 1 sample includes women 17-43 years old (when available, both waves responses are included). Sample in column 2 includes all women surveyed as main respondents in the 2008 survey, and comes from the Mai Mwana Health Surveillance System, which measures at age 1 month all children born to these women since the start of the intervention

**Table 12: Heckman selection equation results**

| | [1] | [2] |
|---|---|---|
| | **Food Index** | **Main Respondent Labor Supply** |
| **Ordinary Least Squares** | | |
| $T_z$ | 0.218* | -0.077 |
| Standard Error | [0.082] | [0.187] |
| Wild Cluster Bootstrap p-value | {0.018} | {0.769} |
| Randomisation Inference p-value | {0.037} | {0.659} |
| | | |
| Observations | 3200 | 2938 |
| R-squared | 0.063 | 0.088 |
| IntraCluster Correlation | 0.087 | 0.165 |
| Mean Control Areas | -0.10 | -0.03 |
| **Heckman Selection Model for Attrition** | | |
| $T_z$ | 0.216* | -0.096 |
| Standard Error | [0.108] | [0.234] |
| Inverse Mills ratio | -0.683 | -0.700 |
| | [0.463] | [0.866] |
| | | |
| **Selection Equation (coefficients)** | | |
| $T_z$ | -0.08 | -0.061 |
| | [0.141] | [0.141] |
| # children 0-3 | 0.221* | 0.252** |
| | [0.092] | [0.090] |
| land size (acres) | -0.017 | -0.015 |
| | [0.014] | [0.015] |
| Observations | 4986 | 4621 |

Notes to Table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the cluster (at which treatment was assigned); wild cluster bootstrap-t p-values in curly brackets. Standard errors for Heckman Selection model computed using a block bootstrap method. ** p<0.01, * p<0.05, + p<0.1. Regressions include controls for dummies for the month of interview and cluster-level education and Chewa ethnicity in 2004. Column 2 regression includes controls for age and age-squared. Excluded variables in the second stage of the Heckman Selection Model are "# children 0-3" (number of children aged 0-3 of first follow-up survey interviewer) and "land size(acres)" (land size in acres of first follow-up survey interviewer).

# Appendix A:
# Proofs

# Appendix A: Proofs

## Proof of Proposition 1

We assume that the solution is an interior one so that the budget constraint is binding at the optimum. Substituting in the health production function and budget constraint for H and A in the objective function, we can express the optimisation problem as:

$$\underset{\{C,L\}}{Max} F(C, L;\ \theta)$$

$$\text{where } F(C, L;\ \theta) = U(\tfrac{w(T-L)-C}{p}, L) + G(h(\theta C))$$

The first order conditions are:

$$F_C(C, L;\ \theta) = -\frac{1}{p}U_A'(\tfrac{w(T-L)-C}{p}, L) + G'(h(\theta C))h'(\theta C)\theta = 0$$

$$F_L(C, L;\ \theta) = -\frac{w}{p}U_A'(\tfrac{w(T-L)-C}{p}, L) + U_L'(\tfrac{w(T-L)-C}{p}, L) = 0$$

Differentiating the two first order conditions, we get

$$\begin{bmatrix} F_{CC} & F_{CL} \\ F_{CL} & F_{LL} \end{bmatrix} \begin{bmatrix} dC \\ dL \end{bmatrix} = \begin{bmatrix} -F_{C\theta} \\ -F_{L\theta} \end{bmatrix} d\theta \text{ (A1)}$$

Noting that $F_{L\theta} = 0$ due to additive separability, we get that

$$\frac{dC}{d\theta} = \frac{\begin{vmatrix} -F_{C\theta} & F_{CL} \\ -F_{L\theta} & F_{LL} \end{vmatrix}}{\begin{vmatrix} F_{CC} & F_{CL} \\ F_{CL} & F_{LL} \end{vmatrix}} = -\frac{F_{C\theta}F_{LL}}{|SOC_2|} \quad \text{(A2)}$$

where

$$|SOC_2| = \begin{vmatrix} F_{CC} & F_{CL} \\ F_{CL} & F_{LL} \end{vmatrix}$$

Since $U(.)$ is concave in L and $G(.)$ and $h(.)$ are concave in their arguments, $F_{LL} < 0$ and $F_{CC} < 0$ at the optimum, and so $|SOC_2| > 0$. Consequently, the sign on $\frac{dC}{d\theta}$ is the same as the sign on $F_{C\theta} = \theta C[(G'')(h')^2 + h''G'] + G'h'$. **QED**

## Proof of Proposition 2

To prove that leisure, $L$ decreases when child consumption, $C$, increases due to an increase in $\theta$, note that from (A1), we obtain that

$$\frac{dL}{d\theta} = -\frac{F_{CL}}{F_{LL}}\frac{dC}{d\theta} \quad \text{(A3)}$$

where:

$$F_{CL} = \frac{1}{p}\left(\frac{w}{p}U_{AA} - U_{LA}\right) \quad \text{(A4)}$$

$$F_{LL} = \left(\frac{w}{p}\right)^2 U_{AA} - 2\frac{w}{p}U_{LA} + U_{LL} \quad \text{(A5)}$$

Note that if $U_{LA} > 0$ or if $wU_{LA} - pU_{LL} > 0$, then both $F_{CL} < 0$ and $F_{LL} < 0$. Then, by (A3),

$$sign\left(\frac{dL}{d\theta}\right) = -sign\left(\frac{dC}{d\theta}\right) \quad \text{(A6)}$$

which proves the first part of the proposition.

The proof of the second part of the proposition (that household consumption increases) then follows immediately. According to the budget constraint, household consumption $(pA + C) = w(T - L)$. Therefore, if L decreases, household consumption increases necessarily.

To prove the third part of the proposition (that adult consumption decreases), write the budget constraint as

$$A = \frac{1}{p}[w(T - L) - C] \quad \text{(A7)}$$

Differentiating (A7) with respect to $\theta$ and using (A3), we obtain that:

$$\frac{dA}{d\theta} = \left(\frac{1}{pF_{LL}}\right)(wF_{CL} - F_{LL})\left(\frac{dC}{d\theta}\right) \quad \text{(A8)}$$

Substituting (A4) and (A5) into (A8), we obtain:

$$\frac{dA}{d\theta} = \left(\frac{1}{pF_{LL}}\right)(\frac{w}{p}U_{LA} - U_{LL})\left(\frac{dC}{d\theta}\right) \quad \text{(A9)}$$

which implies that adult consumption decreases when child consumption increases $\left(\frac{dC}{d\theta}\right) > 0$ because $\left(\frac{1}{pF_{LL}}\right) < 0$ (by the second order conditions), and we have assumed that either $U_{LA} > 0$ following Mortensen 1977 among others or $wU_{LA} - pU_{LL} > 0$ holds. **QED**

## Proof that $U_{LA} > 0$ is sufficient for the Second Order Conditions to hold

The Lagrangian function associated with the optimization problem is

$L = U(A, L) + G(h(\theta C)) + \mu(pA + C - w(T - L))$

The relevant bordered Hessian is $D = \begin{bmatrix} 0 & p & w & 1 \\ p & U_{AA} & U_{LA} & 0 \\ w & U_{LA} & U_{LL} & 0 \\ 1 & 0 & 0 & \frac{d^2L}{dC^2} \end{bmatrix}$,

and the second principal minor is $D_2 = \begin{bmatrix} 0 & p & w \\ p & U_{AA} & U_{LA} \\ w & U_{LA} & U_{LL} \end{bmatrix}$.

The sufficient conditions for optimality are that $|D_2| > 0$ and $|D| < 0$.

$|D_2| = w(pU_{AL} - wU_{AA}) + p(wU_{AL} - pU_{LL})$. If $U_{LA} > 0$, then $|D_2| > 0$.

$|D| = \frac{d^2L}{dc^2}|D_2| - \begin{vmatrix} p & w & 1 \\ U_{AA} & U_{LA} & 0 \\ U_{LA} & U_{LL} & 0 \end{vmatrix} = \frac{d^2L}{dC^2}|D_2| - U_{AA}U_{LL} + (U_{LA})^2$. From above, we know that $|D_2| > 0$ if $U_{LA} > 0$. Then, given concavity of $U(A, L)$, $U_{AA}U_{LL} - (U_{LA})^2 > 0$, and given that $\frac{d^2L}{dC^2} = \theta^2 G''(h')^2 + \theta^2 G'h'' < 0$, the condition $|D| < 0$ is verified if $U_{LA} > 0$. **QED**

# Appendix B:

# Monte Carlo Simulation

## Appendix B. Monte Carlo Simulation

Standard errors based on cluster-correlated Huber-White standard errors might be too small when the number of clusters is relatively small (Donald and Lang 2001, Wooldrige 2004, Duflo *et al.* 2004, and Cameron *et al.* 2008). This might lead to over-rejection of the null hypothesis that the coefficient of interest is zero when it is correct. To deal with this issue, in the paper we report p-values for the null hypothesis of no effect using the two leading approaches for valid inference in this case: wild cluster bootstrap-t (Cameron *et al.* 2008) and randomization inference (Fisher 1935, Rosenbaum 2002). Since there is limited evidence on when these approaches are valid (knowledge on the performance of the wild bootstrap-t is based on simulations from a dataset with features which may not match those of the data we use), in section 5.3 we provide the results of a Monte Carlo simulation to estimate the test size (the probability that the null hypothesis is rejected when it is true) for a nominal significance level of 5%. Below, we provide the details of the Monte Carlo simulation.

We analyze 9 Data Generating Processes (DGPs), one for each of the columns in Table 2[1]. In each DGP, the sample and covariates are the ones that we use to estimate the regressions in Table 2. The parameters of the DGP (coefficients multiplying the covariates, variance of the error term and intra-cluster correlation) are also the ones that we obtain when we estimate the regressions in Table 2. Hence, the results from the Monte Carlo simulation are indeed informative about our case. For each column of Table 2, we follow the steps below:

[1] Except for column 7 – child physical growth for kids aged < 6 months. We were unable to conduct the Monte Carlo for this outcome since it has a 0 intra-cluster correlation once covariates are included.

Step 1: Use OLS to estimate regression (5) in which the dependent variable, $\mathrm{Y_{ict}}$, and the sample are the ones indicated in the heading of the corresponding column in Table 2. The estimates, $[\hat{\alpha}_0, \hat{\beta}_1\, \hat{\beta}_2, \hat{\beta}_3, \widehat{\mu_t}]$, which are the same as those reported in Table 2, are saved and used in the steps below (except $\hat{\beta}_1$, which is discarded). Using the residuals from this OLS regression, we estimate the intra-cluster correlation and the variance of the error term $[\hat{\rho}_u,\ \hat{\sigma}_u^2]$.

Step 2: Obtain 24 draws (our number of clusters) from a standardized normal distribution $\{\tilde{\vartheta}_c\}_{c=1}^{24}$.

Step 3: Obtain N draws (number of observations) from a standardized normal distribution, $\{\tilde{\varepsilon}_i,\}_{i=1}^{N}$.

Step 4: Using the parameter values of step 1, and the random draw from step 2 and 3, $[\hat{\alpha}_0,\ \hat{\alpha}_2,\ \hat{\sigma}_\varepsilon^2]$, we obtain simulated values for the dependent variable, $\tilde{Y}_{\mathrm{ict}}$, under the assumption that the treatment effect is null, that is,

$$\tilde{Y}_{\mathrm{ict}} = \hat{\alpha}_0 + 0x\mathrm{T_c} + \mathrm{X_{ict}}\hat{\beta}_2 + \mathrm{Z_{c0}}\hat{\beta}_3 + \widehat{\mu_t} + \hat{\sigma}_\vartheta \tilde{\vartheta}_c + \hat{\sigma}_\varepsilon \tilde{\varepsilon}_{ict},$$

where $\hat{\sigma}_u^2 = \hat{\sigma}_\vartheta{}^2 + \hat{\sigma}_\varepsilon{}^2$ and $\hat{\rho}_u = \frac{\hat{\sigma}_\vartheta{}^2}{\hat{\sigma}_\vartheta{}^2 + \hat{\sigma}_\varepsilon{}^2}$.

Step 5: We use OLS to estimate regression (5),

$$\mathrm{Y_{ict}} = \alpha + \beta_1 \mathrm{T_c} + \mathrm{X_{ict}}\beta_2 + \mathrm{Z_{c0}}\beta_3 + \mu_t + \mathrm{u_{ict}},$$

using the simulated dependent variable calculated in step 4. We use three different methods for inference (cluster-correlated Huber-White standard errors, wild cluster bootstrap-t, randomization inference) to obtain three different P-values for the null hypothesis that $\beta_1$ is zero. Under each method, we reject the null hypothesis at 5% significance if its respective p-value is less than 0.05.

Step 7: Repeat steps 2-5 1000 times, keeping $T_c, X_{ict}, Z_{0c}$ and the parameters from step 1 $[\hat{\alpha}_0, \hat{\beta}_2, \hat{\beta}_3, \widehat{\mu_t}, \hat{\rho}_u, \hat{\sigma}_u^2]$ fixed. Hence, the only differences across repetitions are the random draws from steps 2 and 3, and hence the simulated values of the dependent variable, which are used in step 5.

For each method (cluster-correlated Huber-White standard errors, wild cluster bootstrap-t, randomization inference), the estimated test size, $\pi$, (reported in Table 9) is the number of repetitions where the null hypothesis is rejected over 1000, the number of simulations. A 95% confidence interval for the estimated test size can be computed using the formula $\pi \pm 1.96\sqrt{0.05\times0.95/100}$, where 1.96 is the 97.5% standard normal critical value. In Table 9, we report whether the estimated test size is significantly different from the nominal one (0.05).

# Appendix C:
# Outcome measures

## Appendix C

In this appendix, we detail the measures for each of our outcomes of interest.

### 1 Child Consumption

We collected information on child-specific intake of liquids and solid foods, focusing on diet variety. These are reported by the main respondent, who is the mother in the majority (92%) of cases. For children under the age of 2, there are three measures of liquid intake - whether or not (s)he had maternal milk, other milk, or water in the 3 days prior to the survey. In the second follow-up survey, there are also data on whether or not certain foods were consumed in the 3 days prior to the survey by all children aged less than 6 years. We use whether the children had any porridge, nsima[1], meat, fish, eggs or beans, and fruit or vegetables.

### 2 Household Consumption

We collected information at the household level on the quantities consumed and purchased of over 25 different food items in the week preceding the survey, and the amounts spent on them. Data were also collected on expenditures on items such as fuel and transport (over the past month), and clothing, health and education (all over the past year).[2] In 2009-10,

[1] Nsima is a thick paste made from maize flour and is a staple food in Malawi. Apart from being difficult to digest for infants, nsima does not contain all of the nutrients required by infants. MaiMwana recommends giving porridge to infants, ideally mixed with vegetables or protein, rather than nsima.

[2] The recall period for these items in the 2009-10 survey was modified to only record expenditures since the 2008-09 survey. This was done so as to avoid double-counting of purchases, since the gap between the two surveys was less than a year (between 9 and 11 months).

information was also collected on conversion factors from the most-frequented markets and trading centres, which are used to convert non-standard measurement units (such as a heap of tomatoes) into standard measurement units (such as kilograms).

Food consumption aggregates are computed by summing up food expenditures and adding on the values of non-purchased food. To impute the latter, we first use conversion factors to convert quantities measured in non-standard units to standard units, and then use median unit values to impute their value.[3] Total household monthly non-durable consumption is then computed as the sum of food consumption and the non-food expenditures outlined above (all converted to monthly terms). Finally, we obtain per-capita consumption values by dividing the relevant value by household size.

## 3 Adult Labor Supply

Labor supply is measured in three ways: whether or not an individual is engaged in an income-generating activity; whether or not an individual has a secondary income-generating activity; and the total number of hours worked in the week preceding the survey (number of days worked in the week preceding the survey multiplied by the number of hours worked per day; set to zero for those not working).

[3] These conversion factors from the second follow-up were applied to data from both waves. Median unit values are computed by dividing expenditure on a certain good by the quantity purchased, and taking the median at the cluster level. In the small number of cases where there were insufficient observations within a cluster to reliably compute the median, it was taken at the district level instead. This method of imputation is similar to that used by Attanasio *et al.* (forthcoming). As a robustness check, we also valued consumption using the market prices rather than the median unit values. This is not our preferred method, since most households rarely purchase the foods they commonly consume from the markets. Reassuringly, though, both methods yield a food consumption share of total non-durable consumption of 0.86.

## 4 Child Health

Both physical growth and morbidity are used as indicators of child health. Physical growth is measured by height and weight. For height, we use the standardized height-for-age z-score. Unlike height, weight is non-monotonic because both having too high a weight and too low a weight is unhealthy and hence undesirable. Hence, we use whether the child has a healthy weight for his/her age, and whether he/she has a healthy weight for his/her height. Healthy weight for his/her age occurs when the weight-for-age z-score is within -2 standard deviations +2 standard deviations from the WHO norm. Healthy weight-for-height is defined in an analogous way. Child morbidity is maternal-reported and includes the prevalence of diarrhea, fast breathing, fever, chills, and vomiting in the 15 days prior to the survey.

# Appendix D:
# Knowledge Questions

## Appendix D: Questions on Nutrition Knowledge

**If an infant is being breastfed and suffers from diarrhoea, should the breastfeeding :**

1 Continue as usual

2 Increase

3 Decrease

4 Stop and replace with another type of milk or liquid

5 Don't Know

**Which of the following is most nutritious for infants between 6 months and 3 year ?**

1 Biscuits

2 Groundnuts or soya

3 They both have the same nutritional value

4 Don't Know

**When should you start to give some solid foods to the baby?**

1 From birth

2 After 1 month old

3 After 3 months old

4 After 6 months old

5 Don't Know

**If a woman is HIV positive, how should she feed her baby?**

1 Exclusive breast feeding for 6 months, followed by early cessation

2 Exclusive breast feeding for 6 months, followed by complementary feeding

3 Complementary feeding from birth

4 Don't know

**What is more nutritious for a child older than 6 months:**

1 Nsima

2 Phala (porridge)

3 Both are the same

**Can you explain to me how best to cook fish with phala for a child older than 6 months (tick all those mentioned).**

1 Pound the fish

2 Sieve the powder

3 Add powder to flower/phala

4 Use powder + flour to prepare phala

5 None of the above

6 Don't Know

**Should eggs be given to an infant aged 9 months and above?**

1 Yes

2 No

3 Don't know

# Appendix E:
# Additional Tables

# APPENDIX E

**Table E1: Outcome Measures for Each Domain**

| Domain | Outcome Measures Constituting Index |
|---|---|
| Nutrition knowledge | See exact questions in Appendix 3 |
| Child Liquid Intake | Water intake in 3 days preceding survey; Intake of milk other than maternal in 3 days preceding survey |
| Child solid intake | Intake of any proteins in 3 days preceding survey; intake of any staples (nsima or porridge) in 3 days preceding survey; intake of any fruit and vegetables in 3 days preceding survey |
| Household Food Consumption | Amounts (in kwacha) of cereals, proteins, fruit and vegetables and other foods |
| Adult Labor Supply | Whether or not the individual works; whether or not the individual has 2 jobs; hours worked |
| Child Physical Growth | Height for age z-score; whether the child has a healthy weight for age z-score; whether the child has a healthy weight for height z-score |
| Child Morbidity | Whether or not the child did not suffer from diarrhoea; vomiting; fast breathing; fever; and chills in the 15 days preceding the survey |
| Adult Health | whether or not the adult can walk 5 kms easily; whether or not the individual can carry a 20 kg load easily; ability to carry out daily activities; whether or not the individual suffered from diarrhoea; fever; cough; chills; and vomiting in 30 days preceding survey |

**Table E2: Index Components for Adult Female Labor Supply**

| | [1] | [2] | [3] | [4] |
|---|---|---|---|---|
| | **Summary Index** | **Works** | **Has at least 2 jobs** | **Weekly Hours Worked** |
| | | **Adult Females** | | |
| $T_z$ | 0.018 | -0.035 | 0.030 | -1.740 |
| Standard Error | [0.165] | [0.101] | [0.025] | [3.308] |
| Wild Cluster Bootstrap p-value | {0.915} | {0.795} | {0.318} | {0.657} |
| Randomization Inference p-value | {0.903} | {0.700} | {0.273} | {0.585} |
| | | | | |
| Observations | 4138 | 4449 | 4447 | 4138 |
| R-squared | 0.136 | 0.132 | 0.044 | 0.149 |
| IntraCluster Correlation | 0.14 | 0.214 | 0.0249 | 0.144 |
| Mean, Control | -0.05 | 0.861 | 0.108 | 24.54 |

Notes to Table: All regressions include controls for age, age-squared, cluster-level education and Chewa ethnicity in 2004 and dummies for the month of interview. Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the the cluster (at which treatment was assigned; wild cluster bootstrap-t and randomisation inference p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. Sample includes all females aged 15-65 years. "Summary Index" contains the variables in columns 2-4 and is computed using the method described in section 4.4. "Works" in an indicator of whether individual had an income-generating activity at the time of the survey, "Has at least 2 jobs" is an indicator for whether individual has 2 income generating activities, "Weekly Hours worked" give the total hours worked in the week prior to the survey on both income generating activities.

**Table E3: Anthropometrics for children aged < 6 months**

| | Age < 6 months | | | |
|---|---|---|---|---|
| | **Summary Index** | **Height for Age** | **Healthy weight for age** | **Healthy weight for height** |
| $T_z$ | 0.073 | 0.226 | 0.041 | 0.023 |
| Standard Error | [0.051] | [0.261] | [0.045] | [0.064] |
| Wild Cluster Bootstrap p-value | {0.293} | {0.548} | {0.675} | {0.801} |
| Randomization Inference p-value | {0.366} | {0.398} | {0.727} | {0.763} |
| | | | | |
| Observations | 312 | 324 | 339 | 319 |
| R-squared | 0.061 | 0.072 | 0.051 | 0.047 |
| IntraCluster Correlation | 0.030 | 0.048 | 0.034 | 0.037 |
| Average, Control | 0.294 | -0.593 | 0.833 | 0.732 |

Notes to Table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the the cluster (at which treatment was assigned); wild cluster bootstrap-t p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. All regressions include controls for age, age-squared, gender, dummies for the month of interview and cluster-level education and Chewa ethnicity in 2004. Sample includes children born after July 2005 and who were aged between 6 and 53 months at time of measurement. "Height-for-Age"is a standardised z-score relative to the WHO reference population, "Not underweight" is a dummy variable =1 if child's weight-for-age z-score is not more than 2 std deviations below the WHO reference population and "Healthy weight for height" is a dummy variable =1 if child's weight-for-height z-score is within 2 std deviations of the WHO reference population.

**Table E4: Intervention Effects on Child Morbidity**

| | [1] | [2] | [3] | [4] | [5] |
|---|---|---|---|---|---|
| | **Summary Index** | **Suffered Diarrhoea** | **Suffered from Vomiting** | **Suffered from Fast Breathing** | **Suffered Fever** |
| | | | **< 6 months** | | |
| $T_z$ | 0.058 | -0.067* | -0.049 | 0.044 | 0.018 |
| Standard Error | [0.070] | [0.028] | [0.042] | [0.050] | [0.060] |
| Wild Cluster Bootstrap p-value | {0.438} | {0.042} | {0.284} | {0.420} | {0.763} |
| Randomisation inference p-value | {0.509} | {0.073} | {0.328} | {0.468} | {0.819} |
| Observations | 376 | 376 | 376 | 376 | 376 |
| R-squared | 0.059 | 0.069 | 0.058 | 0.076 | 0.116 |
| IntraCluster Correlation | 0.021 | 0.000 | 0.026 | 0.037 | 0.066 |
| Mean, Control | -0.034 | 0.13 | 0.164 | 0.124 | 0.418 |
| | | | **> 6 months** | | |
| $T_z$ | -0.013 | -0.007 | -0.026 | 0.028 | 0.025 |
| Standard Error | [0.102] | [0.041] | [0.047] | [0.057] | [0.062] |
| Wild Cluster Bootstrap p-value | {0.861} | {0.833} | {0.593} | {0.719} | {0.713} |
| Randomisation inference p-value | {0.920} | {0.872} | {0.697} | {0.681} | {0.757} |
| Observations | 2356 | 2362 | 2366 | 2363 | 2371 |
| R-squared | 0.053 | 0.118 | 0.018 | 0.027 | 0.015 |
| IntraCluster Correlation | 0.150 | 0.034 | 0.081 | 0.139 | 0.080 |
| Mean, Control | 0.022 | 0.252 | 0.207 | 0.101 | 0.507 |

Notes to Table: Notes to table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, witl level of the cluster (at which treatment was assigned); wild cluster bootstrap-t p-values in curly brackets. ** p<0.01, * p<0.05, + p<0. include controls for age, age-squared, gender, dummies for the month of interview and cluster-level education and Chewa ethnicity in columns 1 and 3 includes children born after June 2005 and who were < 6 months and whose mothers were potentially undergoing the interv of survey. Sample in columns 2 and 4 includes children born after July 2005 and who were aged between 6 and 53 months at time of sur represents a different dependent variable which takes value 1 if the the child has suffered the condition specified in the column headii previous to the survey as reported by the main respondent, 0 otherwise.

**Table E5: Adult Health index components**

| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] | [9] |
|---|---|---|---|---|---|---|---|---|---|
| | **Summary Index** | **Walk 5 kms Easily** | **Carry a 20 kg Load Easily** | **Unable to Carry Out Daily Activities** | **Suffered Diarrhoea** | **Suffered Fever** | **Suffered from Cough** | **Suffered from Chills** | **Suffered from Vomiting** |
| | | | | | **Males** | | | | |
| $T_z$ | -0.007 | -0.041 | 0.020 | 0.066 | 0.003 | 0.077 | 0.024 | 0.024 | 0.011 |
| Standard Error | [0.044] | [0.046] | [0.031] | [0.038] | [0.013] | [0.049] | [0.063] | [0.027] | [0.017] |
| Wild Cluster Bootstrap p-value | {0.873} | {0.438} | {0.561} | {0.132} | {0.803} | {0.236} | {0.713} | {0.432} | {0.551} |
| Randomisation Inference p-value | {0.899} | {0.465} | {0.557} | {0.167} | {0.848} | {0.171} | {0.724} | {0.530} | {0.614} |
| | | | | | | | | | |
| Observations | 3726 | 3809 | 3809 | 3815 | 3751 | 3752 | 3758 | 3748 | 3760 |
| R-squared | 0.022 | 0.123 | 0.106 | 0.021 | 0.008 | 0.014 | 0.007 | 0.007 | 0.010 |
| IntraCluster Correlation | 0.073 | 0.109 | 0.0516 | 0.039 | 0.008 | 0.059 | 0.077 | 0.053 | 0.016 |
| Mean, Control | 0.004 | 0.889 | 0.911 | 0.284 | 0.054 | 0.235 | 0.269 | 0.085 | 0.097 |
| | | | | | **Females** | | | | |
| $T_z$ | -0.020 | -0.049 | 0.025 | 0.049 | -0.004 | 0.096+ | 0.027 | 0.019 | 0.012 |
| Standard Error | [0.038] | [0.046] | [0.031] | [0.043] | [0.014] | [0.044] | [0.060] | [0.036] | [0.030] |
| Wild Cluster Bootstrap p-value | {0.693} | {0.332} | {0.502} | {0.300} | {0.819} | {0.128} | {0.685} | {0.617} | {0.719} |
| Randomisation Inference p-value | {0.685} | {0.360} | {0.540} | {0.345} | {0.841} | {0.082} | {0.694} | {0.712} | {0.791} |
| | | | | | | | | | |
| Observations | 4226 | 4295 | 4294 | 4294 | 4251 | 4251 | 4255 | 4245 | 4240 |
| R-squared | 0.040 | 0.165 | 0.172 | 0.027 | 0.011 | 0.021 | 0.016 | 0.013 | 0.011 |
| IntraCluster Correlation | 0.063 | 0.102 | 0.058 | 0.041 | 0.010 | 0.048 | 0.080 | 0.076 | 0.047 |
| Mean, Control | 0.012 | 0.852 | 0.877 | 0.411 | 0.075 | 0.330 | 0.280 | 0.118 | 0.144 |

Notes to Table: All regressions include controls for age, age-squared, gender, dummies for the month of interview and cluster-level education and Chewa ethnicity in 2004.. Standard errors computed using the cluster-correlated Huber-White estimator are reported in brackets, with clustering at the level of the cluster (at which treatment was assigned); wild cluster bootstrap-t p-values in curly brackets. ** p<0.01, * p<0.05, + p<0.1. Each column represents a different dependent variable which takes value 1 if the column heading is correct according to the main respondent and 0 otherwise. In Columns 1 and 2, the dependent variable takes value 1 if the adult member can do what is specified in the column heading, 0 otherwise. In columns 3-9, the dependent variable takes value 1 if the the adult member has suffered the condition specified in the column heading in the 15 days previous to the survey as reported by the main respondent, 0 otherwise.

**Table E6. Differences in characterisitcs between those that attrited and those who did not**

| | Non-attrited | Difference Attrited - Not Attrited | p-value |
|---|---|---|---|
| **Woman's Characteristics in 2004** | | | |
| Married (dv = 1) | 0.646 | -0.112 | 0.004** |
| Some Primary Schooling or Higher | 0.704 | 0.053 | 0.068+ |
| Some Secondary Schooling or Higher | 0.055 | 0.042 | 0.001** |
| Age (years) | 25.169 | -1.904 | 0.002** |
| Chewa | 0.934 | -0.021 | 0.118 |
| Christian | 0.982 | -0.008 | 0.184 |
| Farmer | 0.661 | -0.104 | 0.002** |
| Student | 0.213 | 0.087 | 0.002** |
| Small Business/Rural Artisan | 0.050 | 0.005 | 0.555 |
| Age less than 16 in 2004 | 0.142 | 0.068 | 0.000** |
| | | | |
| **Household Characteristics in 2004** | | | |
| Agricultural household | 0.996 | -0.010 | 0.088+ |
| Main Flooring Material: Dirt, sand or dung | 0.910 | -0.046 | 0.001** |
| Main roofing Material: Natural Material | 0.859 | -0.044 | 0.062+ |
| HH Members Work on Own Agricultural Land | 0.925 | -0.032 | 0.048+ |
| Piped water | 0.026 | 0.014 | 0.106 |
| Traditional pit toilet (dv = 1) | 0.818 | -0.053 | 0.046* |
| # of hh members | 5.837 | -0.090 | 0.468 |
| # of sleeping rooms | 2.215 | 0.002 | 0.943 |
| HH has electricity | 0.004 | 0.002 | 0.651 |
| HH has radio | 0.646 | -0.003 | 0.833 |
| HH has bicycle | 0.511 | 0.014 | 0.583 |
| HH has motorcycle | 0.006 | 0.006 | 0.210 |
| HH has car | 0.006 | -0.002 | 0.330 |
| HH has paraffin lamp | 0.947 | -0.016 | 0.044** |
| HH has oxcart | 0.048 | 0.007 | 0.472 |
| N | 1594 | 902 | |

Notes to Table: + indicates significant at the 10% level, * indicates significant at the 5% level. p-values reported here are computed using the wild cluster bootstrap-t procedure as in Cameron *et al.* 2008, explained in section 4.1. Non-attrited refers to women (and their households) actually interviewed in 2008-09 (and used in the analysis). Attrited refers to women (and their households) drawn to be part of the sample in 2008-09, but who were not interviewed.