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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 the intervention improved child nutrition, household food consumption and consequently health. We find evidence that labor supply increased, which might have contributed to partially fund the increase in food consumption. 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 contribution, 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 assess whether non-health choices, particularly parental labor supply, might be affected by parents' knowledge of the child health production function.

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 gains in knowledge, we find evidence of improvements in infants' diets and household food consumption, particularly an increase of protein-rich foods and of fruit and vegetables. We also find that household food consumption increases, and there is suggestive evidence that it might have been partially financed through increased labor supply. 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 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 infancy not only decreases welfare, but is also linked to poor cognitive and educational performance and low productivity later on in life.⁵

The paper deals carefully with the increasingly 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, Wooldridge 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-cluster bootstrap-t (Cameron *et al.* 2008). Furthermore, we assess their performance in our data using Monte Carlo experiments, and find that both methods perform relatively well. Presenting the performance of these two methods side-by-side is of

⁵ For long-term consequences of poor health or nutritional status in infancy 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.

interest for many empirical applications, given the increasing trend in randomized trials with a small number of clusters.

Lewycka *et al.* (2013) studies the effect of this intervention on exclusive breastfeeding and infant mortality. Our paper addresses a different question, whether improving knowledge of the health production function affected consumption, labor supply, nutritional practices and child nutrition to the age of around 5 years. We also use a different dataset; they interview mothers until their child is six month old, while we rely on a representative sample of women of reproductive age, and their households. More details about the design of the intervention can be found in Lewycka *et al.* (2010).

Our work fits into at least three strands of the literature. The first is the growing literature on the effects of providing health information on behavior (Dupas, 2011a).⁶ The evidence 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, respectively, 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 - including labor supply - than those directly targeted by the intervention. In doing

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

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 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) 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). Our 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 birth weight 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, and 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.* 2000, 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 (Bezner-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% consuming 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

⁷MaiMwana 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>

of just over 60% (64%), piped water access for 10% (20%) of households, and electricity access for just 2% (7%) of households.⁸

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. Our data show that women who were visited by the peer counselor tend to be poorer: in

⁸ Source: Malawi Population and Housing Census, 2008.

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.

particular, they were 4.8 percentage points (7.5 percentage points) less likely to have a floor (roof) built with good materials.¹¹

Regarding the content of the visits, exclusive breastfeeding is strongly encouraged in all visits starting from the 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 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.

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.¹² This was done in a systematic way, based on the contiguity of enumeration areas and respecting boundaries of Village Development Committees (VDCs)¹³, 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 This analysis is available on request.

¹² The District Administrative Centre was excluded because it is relatively more urbanized and less comparable to the rest of the District.

¹³ 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.¹⁴ 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.¹⁵

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 (see Figure 1).¹⁶ 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.¹⁷ Specifically,

¹⁴ 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.

¹⁵ 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.

¹⁶ 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).

¹⁷ 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 status¹⁸, 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 the left hand panel of 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.¹⁹

[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

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/\(study 6996\)](http://www.esds.ac.uk/(study 6996)).

¹⁸This 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.

¹⁹Other 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 middle 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 Appendix A, 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 of these women one year later, in 2009-10, successfully interviewing around 92% of the women interviewed at first follow-up: 92.5% and 90% in intervention and control areas respectively. The baseline balance for this sample, displayed in the right hand panel of Table 1, is very similar to that for the first wave.

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 of a combination of nutrition inputs. For simplicity we assume that this is a bundle of two inputs, C_1 and C_2 . We also assume that households have 1 adult and 1 child. The adult chooses simultaneously the amounts to spend on each child consumption inputs, C_1 and C_2 , 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:

$$\max_{\{C_1, C_2, A, L\}} U(A, L, H) \quad (1)$$

$$st: \quad A + p_1 C_1 + p_2 C_2 \leq w(T - L) \quad (2)$$

$$H = F(C_1, C_2) \quad (3)$$

where $U(.,.,.)$ captures the utility from adult consumption, leisure, and child health, p_1 and p_2 are the prices of child nutrition inputs relative to adult consumption, and w is the wage per unit of time.²⁰ The function $F(.,.)$ represents the health production function, which is

²⁰We 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.

increasing in both C_1 and C_2 , and concave. Following Cunha, Elo, and Culhane (2013) and Del Boca, Flinn and Wiswall (2014), we assume that both the utility function and the production function are Cobb-Douglas, that is, $U(A, L, H) = A^\alpha L^\beta H^\gamma$ and $H = C_1^\delta C_2^\theta$, with $\alpha, \beta, \gamma, \delta, \theta > 0$, and $\delta + \theta < 1$. We can therefore rewrite the optimization problem as:

$$\max_{\{C_1, C_2, A, L\}} A^\alpha L^\beta C_1^{\gamma_1} C_2^{\gamma_2} \quad (1)$$

$$st: \quad A + p_1 C_1 + p_2 C_2 \leq w(T - L), \quad (2)$$

where $\gamma_1 = \gamma\delta$ and $\gamma_2 = \gamma\theta$.²¹

Households make their consumption and labor decisions under their own perception of the child health production function, $C_1^\delta C_2^\theta$, which might differ from the true one (see Cunha, Elo, and Culhane, 2013). This perceived production function depends on δ and θ , two parameters that measure the household's perception of the returns to child nutrition inputs. Changes in these parameters will change γ_1 and γ_2 .

To study the effect of the intervention, we differentiate the first order conditions with respect to γ_1 (see Appendix B), and find that: $\frac{dC_1}{d\gamma_1} > 0$, but that $\frac{dC_2}{d\gamma_1} < 0$, $\frac{dA}{d\gamma_1} < 0$, and $\frac{dL}{d\gamma_1} < 0$. This allows us to establish the following proposition:

Proposition 1. *If γ_1 increases, then C_1 and total household consumption increases, but C_2 , A , and L decrease. Similarly, if γ_2 increases, then C_2 and total household consumption increases, but C_1 , A , and L decrease.*

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).

The intuition is as follows. If the perceived productivity of C_1 , γ_1 , increases, then more will be consumed of this input. Given the concavity of the utility function, this increase is better accommodated by a small decrease in all other arguments of the utility function (C_2 , A , and L) rather than a large decrease in only one of them. Note that the increase in C_1 is not fully offset by the decrease in C_2 and A , because L also decreases, which implies that labour supply increases. As there is no borrowing or savings, the increase in labour supply implies an increase in overall household consumption.²²

The intervention promotes the consumption of protein rich foods, fruits and vegetables relative to others such as staples. If C_I summarizes the goods that the intervention promotes, and C_2 summarizes the consumption of staples, then the effect of the intervention can be summarized in terms of increasing γ_1 but decreasing γ_2 . Following proposition 1, we expect an important composition effect (increase in C_I and a decrease in C_2) but the predictions on labour supply, adult and total consumption are in principle ambiguous because these will depend on whether the γ_1 or the γ_2 effect dominates. This is ultimately an empirical issue that we study below.

²² 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.

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

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

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).²³ In line with the model, the dimensions of household behavior likely to be affected include household and child consumption, labor supply, and child health²⁴; T_c 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. μ_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

²³ For binary outcomes, results using Probit models are very similar and are not reported.

²⁴ Adult consumption also may be affected but, unfortunately, no good measure of adult-specific goods is available in our data.

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 , takes the value 1 if the respondent was living in a treatment cluster at the time of the 2004 baseline census, and 0 if living in a control cluster at that time. Therefore, we identify an intention-to-treat parameter. Moreover defining T_c on the basis of baseline rather than current residence circumvents any bias that might arise from selective migration from control to treatment clusters.

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, 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).²⁵

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 ,

²⁵ 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 applications of the wild cluster bootstrap-t.

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.²⁶ 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 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 Appendix C, we perform 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). The simulations (results reported in Table C1 of Appendix C) indicate that both inference methods perform relatively well.

²⁶ 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.

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 likely to be most 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.²⁷ 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.

A more nuanced issue is how the reduction in infant mortality and improvement in child health could have affected parental labor supply, through changing the demand for childcare. It is plausible that if infant mortality declines and there are more surviving children, mothers in treated clusters may increase their time devoted to childcare, therefore working less, leading to fathers working more to compensate for this. However, as we show in section 5.1 below, the intervention does not appear to have reduced female labor supply, suggesting that

²⁷This 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.

this mechanism is not at play in our context. Another potential channel through which labor supply may change as a result of improvements in children's health is through reducing the need for fathers to be at home to help take care of children, thus facilitating an increase in their labor supply.

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 appendix A, 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. For child health and morbidity, which were the main focus of the intervention, we focus on children aged over 6 months, for whom the intervention would have completed. We pool data from the 2008-09 and 2009-10 follow-up surveys for the analysis. Details on the various measures within each domain are provided in Appendix D. 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 over 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

outcome measures within a domain into a summary index, following Anderson (2008).²⁸ 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; 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.

Descriptive statistics pertaining to the outcomes and the indices for households and individuals in the control clusters are provided in Table 2. From the Table, we see that maternal knowledge on infant nutrition is mixed: questions related to weaning and the relative nutritious value of different types of staple foods were answered correctly by most women, while those related to food preparation and to feeding the child when it or its mother were unwell were frequently incorrectly answered. The food intake information indicates

²⁸ While this helps to limit the problem of multiple inference, it does not address it fully because we still use 8 indices. Indeed, if the data on the 8 indices were independent, the Family Wise Error Rate would be at 40%. Adjusting for multiple inference within domains but not across domains is the most commonly used option (see for instance, Finkelstein *et al.*, 2012).

poor feeding practices: almost half of infants aged < 6 months were given water, while each of the protein-rich foods was consumed by fewer than half the children aged > 6 months. Low consumption of protein-rich foods is also apparent from the data on household consumption. The data on labor supply indicate similar rates of labor supply for males and females: over 80% have at least one paid job, while around 9% had an additional job, and work on average around 25 hours weekly. Finally, child health in this setting is very poor: the average child has a height-for-age z-score that is below -2 std deviations of the WHO benchmark (and thus is considered to be stunted); and the incidence of illness is relatively high, as is evident from the data on morbidity.

[TABLE 2 HERE]

5. Results

In this section, we first show the impacts on all six composite indices: pooled across waves in Table 3, and separated by wave in Table 4. The subsequent tables (Tables 5-10) 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.²⁹ Note that for ease of reading, each of Tables 5-10 reproduces, in its first column, the summary index from Table 3. 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.

²⁹ Tables E2-E4 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 3 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, and report impacts on health outcomes for the latter group only. For the former group of children, the health outcomes can be considered to be an ‘intermediary’ rather than ‘final’ outcome. 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.

[TABLE 3 HERE]

The key rationale underlying the intervention is that households are inefficient producers of child health because they do not have the correct knowledge. In other words, the child health production function that households optimize over is “distorted”. In line with this, the first column of Table 3 reports that the intervention improved mothers’ knowledge of child nutrition and health. 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 3).³⁰ The positive impacts on the latter group imply that positive

³⁰ Note child-specific consumption is measured at second follow-up only.

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, household food consumption could increase (see section 3). In line with this, column 4 of Table 3 shows that the intervention increases total household food consumption, measured using the composite index, at 5% significance. The increase in household consumption might have been partially funded by improvements in adult labor supply, particularly of males (column 5); female labor supply is unchanged by the intervention (column 6). Although our model of section 3 already indicated that labor supply could increase, other factors may also explain increased consumption, including borrowing and/or drawing down savings. Increases in labor supply could also be due to a reduction in time devoted to take care of sick children.

A key policy question is whether the observed adjustments on various margins of household behavior (increased consumption and labor supply) improved child health. Column 7 shows that these changes in behavior translate into improved child physical growth for children aged above 6 months. No significant effect is found on child morbidity.³¹ 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 *underestimate* the true effect of the intervention on child health.

³¹ We also considered the intervention impacts on child anthropometrics and morbidity for children aged < 6 months who were undergoing the intervention at the time of the survey, and for whom these would be intermediary stage data. We find a positive, but statistically insignificant effect on both outcomes. Interestingly, we find that the prevalence of diarrhea decreases for children below 6 months, consistent with the result that intake of water and non-maternal milk decreases for this group of children.

[TABLE 4 HERE]

Table 4 shows the results by follow-up survey round ('wave'), which are of interest in order to see whether the effects are sustained over time. In general, the table shows that the point estimates share the same signs across both waves, and are not significantly different from each other. Notably, the point estimates of household food consumption, male labor supply, and child physical growth all show a tendency to be larger in wave 2 than in wave 1, and they are statistically significant in wave 2 only, although they are not significantly different from the wave 1 estimates.³² The tendency for larger treatment effects on consumption and male labor supply in wave 2 may be due to some heterogeneity of treatment effect according to the time when the surveys were conducted. Wave 1 data were collected between mid November and the end of March, while wave 2 data were collected between October and the end of December. The level of the consumption and male labor supply index are the lowest in the October to mid November period, which is when the treatment effect is the highest.

While the composite indices allow us to assess the general impact of the intervention on each domain, their magnitudes cannot be interpreted, as the weighting used to build the index distorts the scale. To shed more light on the magnitude of the effects, we next report and discuss findings for individual outcomes for those composite indices for which there is a statistically significant effect of the intervention. We note that the results on the index components must be considered exploratory and interpreted carefully since the Family Wise

³² Note that there are more children aged > 6 months who would have been eligible for the intervention in wave 2 than wave 1 since the former includes children born between July 2005 and July 2009 while the latter includes children born between July 2005 and October 2008.

Error Rate is not being controlled for. In Appendix F, we report the results on individual outcomes by wave.

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 G). Columns 2-8 of Table 5 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 detect statistically significant differences.³³

[TABLE 5 HERE]

Improvements in child consumption were detected both for children below and above 6 months. For the former group, we see from Table 6 that the improvement comes from a reduction in non-maternal milk. There is also a reduction (though not statistically significant) in the consumption of water. Table 7 shows that improvements for the latter group are driven

³³ Note that the number of observations is lower than for other household level variables. This is because we combine wave 1 and wave 2 questions into a single index, to maximize its informational content, and drop households without a female main respondent aged 15 years or above. Note that the three questions in wave 1 are a subset of the seven questions asked in wave 2. We construct the index to include responses from wave 1 to the three common questions and the responses to the four questions unique to wave 2. This is because there was evidence of households having learnt or found out answers to the three questions carried over from wave 1 to wave 2.

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) are also positive, although not statistically significant, most likely due to the reduced sample size (child food intake was collected at second follow-up only). Overall, these results indicate that the intervention significantly affected the composition of child nutritional intake.

[TABLES 6 AND 7 HERE]

We saw from Table 3 that the intervention resulted in improvements in overall household food consumption. Columns 2 – 5 of Table 8 show that the improvement is due to an increase in the consumption of proteins, and of fruit and vegetables. The effects are relatively large. Focusing on proteins, which are particularly important for child growth, we decompose the effect on the extensive (i.e. moving from consuming no proteins to some proteins) and intensive margin (calculations available upon request). Around 26% of households in control clusters report consuming no protein-rich foods in the 7 days prior to interview; hence there is clear potential for improvement in the extensive margin. Indeed, the extensive margin accounts for one third of the consumption increase.³⁴ The increase in the intensive margin corresponds to 210 grams of meat/poultry extra and 640 grams beans extra per child per month. To put these quantities in perspective, a toddler will usually consume 50 grams of

³⁴ The consumption increase coming from the extensive margin is calculated under the assumption that the households in the treated clusters who are induced to consume protein-rich foods as a result of the intervention all consume proteins equivalent to the average consumed by control cluster households with non-zero protein consumption. The increase on the intensive margin – corresponding to the rest of the consumption increase – is further decomposed into food quantities (beans and meat/poultry) under the assumption that the entire amount is consumed by children aged < 12 years only (who are, in control clusters, 2.4 per household on average), and households pay prices equivalent to the average cluster-level median unit values.

beans in one portion, together with some vegetables and carbohydrates.

[TABLE 8 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 already been up and running for over 3.5 years by the time consumption was first measured); second, the intervention was intensive, involving up to 5 one-to-one home visits; third, as we have seen from the labor supply results in Table 3, there was scope for labor supply to increase, and thereby fund at least some of the increased consumption.

Table 3 also showed that the male labor supply index 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 9 reports positive effects of the intervention on all three, though only statistically significant for the probability of having at least two jobs. However, 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 the power to detect a significant effect of the intervention on the former.

[TABLE 9 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 2015). In the data that we use, only 12% of males in control clusters have a second job, most

of them in non-agricultural self-employment activities.³⁵ 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 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 labor supply responses to changes in the perceived child health production function.

Beyond the mechanism for the increase in labor supply indicated in section 3, important cultural features of Malawian society are likely to contribute to the increase in male, rather than female, labor supply. In particular, the main ethnic group in the Mchinji District - the Chewa - is a matrilineal and matrilineal group, where men usually move to their wives' villages on marriage, and wealth (predominantly land) is 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 9 and Table E2).³⁶ Finally, mothers are generally the main caregivers of children. So the finding that male labor supply increases in response to the

³⁵ 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%).

³⁶ This has been documented by others for the Malawian context including Goldberg (2015) 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).

mother receiving information on child nutrition is in line with the cultural background, where females are relatively empowered.

5.2 Child Health

Table 3 documented improvements in child physical growth for children older than 6 months. Looking at the sub-components of the physical growth index in Table 10, we see that the 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.³⁷ 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 10 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 intervention by increasing consumption and working more, which is the first such finding in this literature.

We further disaggregate the results on child physical growth by age to shed light on heterogeneity of the intervention effects by child age. Table 11 reports these results separately for children aged between 6 and 24 months, and between 25 and 53 months (the oldest a child could be at the second follow-up if he was born just after the intervention

³⁷ 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.

started). The estimated effects of the intervention are positive in both age groups, but are much stronger and only statistically significant in the 6-24 months group. The fact that the estimated effects are much weaker in the 25-53 months age group is consistent with two possible non-competing explanations: that the intervention did not work well at the beginning, and/or that the children from control clusters experienced catch-up growth at slightly older ages.^{38, 39}

[TABLE 11 HERE]

6. Alternative Explanations

We have argued, using the model of section 3, that consumption and labor supply will increase because the perceived 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; and third, information provided on issues other than child nutrition could have generated the observed improvements in child health. We discuss each in turn and provide evidence to rule them out as explanations for the observed findings.

³⁸ See Crookston et al. 2013 for recent evidence on catch-up growth at older ages.

³⁹ We have also examined the heterogeneity of the effect of the intervention on the anthropometric and morbidity indices according to whether the mother has had more than one child since the intervention started. The interaction terms were far from statistically significant (p-value of 0.45 or larger).

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 12 attests to.⁴⁰

[TABLE 12 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.⁴¹ Results are displayed in Table 13. The coefficients are small and far from

⁴⁰ The non-significant effects on the sub-components of the health indices are shown in Table E4 of Appendix E.

⁴¹ 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.

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 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 13 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 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.⁴² This is not all that surprising, since the intervention only encouraged women to get tested for HIV, and did not provide any resources

⁴² 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.

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 - 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 (Tables E3 and 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.⁴³

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 document that the intervention improved mothers' knowledge of nutrition. Using a simple theoretical model, we show that households should react to this improved knowledge by changing the composition of child food intake in favor of protein-rich foods, fruits and

⁴³ Because the intervention decreased infant mortality, an alternative explanation for our findings is that the children who survive (a) tend to have worse health and (b) parents compensate for the worse health by providing them with more resources. Based on the results of Lewycka *et al.* 2013, we estimate that the marginal surviving children would be approximately 2.3% of the intervention sample, which is too small to explain the magnitude of the treatment effects if these were to be driven entirely by these marginal children.

vegetables. The intervention could also increase household food consumption and adult labor supply, although the theoretical predictions are ultimately ambiguous. Our empirical results show that, indeed, both child's food intake and child nutritional status improved, and that ultimately both labor supply and food consumption increased.

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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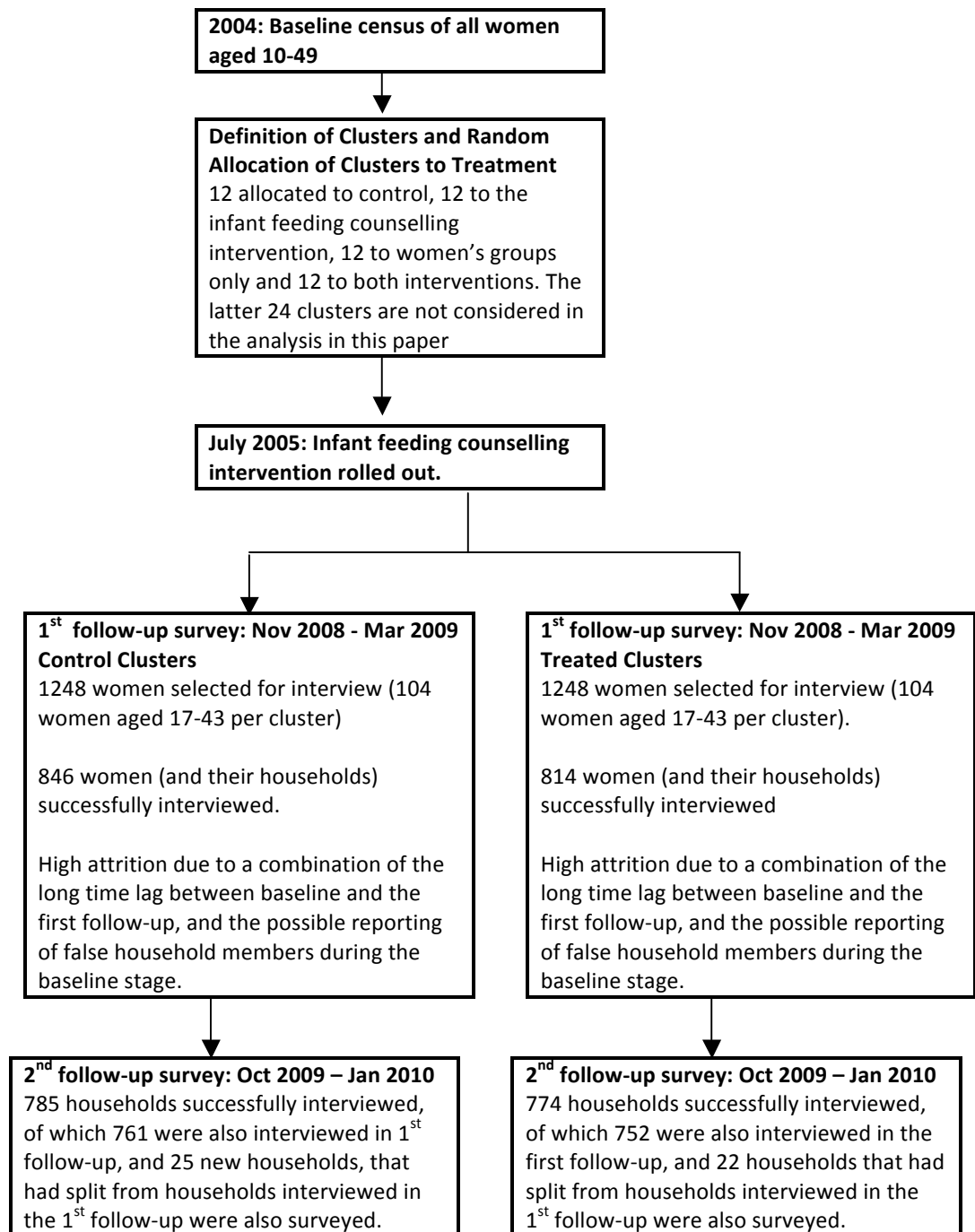


Figure 1: Flowchart

Table 1: Baseline Sample Balance

	Full Sample			Analysis Sample - Wave 1			Analysis Sample - Wave 2		
	Control Group	Difference: Treatment - Control	p-value	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	0.654	-0.024	0.340
Some Primary Schooling or Higher	0.707	0.033	0.402	0.682	0.040	0.340	0.68	0.037	0.438
Some Secondary Schooling or Higher	0.066	0.010	0.535	0.060	-0.007	0.545	0.059	-0.006	0.607
Age (years)	24.571	-0.180	0.637	25.492	-0.429	0.376	25.397	-0.217	0.621
Chewa	0.948	-0.044	0.330	0.957	-0.050	0.246	0.959	-0.054	0.268
Christian	0.977	0.006	0.476	0.979	0.008	0.336	0.981	0.005	0.454
Farmer	0.661	-0.075	0.108	0.688	-0.060	0.128	0.678	-0.055	0.220
Student	0.236	0.015	0.438	0.204	0.022	0.274	0.208	0.017	0.410
Small Business/Rural Artisan	0.036	0.030	0.129	0.037	0.024	0.220	0.039	0.025	0.264
Household Characteristics									
Agricultural household	0.995	-0.005	0.471	0.995	0.002	0.591	0.995	0.003	0.500
Main Flooring Material: Dirt, sand or dung	0.913	-0.041	0.232	0.916	-0.027	0.474	0.916	-0.028	0.422
Main roofing Material: Natural Material	0.853	-0.018	0.697	0.857	-0.004	0.891	0.86	-0.008	0.861
HH Members Work on Own Agricultural Land	0.942	-0.057	0.124	0.950	-0.056	0.120	0.95	-0.06	0.140
Piped water	0.011	0.040	0.314	0.009	0.032	0.340	0.01	0.034	0.440
Traditional pit toilet (dv = 1)	0.772	0.054	0.218	0.791	0.054	0.182	0.796	0.044	0.324
# of hh members	5.771	0.066	0.817	5.848	0.132	0.863	5.903	0.096	0.833
# of sleeping rooms	2.116	0.199	0.038*	2.152	0.166	0.128	2.174	0.155	0.136
HH has electricity	0.002	0.007	0.166	0.002	0.004	0.338	0.003	0.004	0.394
HH has radio	0.630	0.030	0.408	0.641	0.015	0.709	0.645	0.014	0.655
HH has bicycle	0.509	0.015	0.643	0.512	0.008	0.843	0.512	0.01	0.769
HH has motorcycle	0.008	0.001	0.925	0.007	0.002	0.779	0.008	0.003	0.685
HH has car	0.006	-0.002	0.612	0.007	-0.003	0.298	0.008	-0.004	0.302
HH has paraffin lamp	0.925	0.032	0.262	0.926	0.036	0.178	0.935	0.026	0.360
HH has oxcart	0.058	-0.015	0.204	0.059	-0.022	0.090+	0.06	-0.022	0.072+
N	1248	1248		846	814		785	774	

Notes to Table: P-values 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. 'Analysis Sample - Wave 1' includes women (and their households) who were interviewed in 2008-09 (wave 1), while 'Analysis Sample - Wave 2' includes women (and their households) who were interviewed in 2009-10 (wave 2). ** p<0.01, * p<0.05, + p<0.1.

Table 2: Descriptive Statistics of Outcome Variables, Control Clusters

Outcome Variable	Pooled		Wave 1		Wave 2	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Nutrition Knowledge (correct answer=1)						
Knowledge Index	-0.040	0.434	n/a	n/a	n/a	n/a
Breastfeeding when infant has diarrhoea	0.216	0.412	0.216	0.412	n/a	n/a
Biscuits or groundnuts/soya more nutritious for kids aged 6-36 months?	0.938	0.242	0.938	0.242	n/a	n/a
Age when solid foods should be given	0.880	0.325	0.880	0.325	n/a	n/a
Feeding baby when woman is HIV positive	0.394	0.489	n/a	n/a	0.394	0.489
Is nsima or porridge more nutritious for infant aged > 6 months	0.858	0.349	n/a	n/a	0.858	0.349
Best way of cooking fish with porridge	0.140	0.348	n/a	n/a	0.140	0.348
Should eggs be given to an infant aged > 9 months?	0.718	0.450	n/a	n/a	0.718	0.450
Child Food Intake, < 6 months						
Index	0.010	0.824	n/a	n/a	0.010	0.824
Water	0.474	0.503	n/a	n/a	0.474	0.503
Non-maternal milk	0.103	0.305	n/a	n/a	0.103	0.305
Child Food Intake, > 6 months						
Index	-0.001	0.489	n/a	n/a	-0.001	0.489
Any beans	0.256	0.437	n/a	n/a	0.256	0.437
Any meat	0.289	0.453	n/a	n/a	0.289	0.453
Any fish	0.461	0.499	n/a	n/a	0.461	0.499
Any eggs	0.160	0.367	n/a	n/a	0.160	0.367
Any vegetables	0.958	0.200	n/a	n/a	0.958	0.200
Any fruit	0.699	0.459	n/a	n/a	0.699	0.459
Any nsima	0.929	0.257	n/a	n/a	0.929	0.257
Any porridge	0.799	0.401	n/a	n/a	0.799	0.401
Household Consumption						
Food Index	-0.098	0.654	-0.076	0.664	-0.132	0.670
Per capita cereal consumption (MK)	605.911	379.674	731.243	403.121	471.466	299.458
Per capita fruit and vegetable consumption (MK)	679.831	585.218	572.906	537.757	794.530	612.081
Per capita protein-rich food consumption (MK)	349.086	483.191	370.902	525.027	325.684	432.968
Per capita other foods consumption (MK)	149.492	495.483	164.119	225.059	133.801	156.341
Male Labor Supply						
Index	-0.065	0.723	-0.085	0.721	-0.044	0.727
Works (yes=1)	0.818	0.386	0.825	0.380	0.812	0.391
Works in two jobs (yes=1)	0.094	0.292	0.096	0.294	0.092	0.289
Hours worked	25.728	20.341	24.550	17.978	26.858	22.327
Female Labor Supply						
Index	-0.051	0.719	-0.067	0.729	-0.032	0.712
Works (yes=1)	0.846	0.361	0.827	0.378	0.866	0.341
Works in two jobs (yes=1)	0.086	0.280	0.098	0.297	0.074	0.261
Hours worked	24.449	17.409	23.692	16.895	25.213	17.889
Child Anthropometrics, > 6 months						
Index	0.287	0.525	0.254	0.522	0.311	0.528
Height for age z-score	-2.326	1.499	-2.339	1.500	-2.315	1.499
Healthy height for weight (yes=1)	0.852	0.355	0.859	0.348	0.847	0.360
Healthy weight (yes=1)	0.829	0.377	0.785	0.411	0.863	0.344
Child Morbidity, > 6 months						
Index (reversed)	0.000	0.591	0.001	0.594	-0.001	0.577
Suffered diarrhoea (yes=1)	0.253	0.435	0.354	0.479	0.164	0.370
Suffered from vomiting (yes=1)	0.207	0.405	0.237	0.426	0.181	0.385
Suffered from fast breathing (yes=1)	0.100	0.301	0.112	0.315	0.090	0.287
Suffered fever (yes=1)	0.507	0.500	0.551	0.498	0.469	0.499
Suffered from chills (yes=1)	0.146	0.353	0.155	0.363	0.138	0.345

Notes to Table: The table includes data on control clusters only. Sample for knowledge index includes households present in both waves of the survey, with a female main respondent aged 15 years or more; Sample of children aged > 6 months includes those born after July 2005 (when the intervention began), and who would have been aged at most around 53 months at wave 2; Sample for Household Consumption includes all households; Sample for male (female) labor supply includes males (females) aged 15-65. Child food consumption data collected in wave 2 only. Knowledge index constructed from wave 1 responses to 3 questions, and wave 2 responses to 4 questions asked in this wave only.

Table 3: Effects on summary indices

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	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
T _z	0.169+	0.250*	0.143+	0.218*	0.262+	0.018	0.102*	-0.013
Standard Error	[0.086]	[0.098]	[0.074]	[0.082]	[0.131]	[0.165]	[0.036]	[0.102]
Wild Cluster Bootstrap p-value	{0.058}	{0.016}	{0.076}	{0.018}	{0.086}	{0.955}	{0.022}	{0.861}
Randomization Inference p-value	{0.065}	{0.028}	{0.099}	{0.037}	{0.062}	{0.903}	{0.035}	{0.920}
Observations	1512	151	1280	3200	3642	4138	2175	2356
R-squared	0.107	0.214	0.099	0.063	0.183	0.136	0.026	0.053
IntraCluster Correlation	0.169	0.041	0.085	0.087	0.146	0.140	0.021	0.150
Mean Control Areas	-0.040	-0.109	-0.054	-0.099	-0.135	-0.050	0.266	0.022

Notes to Table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in square 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. All regressions include controls for cluster-level average education and Chewa ethnicity, both measured in 2004, and dummies for month of interview. All regressions other than in column 4 include 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 4.3. Higher values of the index in columns 9 and 10 indicate lower morbidity. The component variables for each index are outlined in Table E1 in the appendix. Sample of children includes all those born after the intervention began in July 2005, and were therefore aged 0-53 months at time of interview. Specific samples are as follows. Column 1: all households present in waves 1 and 2 with a female main respondent aged 15 years or more; column 2: all children at wave 2 aged <6 months (some components of food consumption for this group not measured at wave 1); column 3: all children at wave 2 aged 6-53 months (food consumption for this group not measured at wave 1); column 4: all households at waves 1 or 2; columns 5 (6): all adult males (females) aged 15-65 years at waves 1 or 2; columns 7, 8: all children at wave 1 or wave 2 aged 6-53 months. Note small discrepancies in samples between columns 8 and 10 due to missing values of outcome indicators. ** p<0.01, * p<0.05, + p<0.1.

Table 4: Effects on summary indices by wave

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
<i>Top Panel: Wave 1 Results</i>								
	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	Females	> 6 months	> 6 months
T _z	0.195			0.156	0.183	-0.016	0.093	0.027
Standard Error	[0.136]			[0.113]	[0.135]	[0.163]	[0.045]	[0.103]
Wild Cluster Bootstrap p-value	{0.228}			{0.212}	{0.216}	{0.985}	{0.108}	{0.769}
Randomization Inference p-value	{0.143}			{0.206}	{0.244}	{0.920}	{0.107}	{0.853}
Observations	1512			1644	1790	2080	932	1061
R-squared	0.079			0.069	0.177	0.157	0.032	0.040
IntraCluster Correlation	0.156			0.141	0.140	0.183	0.026	0.175
Mean Control Areas	-0.054			-0.075	-0.119	-0.033	0.286	0.001
<i>Bottom Panel: Wave 2 Results</i>								
	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	Females	> 6 months	> 6 months
T _z	0.152	0.250*	0.143+	0.305**	0.323*	0.050	0.112*	-0.051
Standard Error	[0.119]	[0.098]	[0.074]	[0.092]	[0.148]	[0.193]	[0.040]	[0.124]
Wild Cluster Bootstrap p-value	{0.273}	{0.016}	{0.076}	{0.002}	{0.036}	{0.877}	{0.022}	{0.743}
Randomization Inference p-value	{0.248}	{0.028}	{0.099}	{0.014}	{0.036}	{0.768}	{0.032}	{0.746}
Observations	1512	151	1280	1556	1852	2058	1243	1295
R-squared	0.043	0.214	0.10	0.050	0.184	0.125	0.028	0.043
IntraCluster Correlation	0.190	0.041	0.085	0.085	0.192	0.150	0.017	0.197
Mean Control Areas	-0.035	-0.109	-0.0541	-0.132	-0.148	-0.073	0.238	0.045

Notes to Table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in square 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. All regressions include controls for cluster-level average education and Chewa ethnicity, both measured in 2004, and dummies for month of interview. All regressions other than in column 4 include controls for age and age-squared. Those in Cols 5 and 6 also control for education. 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 column 8 indicates lower morbidity. The component variables for each index are outlined in Table E1 in the appendix. Sample of children includes all those born after the intervention began in July 2005, and were therefore aged 0-53 months at time of interview. Specific samples are as follows. Column 1, both panels: all households present in both waves 1 and 2 with a female main respondent aged 15 years or more; column 2 bottom panel: all children at wave 2 aged <6 months; column 3, bottom panel: all children at wave 2 aged 6-53 months (food consumption for this group not measured at wave 1); column 4, top (bottom) panel: all households at wave 1 (2); column 5, top (bottom) panel: all adult males aged 15-65 years at wave 1 (2); column 6, top (bottom) panel: all adult females aged 15-65 years at wave 1 (2) columns 7, 8: top (bottom) panel: all children at wave 1 (2) aged 6-44 months (6-53 months). Note small discrepancies in samples between columns 7 and 8 due to missing values of outcome indicators. Knowledge index in wave 1 constructed with 3 questions asked in wave 1: and that in wave 2 with 4 questions asked in wave 2 only. ** p<0.01. * p<0.05. + p<0.1.

Table 5: Effects on components of the knowledge index

	Summary Index	Breastfeedin g when infant has diarrhoea	Are biscuits or groundnuts/soy a 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, average cluster-level education and Chewa ethnicity, both measured in 2004, and dummies for the month of interview. Standard errors computed using the cluster-correlated Huber-White estimator are reported in square 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. Sample includes all households with a female main respondent, at wave 2. "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. ** p<0.01, * p<0.05, + p<0.1.

Table 6: Effects on intake of liquids by children < 6 months.

	[1]	[2]	[3]
	Summary Index	Water	Milk other than maternal
T _z	0.250*	-0.107	-0.082*
Standard Error	[0.098]	[0.069]	[0.034]
Wild Cluster Bootstrap p-value	{0.016}	{0.122}	{0.012}
Randomization Inference p-value	{0.028}	{0.212}	{0.115}
Observations	151	151	151
R-squared	0.214	0.362	0.087
IntraCluster Correlation	0.0405	0.000	0.060
Mean, Control	-0.109	0.474	0.101

Notes to Table: All regressions include controls for age, age-squared, gender, average cluster-level education and Chewa ethnicity, both measured in 2004, and dummies for the month of interview. Standard errors computed using the cluster-correlated Huber-White estimator are reported in square 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. Sample includes children at wave 2 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. ** p<0.01, * p<0.05, + p<0.1.

Table 7: Effects on child food consumption (6-53 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**	0.089	0.006	0.025	-0.010	-0.009	0.025	0.096
Standard Error	[0.074]	[0.056]	[0.095]	[0.099]	[0.052]	[0.020]	[0.058]	[0.015]	[0.064]
Wild Cluster Bootstrap p-value	{0.076}	{0.002}	{0.474}	{0.925}	{0.655}	{0.723}	{0.941}	{0.144}	{0.208}
Randomization Inference p-value	{0.099}	{0.007}	{0.289}	{0.954}	{0.632}	{0.634}	{0.895}	{0.140}	{0.251}
Observations	1280	1280	1280	1280	1280	1280	1280	1280	1280
R-squared	0.099	0.067	0.021	0.012	0.010	0.142	0.153	0.144	0.035
IntraCluster Correlation	0.085	0.116	0.084	0.112	0.048	0.018	0.093	0.000	0.136
Mean, Control	-0.054	0.258	0.290	0.462	0.163	0.959	0.699	0.929	0.800

Notes to Table: All regressions include controls for age, age-squared, gender, average cluster-level Chewa ethnicity and education, both measured in 2004, and dummies for the month of interview. Standard errors computed using the cluster-correlated Huber-White estimator are reported in square 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. Sample contains all children at wave 2 aged 6-53 months (data on child solid intake collected at wave 2 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. ** p<0.01, * p<0.05, + p<0.1.

Table 8: Effects on household food 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*	-9.768	129.15+	269.987*	60.701
Standard Error	[0.082]	[52.432]	[54.802]	[108.591]	[33.552]
Wild Cluster Bootstrap p-value	{0.018}	{0.863}	{0.066}	{0.044}	{0.126}
Randomization Inference p-value	{0.030}	{0.865}	{0.025}	{0.033}	{0.069}
Observations	3200	3200	3200	3200	3200
R-squared	0.063	0.117	0.02	0.195	0.025
IntraCluster Correlation	0.087	0.074	0.042	0.173	0.053
Mean Control Areas	-0.10	605.80	349.10	679.80	149.50

Notes to Table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in square 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. Sample includes all households at waves 1 or 2. All regressions include controls for age, age-squared, average cluster-level education and Chewa ethnicity, both measured 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. ** p<0.01, * p<0.05, + p<0.1.

Table 9: Effects on labor supply

	Males			
	[1]	[2]	[3]	[4]
	Summary Index	Works	Has at least 2 jobs	Weekly Hours Worked
T_z	0.262+	0.106	0.080**	4.310
Standard Error	[0.131]	[0.080]	[0.025]	[2.918]
Wild Cluster Bootstrap p-value	{0.074}	{0.272}	{0.010}	{0.240}
Randomization Inference p-value	{0.062}	{0.220}	{0.011}	{0.202}
Observations	3642	3642	3642	3642
R-squared	0.183	0.18	0.06	0.16
IntraCluster Correlation	0.146	0.213	0.033	0.100
Mean, Control	-0.135	0.819	0.094	25.740

Notes to Table: All regressions include controls for age, age-squared, average cluster-level education and Chewa ethnicity, both measured in 2004, and dummies for the month of interview. Standard errors computed using the cluster-correlated Huber-White estimator are reported in square 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. Sample includes all males aged 15-65 years at waves 1 or 2. "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. ** p<0.01, * p<0.05, + p<0.1.

Table 10: Effects on physical growth, children aged 6-53 months

	[1]	[2]	[3]	[4]
	Summary Index	Height for Age	Healthy weight for age	Healthy weight for height
T _z	0.102*	0.274*	0.028	0.042+
Standard Error	[0.036]	[0.100]	[0.017]	[0.024]
Wild Cluster Bootstrap p-value	{0.022}	{0.022}	{0.120}	{0.132}
Randomization Inference p-value	{0.035}	{0.055}	{0.308}	{0.147}
Observations	2175	2175	2175	2175
R-squared	0.026	0.048	0.02	0.029
IntraCluster Correlation	0.021	0.023	0.018	0.014
Average, Control	0.266	-2.326	0.829	0.852

Notes to Table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in square brackets, with clustering at the level of the the cluster (at which treatment was assigned); wild cluster bootstrap-t p-values in curly brackets. All regressions include controls for age, age-squared, gender, dummies for the month of interview and average cluster-level education and Chewa ethnicity, both measured in 2004. Sample includes children aged 6-53 months at waves 1 or 2. "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. ** p<0.01, * p<0.05, + p<0.1.

Table 11: Effects on physical growth, children aged 6-53 months, by age groups

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Summary Index	Height for Age	Healthy weight for age	Healthy weight for height	Summary Index	Height for Age	Healthy weight for age	Healthy weight for height
	6-24 Months				24-53 months			
T _z	0.176**	0.554**	0.025	0.083+	0.050	0.087	0.032	0.019
Standard Error	[0.049]	[0.118]	[0.025]	[0.038]	[0.038]	[0.126]	[0.031]	[0.020]
Wild Cluster Bootstrap p-value	{0.008}	{0.000}	{0.372}	{0.060}	{0.296}	{0.492}	{0.316}	{0.500}
Randomization Inference p-value	{0.008}	{0.000}	{0.448}	{0.087}	{0.338}	{0.624}	{0.429}	{0.461}
Observations	952	952	952	952	1,223	1,223	1,223	1,223
R-squared	0.049	0.124	0.041	0.029	0.026	0.017	0.014	0.023
IntraCluster Correlation	0.038	0.0217	0.0092	0.038	0.0118	0.0404	0.03	0.000138
Average, Control	0.248	-2.306	0.845	0.795	0.275	-2.339	0.817	0.893

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 in Cols 1-4 (5-8) includes children born after July 2005 and who were aged between 6 and 24 (24 and 53) months at time of measurement. "Summary Index" in Col. 1(5) contains the variables in columns 2-4 (6-8) 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 12: Effects on adult health

	[1]	[2]
	Summary Index	Summary Index
	Males	Females
T_z	-0.004	-0.019
Standard Error	[0.044]	[0.038]
Wild Cluster Bootstrap p-value	{0.873}	{0.693}
Randomization Inference p-value	{0.899}	{0.685}
Observations	3760	4252
R-squared	0.015	0.030
IntraCluster Correlation	0.074	0.060
Mean, Control	0.004	0.011

Notes to Table: All regressions include controls for age, age-squared, gender, average cluster-level education and Chewa ethnicity, both measured in 2004, and dummies for month of interview. Sample in column 1 (2) includes all adult males (females) aged 15-65 years at waves 1 or 2. Standard errors computed using the cluster-correlated Huber-White estimator are reported in square 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. Summary Index calculated based on 8 outcome measures outlined in Table B2 using the method described in section 4.3. ** p<0.01, * p<0.05, + p<0.1.

Table 13: Effects on family planning and fertility

	[1]	[2]
	Use of any modern family planning method	Number of children since intervention began
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 square brackets, with clustering at the level of the cluster (at which treatment was assigned); wild cluster bootstrap-t p-values in curly brackets. All regressions includes controls for age, age-squared, and (family planning regression only) for cluster-level Chewa ethnicity and average cluster-level education, both measured 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 main respondents in wave 1 linked to the Mai Mwana Health Surveillance System, which measures at age 1 month, all children born to these women since the start of the intervention. ** p<0.01, * p<0.05, + p<0.1.

Appendix A:

Attrition

Appendix A: Attrition

We here address the potential concern 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 A1), the 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 9) 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 9 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 in the follow-up surveys 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.¹

¹A 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 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.

Table A2 reports the estimates of the program effects for two outcomes, household consumption and main respondent's labor supply.² 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.

²The baseline census does not include information on men or individual children, so we do not know who attrited.

Table A1. Differences in characteristics 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 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.

Table A2: 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. 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. Sample in column 1, upper panel, includes all households at waves 1 or 2; sample in column 2, upper panel, includes all main respondents aged 15-65 in waves 1 or 2. Sample in column 1, lower panel, includes all households of women drawn to be surveyed in wave 1 or 2 regardless of whether surveyed; sample in column 2, lower panel, includes all women drawn to be surveyed in wave 1 or 2 regardless of whether surveyed. Households/women who attrited between the baseline and wave 1 are considered to have attrited in wave 2 as well. Excluded variables in the second stage of the Heckman Selection Model are "# children 0-3" (number of children of interviewer aged 0-3 at wave 1) and "land size(acres)" (interviewer's land size in acres at wave 1). ** p<0.01, * p<0.05, + p<0.1.

Appendix B:

Proofs

Appendix B: Proofs

Proof of Proposition 1

The optimisation problem that the household solves is

$$\begin{aligned} \underset{\{A, L, C_1, C_2\}}{Max} \quad & A^\alpha L^\beta C_1^{\gamma_1} C_2^{\gamma_2} \\ \text{s.t. :} \quad & A + p_1 C_1 + p_2 C_2 \leq w(T - L) \end{aligned}$$

Given that the objective function is increasing in each argument, the budget constraint will be binding at the optimum. We use the budget constraint to solve for A and substitute in the objective function to obtain:

$$\underset{\{L, C_1, C_2\}}{Max} \quad F(L, C_1, C_2)$$

where $F(L, C_1, C_2) \equiv (w(T - L) - p_1 C_1 - p_2 C_2)^\alpha L^\beta C_1^{\gamma_1} C_2^{\gamma_2}$. The first order conditions are:

$$F_{C_1}(L, C_1, C_2) \equiv -\frac{\alpha p_1}{w(T - L) - p_1 C_1 - p_2 C_2} + \frac{\gamma_1}{C_1} = 0 \quad (\text{a})$$

$$F_{C_2}(L, C_1, C_2) \equiv -\frac{\alpha p_2}{w(T - L) - p_1 C_1 - p_2 C_2} + \frac{\gamma_2}{C_2} = 0 \quad (\text{b})$$

$$F_L(L, C_1, C_2) \equiv -\frac{\alpha w}{w(T-L) - p_1 C_1 + p_2 C_2} + \frac{\beta}{L} = 0. \quad (c)$$

It will be useful to use how the different cross-derivatives relate to F_{LC_1} :

$$F_{c_1 c_2} = F_{LC_1} \frac{p_2}{w}, \quad (d)$$

$$F_{c_2 c_2} = F_{LC_1} \frac{p_2^2}{w p_1} - \frac{\gamma_2}{c_2^2}, \quad (e)$$

$$F_{c_2 L} = F_{LC_1} \frac{p_2}{p_1}, \quad (f)$$

$$F_{LL} = F_{LC_1} \frac{w}{p_1} - \frac{\beta}{L^2}. \quad (g)$$

Differentiating the first order conditions (a)-(c) with respect to γ_1 , we get:

$$\begin{bmatrix} F_{c_1 c_1} & F_{c_1 c_2} & F_{c_1 L} \\ F_{c_1 c_2} & F_{c_2 c_2} & F_{c_2 L} \\ F_{c_1 L} & F_{c_2 L} & F_{LL} \end{bmatrix} \begin{bmatrix} dC_1 \\ dC_2 \\ dL \end{bmatrix} = - \begin{bmatrix} F_{c_1 \gamma_1} \\ F_{c_2 \gamma_1} \\ F_{L \gamma_1} \end{bmatrix} d\gamma_1,$$

where $F_{c_2 \gamma_1} = 0$ and $F_{L \gamma_1} = 0$. Using Cramer's rule, we obtain that

$$\frac{dC_1}{d\gamma_1} = -\frac{F_{c_1 \gamma_1} (F_{c_2 c_2} F_{LL} - F_{c_2 L}^2)}{|H|},$$

$$\frac{dC_2}{d\gamma_1} = -\frac{F_{c_1 \gamma_1} (F_{c_1 c_2} F_{LL} - F_{c_1 L} F_{c_2 L})}{|H|},$$

$$\frac{dL}{d\gamma_1} = -\frac{F_{c_1\gamma_1}(F_{c_1c_2}F_{c_2L} - F_{c_1L}F_{c_2c_2})}{|H|},$$

where

$$|H| = \begin{vmatrix} F_{c_1c_1} & F_{c_1c_2} & F_{c_1L} \\ F_{c_1c_2} & F_{c_2c_2} & F_{c_2L} \\ F_{c_1L} & F_{c_2L} & F_{LL} \end{vmatrix}$$

Note that $F_{c_1\gamma_1} > 0$, and that the second order condition ensure both $(F_{c_2c_2}F_{LL} - F_{c_2L}^2) > 0$, $|H| < 0$. Hence, we get that $\frac{dC_1}{d\gamma_1} > 0$. Using (d)-(g), the above comparative statics can be simplified as:

$$\frac{dC_1}{d\gamma_1} = \frac{F_{c_1\gamma_1}(F_{c_1L}(\frac{\beta p_2^2}{L^2 w p_1} + \frac{\gamma_2 w}{C_2^2 p_1}) - \frac{\beta \gamma_2}{C_2^2 L^2})}{|H|} > 0, \quad (\text{h})$$

$$\frac{dC_2}{d\gamma_1} = -\frac{F_{c_1\gamma_1}F_{c_1L}(\frac{\beta p_2}{w L^2})}{|H|} < 0, \quad (\text{i})$$

$$\frac{dL}{d\gamma_1} = -\frac{F_{c_1\gamma_1}F_{c_1L}(\frac{\gamma_2}{c_2^2})}{|H|} < 0, \quad (\text{j})$$

where we have used that $F_{c_1L} < 0$.

Using the budget constraint, we have that

$$\frac{dA}{d\gamma_1} = -w \frac{dL}{d\gamma_1} - p_1 \frac{dC_1}{d\gamma_1} - p_2 \frac{dC_2}{d\gamma_1}, \quad (\text{k})$$

which simplifies to

$$\frac{dA}{d\gamma_1} = \frac{F_{c_1\gamma_1} \left(\frac{\gamma_2\beta p_1}{LC_2^2} \right)}{|H|} < 0,$$

after substituting (h)-(j) into (k).

Denote total consumption by $TC = A + p_1C_1 + p_2C_2$. Using the budget constraint, and (j), we can conclude that $\frac{dTC}{d\gamma_1} = -w \frac{dL}{d\gamma_1} > 0$

Appendix C:

Monte Carlo Simulation

Appendix C. 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, Wooldridge 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), we here 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%. We next provide the details of the Monte Carlo simulation.

We analyze 8 Data Generating Processes (DGPs), one for each of the columns in Table 3. In each DGP, the sample and covariates are the ones that we use to estimate the regressions in Table 3. 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 3. Hence, the results from the Monte Carlo simulation are indeed informative about our case. For each column of Table 3, we follow the steps below:

Step 1: Use OLS to estimate regression (5) in which the dependent variable, Y_{ict} , and the sample are the ones indicated in the heading of the

corresponding column in Table 3. The estimates, $[\hat{\alpha}_0, \hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\mu}_t]$, which are the same as those reported in Table 3, 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}_{ict} , under the assumption that the treatment effect is null, that is,

$$\tilde{Y}_{ict} = \hat{\alpha}_0 + 0xT_c + X_{ict}\hat{\beta}_2 + Z_{c0}\hat{\beta}_3 + \hat{\mu}_t + \hat{\sigma}_\vartheta\tilde{\vartheta}_c + \hat{\sigma}_\varepsilon\tilde{\varepsilon}_{ict},$$

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

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

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

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 β_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 $[\hat{\alpha}_0, \hat{\beta}_2, \hat{\beta}_3, \hat{\mu}_t, \hat{\rho}_u, \hat{\sigma}_u^2]$ 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, π (reported in Table F1) 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 $\pi \pm 1.96\sqrt{0.05 \times 0.95 / 100}$, where 1.96 is the 97.5% standard normal critical value. In Table C1, we report whether the estimated test size is significantly different from the nominal one (0.05).

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 3-10. 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 side by side the two leading approaches for carrying out inference with a small number of clusters, which, to our knowledge has not been done so far.

Appendix D:

Outcome measures

Appendix D

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, nsima¹, meat, fish, eggs or beans, and fruit or vegetables.

2 Food 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. In 2009-10, 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

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.

values to impute their value.² 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).

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

² 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.* (2013). 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.

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 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	-0.03	0.040	-1.740
Standard Error	[0.165]	[0.104]	[0.023]	[3.308]
Wild Cluster Bootstrap p-value	{0.915}	{0.799}	{0.120}	{0.633}
Randomization Inference p-value	{0.903}	{0.742}	{0.101}	{0.585}
Observations	4138	4138	4138	4138
R-squared	0.136	0.144	0.045	0.149
IntraCluster Correlation	0.14	0.222	0.0265	0.144
Mean, Control	-0.05	0.847	0.0867	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 square 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 as described in section 4.4. "Works" is 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 had at least 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: Intervention Effects on Child Morbidity

	[1]	[2]	[3]	[4]	[5]	[6]
	Summary Index	Suffered Diarrhoea	Suffered from Vomiting	Suffered from Fast Breathing	Suffered Fever	Suffered from Chills
	> 6 months					
T _z	-0.013	-0.009	-0.026	0.028	0.027	0.003
Standard Error	[0.102]	[0.040]	[0.047]	[0.057]	[0.063]	[0.050]
Wild Cluster Bootstrap p-value	{0.861}	{0.861}	{0.631}	{0.683}	{0.691}	{0.913}
Randomisation inference p-value	{0.920}	{0.838}	{0.705}	{0.682}	{0.742}	{0.962}
Observations	2356	2356	2356	2356	2356	2356
R-squared	0.053	0.118	0.018	0.027	0.015	0.013
IntraCluster Correlation	0.150	0.034	0.082	0.140	0.081	0.111
Mean, Control	0.022	0.253	0.208	0.101	0.507	0.147

Notes to Table: Standard errors computed using the cluster-correlated Huber-White estimator are reported in square 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 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 survey. Each column represents a different dependent variable which takes value 1 if the the child has suffered the condition specified in the column heading in the 15 days previous to the survey, as reported by the main respondent, and is 0 otherwise.

Table E4: 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	-0.004	-0.042	0.025	0.066	0.005	0.071	0.019	0.018	0.012
Standard Error	[0.044]	[0.046]	[0.034]	[0.039]	[0.013]	[0.048]	[0.063]	[0.027]	[0.017]
Wild Cluster Bootstrap p-value	{0.873}	{0.442}	{0.486}	{0.162}	{0.711}	{0.302}	{0.791}	{0.565}	{0.521}
Randomisation Inference p-value	{0.899}	{0.445}	{0.503}	{0.180}	{0.738}	{0.204}	{0.778}	{0.632}	{0.594}
Observations	3760	3760	3760	3760	3760	3760	3760	3760	3760
R-squared	0.015	0.099	0.081	0.022	0.008	0.011	0.008	0.007	0.010
IntraCluster Correlation	0.074	0.120	0.0703	0.042	0.008	0.059	0.076	0.053	0.015
Mean, Control	0.004	0.904	0.918	0.287	0.052	0.236	0.269	0.086	0.099
Females									
T _z	-0.019	-0.050	0.030	0.043	-0.004	0.090	0.025	0.014	0.005
Standard Error	[0.038]	[0.046]	[0.033]	[0.044]	[0.014]	[0.044]	[0.062]	[0.036]	[0.031]
Wild Cluster Bootstrap p-value	{0.693}	{0.352}	{0.386}	{0.382}	{0.831}	{0.118}	{0.739}	{0.731}	{0.869}
Randomisation Inference p-value	{0.685}	{0.353}	{0.480}	{0.419}	{0.839}	{0.103}	{0.722}	{0.782}	{0.913}
Observations	4252	4252	4252	4252	4252	4252	4252	4252	4252
R-squared	0.030	0.114	0.106	0.02	0.011	0.019	0.017	0.011	0.01
IntraCluster Correlation	0.060	0.110	0.067	0.042	0.010	0.048	0.085	0.077	0.048
Mean, Control	0.011	0.870	0.888	0.412	0.073	0.329	0.277	0.119	0.148

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 square 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 the value 1 if the column heading is "Yes" according to the main respondent and 0 otherwise.

Appendix F:

Results by Wave

Appendix F: Results by Wave

Table F1: Effects on components of the knowledge index - wave 1

	Summary Index	Breastfeedin g when infant has diarrhoea	Are biscuits or groundnuts/soy a more nutritious for kids aged 6 months-3 yrs?	From what age should solid foods be given infants?
	[1]	[2]	[3]	[4]
T_z	0.195	0.253**	-0.052	0.037
Standard Error	[0.136]	[0.115]	[0.041]	[0.026]
Wild Cluster Bootstrap p-value	{0.228}	{0.094}	{0.328}	{0.220}
Randomization Inference p-value	{0.143}	{0.029}	{0.223}	{0.293}
Observations	1512	1512	1512	1512
R-squared	0.08	0.10	0.05	0.04
IntraCluster Correlation	0.156	0.277	0.082	0.050
Mean, Control	-0.0544	0.216	0.938	0.88

Notes to Table: All regressions include controls for age, age-squared, average cluster-level education and Chewa ethnicity, both measured in 2004, and dummies for the month of interview. Standard errors computed using the cluster-correlated Huber-White estimator are reported in square 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. Sample includes all households present in both waves, with a female main respondent aged 15 years or over. "Summary Index" aggregates the measures in columns 2-5 using the method described in section 4.3. The variables in columns 2-5 are dummy variables equal to 1 if the respondent answered correctly. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table F2: Effects on components of the knowledge index - wave 2

	Summary Index	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]
T_z	0.152	0.138	-0.101	0.067***	0.104
Standard Error	[0.119]	[0.150]	[0.078]	[0.019]	[0.069]
Wild Cluster Bootstrap p-value	{0.273}	{0.458}	{0.204}	{0.002}	{0.186}
Randomization Inference p-value	{0.248}	{0.400}	{0.182}	{0.008}	{0.194}
Observations	1512	1512	1512	1512	1512
R-squared	0.04	0.05	0.07	0.04	0.02
IntraCluster Correlation	0.190	0.408	0.183	0.057	0.107
Mean, Control	-0.0354	0.394	0.858	0.026	0.718

Notes to Table: All regressions include controls for age, age-squared, average cluster-level education and Chewa ethnicity, both measured in 2004, and dummies for the month of interview. Standard errors computed using the cluster-correlated Huber-White estimator are reported in square 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. Sample includes all households with a female main respondent, at wave 2. "Summary Index" aggregates the measures in columns 2-5 using the method described in section 4.3. The variables in columns 2-5 are dummy variables equal to 1 if the respondent answered correctly. Questions in columns 2, 3 and 5

Table F3: Effects on Intake of Liquids by Children Aged < 6 months - Wave 2

	[1]	[2]	[3]
	Summary Index	Water	Milk other than maternal
T_z	0.250*	-0.107	-0.082*
Standard Error	[0.098]	[0.069]	[0.034]
Wild Cluster Bootstrap p-value	{0.016}	{0.122}	{0.012}
Randomization Inference p-value	{0.028}	{0.212}	{0.115}
Observations	151	151	151
R-squared	0.214	0.362	0.087
IntraCluster Correlation	0.0405	0.000	0.060
Mean, Control	-0.109	0.474	0.101

Notes to Table: Sample includes children at wave 2 aged less than 6 months. ** p<0.01, * p<0.05, + p<0.1. Other notes as in those for Table 6.

Table F4: Effects on Household Food Consumption - Wave 1

	[1]	[2]	[3]	[4]	[5]
	Per Capita Monthly Food Consumption for:				
	Summary			Fruit and	
	Index	Cereals	Proteins	Vegetables	Other Foods
T_z	0.156	-29.908	86.76	182.454	68.369
Standard Error	[0.113]	[70.662]	[77.923]	[118.338]	[44.196]
Wild Cluster Bootstrap p-value	{0.212}	{0.729}	{0.464}	{0.190}	{0.212}
Randomization Inference p-value	{0.206}	{0.952}	{0.016}	{0.042}	{0.020}
Observations	1644	1644	1644	1644	1644
R-squared	0.069	0.03	0.014	0.227	0.019
IntraCluster Correlation	0.141	0.167	0.047	0.263	0.069
Mean Control Areas	-0.08	731.20	370.90	572.90	164.10

Notes as in those for Table 8. Sample includes all households at wave 1.

Table F5: Effects on Household Consumption - Wave 2

	[1]	[2]	[3]	[4]	[5]
	Per Capita Monthly Food Consumption for:				
	Summary			Fruit and	
	Index	Cereals	Proteins	Vegetables	Other Foods
T_z	0.305**	10.390	171.270**	368.329**	52.133
Standard Error	[0.092]	[52.752]	[59.147]	[122.116]	[29.888]
Wild Cluster Bootstrap p-value	{0.002}	{0.825}	{0.016}	{0.014}	{0.144}
Randomization Inference p-value	{0.014}	{0.952}	{0.016}	{0.042}	{0.020}
Observations	1556	1556	1556	1556	1556
R-squared	0.05	0.01	0.037	0.119	0.028
IntraCluster Correlation	0.085	0.105	0.070	0.177	0.083
Mean Control Areas	-0.13	471.20	325.60	794.50	133.80

Notes as in those for Table 8. Sample includes all households at wave 2.

Table F6: Effects on Male Labor Supply - Wave 1

	Male Adults			
	[1]	[2]	[3]	[4]
	Summary Index	Works	Has at least 2 jobs	Weekly Hours Worked
T_z	0.183	0.086	0.045	4.315+
Standard Error	[0.135]	[0.080]	[0.040]	[2.363]
Wild Cluster Bootstrap p-value	{0.216}	{0.368}	{0.370}	{0.088}
Randomization Inference p-value	{0.244}	{0.341}	{0.403}	{0.141}
Observations	1790	1790	1790	1790
R-squared	0.177	0.23	0.05	0.18
IntraCluster Correlation	0.14	0.214	0.060	0.081
Mean, Control	-0.119	0.826	0.097	24.580

Notes to Table as in those for Table 9. Sample includes all males aged 15-65 years at wave 1.

Table F7: Effects on Male Labor Supply - Wave 2

	Male Adults			
	[1]	[2]	[3]	[4]
	Summary Index	Works	Has at least 2 jobs	Weekly Hours Worked
T_z	0.323*	0.124	0.113**	4.249
Standard Error	[0.148]	[0.087]	[0.020]	[3.785]
Wild Cluster Bootstrap p-value	{0.036}	{0.193}	{0.000}	{0.296}
Randomization Inference p-value	{0.036}	{0.192}	{0.001}	{0.327}
Observations	1852	1852	1852	1852
R-squared	0.184	0.15	0.07	0.15
IntraCluster Correlation	0.192	0.263	0.029	0.150
Mean, Control	-0.148	0.812	0.092	26.850

Notes to Table as in those for Table 9. Sample includes all males aged 15-65 years at wave 2.

Table F8: Effects on Female Labor Supply - Wave 1

	Female Adults			
	[1]	[2]	[3]	[4]
	Summary Index	Works	Has at least 2 jobs	Weekly Hours Worked
T_z	-0.016	-0.049	0.030	-2.288
Standard Error	[0.163]	[0.110]	[0.036]	[3.310]
Wild Cluster Bootstrap p-value	{0.985}	{0.671}	{0.519}	{0.529}
Randomization Inference p-value	{0.920}	{0.635}	{0.524}	{0.489}
Observations	2080	2080	2080	2080
R-squared	0.157	0.19	0.06	0.17
IntraCluster Correlation	0.183	0.301	0.052	0.170
Mean, Control	-0.033	0.828	0.099	23.780

Notes to Table as in those for Table E2. Sample includes all females aged 15-65 years at wave 1.

Table F9: Effects on Female Labor Supply - Wave 2

	Female Adults			
	[1]	[2]	[3]	[4]
	Summary Index	Works	Has at least 2 jobs	Weekly Hours Worked
T_z	0.050	-0.015	0.056+	-1.262
Standard Error	[0.193]	[0.106]	[0.024]	[3.739]
Wild Cluster Bootstrap p-value	{0.877}	{0.993}	{0.068}	{0.787}
Randomization Inference p-value	{0.768}	{0.886}	{0.031}	{0.733}
Observations	2058	2058	2058	2058
R-squared	0.125	0.108	0.038	0.134
IntraCluster Correlation	0.150	0.221	0.023	0.194
Mean, Control	-0.073	0.867	0.074	25.300

Notes to Table as in those for Table E2. Sample includes all females aged 15-65 years at wave 2.

Table F10: Effects on Child Physical Growth, Children aged > 6 months - Wave 1

	[1]	[2]	[3]	[4]
	Summary		Healthy weight	Healthy weight
	Index	Height for Age	for age	for height
T _z	0.093	0.320+	0.072+	0.018
Standard Error	[0.045]	[0.132]	[0.032]	[0.030]
Wild Cluster Bootstrap p-value	{0.108}	{0.054}	{0.068}	{0.577}
Randomization Inference p-value	{0.107}	{0.070}	{0.136}	{0.601}
Observations	932	932	932	932
R-squared	0.032	0.064	0.029	0.031
IntraCluster Correlation	0.026	0.029	0.036	0.013
Average, Control	0.286	-2.339	0.785	0.859

Notes to Table as in Table 10. Sample includes children born after the intervention began, and who were measured in wave 1 (aged 6-45 months).

Table F11: Effects on Child Physical Growth, Children aged > 6 months - Wave 2

	[1]	[2]	[3]	[4]
	Summary		Healthy weight	Healthy weight
	Index	Height for Age	for age	for height
T _z	0.112*	0.236+	-0.006	0.061+
Standard Error	[0.040]	[0.106]	[0.025]	[0.029]
Wild Cluster Bootstrap p-value	{0.022}	{0.066}	{0.827}	{0.078}
Randomization Inference p-value	{0.032}	{0.091}	{0.843}	{0.078}
Observations	1243	1243	1243	1243
R-squared	0.028	0.039	0.009	0.038
IntraCluster Correlation	0.017	0.013	0.017	0.019
Average, Control	0.238	-2.315	0.863	0.847

Notes to Table as in Table 10. Sample includes children born after the intervention began, and who were measured in wave 2 (aged 6-53 months).

Table F12: Effects on Adult Health - Wave 1

	[1]	[2]
	Summary Index	Summary Index
	Males	Females
T_z	0.01	0.014
Standard Error	[0.053]	[0.047]
Wild Cluster Bootstrap p-value	{0.849}	{0.787}
Randomization Inference p-value	{0.863}	{0.791}
Observations	1991	2269
R-squared	0.022	0.027
IntraCluster Correlation	0.087	0.070
Mean, Control	-0.005	0.000

Notes to Table as in those for Table 12. Sample in column 1(2) includes all adult males (females) aged 15-65 years at wave 1.

Table F13: Effects on Adult Health - Wave 2

	[1]	[2]
	Summary Index	Summary Index
	Males	Females
T_z	-0.02	-0.053
Standard Error	[0.039]	[0.036]
Wild Cluster Bootstrap p-value	{0.619}	{0.190}
Randomization Inference p-value	{0.694}	{0.311}
Observations	1769	1983
R-squared	0.018	0.022
IntraCluster Correlation	0.077	0.067
Mean, Control	0.014	0.023

Notes to Table as in those for Table 12. Sample in column 1(2) includes all adult males (females) aged 15-65 years at wave 1.

Table F14: Effects on Family Planning and Fertility - Wave 1

	[1]
	Use of any modern family planning method
T_z	0.005
Standard Error	[0.0451]
Wild Cluster Bootstrap p-value	{0.943}
Randomisation Inference p-value	{0.907}
Observations	1462
R-squared	0.088
IntraCluster Correlation	0.023
Mean, Control	0.369

Notes to Table as in Table 13. Sample includes women 17-43 years old at wave 1.

Table F15: Effects on Family Planning and Fertility - Wave 2

	[1]
	Use of any modern family planning method
T_z	0.042
Standard Error	[0.0711]
Wild Cluster Bootstrap p-value	{0.597}
Randomisation Inference p-value	{0.568}
Observations	1347
R-squared	0.048
IntraCluster Correlation	0.069
Mean, Control	0.388

Notes to Table as in Table 13. Sample includes women 17-43 years old at wave 2.

Table F16: Effects on Child Morbidity - Wave 1

	[1]	[2]	[3]	[4]	[5]	[6]
	Summary Index	Suffered Diarrhoea	Suffered from Vomiting	Suffered from Fast Breathing	Suffered Fever	Suffered from Chills
	> 6 months					
T _z	0.027	-0.066	-0.041	0.014	0.014	0.03
Standard Error	[0.103]	[0.059]	[0.051]	[0.048]	[0.059]	[0.058]
Wild Cluster Bootstrap p-value	{0.769}	{0.310}	{0.430}	{0.781}	{0.869}	{0.567}
Randomisation inference p-value	{0.853}	{0.338}	{0.574}	{0.818}	{0.882}	{0.701}
Observations	1061	1061	1061	1061	1061	1061
R-squared	0.04	0.097	0.022	0.046	0.014	0.017
IntraCluster Correlation	0.175	0.069	0.089	0.133	0.078	0.137
Mean, Control	0.001	0.355	0.238	0.114	0.551	0.158

Notes to Table as in those for Table E3. Sample includes children aged 6-45 months at wave 1.

Table F17: Effects on Child Morbidity - Wave 2

	[1]	[2]	[3]	[4]	[5]	[6]
	Summary Index	Suffered Diarrhoea	Suffered from Vomiting	Suffered from Fast Breathing	Suffered Fever	Suffered from Chills
	> 6 months					
T _z	-0.051	0.04	-0.014	0.039	0.036	-0.018
Standard Error	[0.124]	[0.037]	[0.054]	[0.068]	[0.085]	[0.060]
Wild Cluster Bootstrap p-value	{0.743}	{0.352}	{0.819}	{0.637}	{0.741}	{0.822}
Randomisation inference p-value	{0.746}	{0.377}	{0.856}	{0.648}	{0.714}	{0.829}
Observations	1295	1295	1295	1295	1295	1295
R-squared	0.043	0.102	0.017	0.015	0.016	0.01
IntraCluster Correlation	0.197	0.030	0.110	0.165	0.129	0.187
Mean, Control	0.045	0.164	0.181	0.0906	0.47	0.138

Notes to Table as in those for Table E3. Sample includes children aged 6-45 months at wave 2.

Table F18: Adult Health index components - wave 1

	[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	0.010	-0.028	0.053	0.067	0.010	0.046	0.027	0.025	0.011
Standard Error	[0.053]	[0.050]	[0.044]	[0.051]	[0.016]	[0.055]	[0.066]	[0.031]	[0.027]
Wild Cluster Bootstrap p-value	{0.849}	{0.607}	{0.290}	{0.253}	{0.627}	{0.466}	{0.769}	{0.454}	{0.725}
Randomisation Inference p-value	{0.863}	{0.651}	{0.294}	{0.295}	{0.582}	{0.454}	{0.706}	{0.550}	{0.710}
Observations	1991	1991	1991	1991	1991	1991	1991	1991	1991
R-squared	0.022	0.094	0.085	0.022	0.011	0.014	0.016	0.008	0.016
IntraCluster Correlation	0.087	0.141	0.104	0.066	0.010	0.072	0.091	0.053	0.028
Mean, Control	-0.005	0.894	0.883	0.285	0.052	0.250	0.264	0.098	0.100
Females									
T _z	0.014	-0.010	0.077	0.029	0.003	0.040	0.016	0.013	-0.004
Standard Error	[0.047]	[0.054]	[0.053]	[0.059]	[0.020]	[0.060]	[0.069]	[0.041]	[0.037]
Wild Cluster Bootstrap p-value	{0.787}	{0.851}	{0.230}	{0.625}	{0.871}	{0.631}	{0.847}	{0.723}	{0.903}
Randomisation Inference p-value	{0.791}	{0.873}	{0.296}	{0.689}	{0.897}	{0.552}	{0.833}	{0.825}	{0.929}
Observations	2269	2269	2269	2269	2269	2269	2269	2269	2269
R-squared	0.027	0.12	0.113	0.021	0.016	0.016	0.021	0.011	0.008
IntraCluster Correlation	0.070	0.147	0.146	0.072	0.022	0.065	0.107	0.091	0.050
Mean, Control	0.000	0.843	0.831	0.405	0.076	0.349	0.269	0.134	0.166

Notes to Table as in those for Table E4. Sample in top (bottom) panel includes all males (females) aged 15-65 years at wave 1.

Table F19: Adult Health index components - wave 2

	[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	-0.02	-0.051	-0.002	0.065	0.000	0.100	0.011	0.013	0.012
Standard Error	[0.039]	[0.046]	[0.027]	[0.038]	[0.013]	[0.049]	[0.068]	[0.032]	[0.017]
Wild Cluster Bootstrap p-value	{0.619}	{0.334}	{0.943}	{0.122}	{0.947}	{0.182}	{0.915}	{0.721}	{0.537}
Randomisation Inference p-value	{0.694}	{0.328}	{0.947}	{0.166}	{0.999}	{0.091}	{0.884}	{0.772}	{0.553}
Observations	1769	1798	1798	1798	1798	1798	1798	1798	1798
R-squared	0.018	0.126	0.074	0.026	0.009	0.019	0.010	0.006	0.010
IntraCluster Correlation	0.077	0.103	0.0402	0.033	0.009	0.063	0.092	0.087	0.007
Mean, Control	0.014	0.904	0.951	0.291	0.051	0.221	0.275	0.073	0.095
Females									
T _z	-0.053	-0.094	-0.022	0.059	-0.011	0.145**	0.035	0.016	0.015
Standard Error	[0.036]	[0.048]	[0.019]	[0.045]	[0.020]	[0.043]	[0.062]	[0.043]	[0.039]
Wild Cluster Bootstrap p-value	{0.190}	{0.104}	{0.368}	{0.254}	{0.637}	{0.020}	{0.625}	{0.731}	{0.721}
Randomisation Inference p-value	{0.311}	{0.091}	{0.342}	{0.263}	{0.631}	{0.007}	{0.633}	{0.790}	{0.775}
Observations	1983	1983	1983	1983	1983	1983	1983	1983	1983
R-squared	0.022	0.118	0.055	0.02	0.01	0.037	0.018	0.009	0.009
IntraCluster Correlation	0.067	0.113	0.019	0.031	0.021	0.051	0.086	0.112	0.061
Mean, Control	0.023	0.903	0.956	0.422	0.069	0.306	0.286	0.101	0.126

Notes to Table as in those for Table E4. Sample in top (bottom) panel includes all males (females) aged 15-65 years at wave 2.