APPENDIX H. BASELINE REPORT – SEASONALITY

Seasonality

EXTERNAL IMPACT EVALUATION OF THE MILLENNIUM VILLAGES PROJECT, NORTHERN GHANA

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itad
Results in development

IDS Institute of Development Studies

Participatory Development Associates Ltd.

London School of Hygiene & Tropical Medicine

Table of Contents

Tables

Figures

Acronyms

CPI	Consumer Price Index
CV	Control Village
DD	Difference-in-Differences
DHS	Demographic and Health Surveys
DFID	Department for International Development
HFA	Height-for-Age
GSS	Ghana Statistical Service
GLSS	Ghana Living Standards Survey
LSHTM	London School of Hygiene & Tropical Medicine
MV	Millennium Village
MVP	Millennium Villages Project
PRG	Peer Review Group
PSM	Propensity Score Matching
WFA	Weight-for-Age
WFH	Weight-for-Height

Appendix on seasonality[1]

The baseline survey, anthropometric data, and medical data were collected at different periods in the Millennium Village (MV) and control village (CV) sites. Data were collected in the MVs between 16 April until 14 June 2012 and in the CV areas from 1 August until 18 September 2012. The time lag is worrying because in Northern Ghana May is typically the height of the dry season and September is the height of the rainy season.[2] Therefore, differences in baseline characteristics between the control and treatment sites may be due to seasonal effects. Given that the methodology for identifying the effects of the Millennium Villages Project (MVP) depends on propensity score matching (PSM) and difference-in-differences (DD), any initial differences (or lack thereof) are problematic because it cannot determine if observed differences (or lack thereof) are due to seasonal effects or static underlying differences that would be controlled for using the DD approach.

After reviewing questions in the baseline survey and a discussion between representatives of the MV peer review group (PRG), Itad, and the UK Department for International Development (DFID), the following groups of variables were highlighted as being most susceptible to seasonality concerns:

a) Anthropometric data (e.g. height-for-weight, weight-for-age, height for age)

b) Measures of anaemia

c) Malaria measurements

d) Income and expenditure data

This document will attempt to examine how much of an issue, if any, seasonality is when looking at variables associated with variables a-c. We will analyse available data and review the relevant papers in the background section. Then we will provide options for dealing with seasonality concerns (the list of options will not be exhaustive) before outlining our preferred approach.

Anthropometry, malaria, and anaemia

There are two main sources of data for anthropometric measurements in Northern Ghana: the Demographic and Health Survey (DHS) and the Ghana Living Standards Survey (GLSS). The GLSS cannot be used because the number of observations is too small. Only the 1988 and 1989 surveys collected anthropometric data and the final sample of children under five years of age was less than 30, which is spread over 12 months and thus does not allow a monthly disaggregated analysis. The DHS collects data on anthropometrics, in addition to fever and anaemia.[3] DHS surveys are conducted on large samples of children, but over a limited number of months (typically three or four months). It is unfortunate that the calendar period of the survey does not coincide with any of the time periods for data collection adopted by the DHS (see Table 1).

[1] This document was prepared by Edoardo Masset and Patrick Nolen with assistance from Edgar Salgado.

[2] The seasonal description is based on field visits by Itad and DFID staff. Furthermore, Koram et al. (2003) discusses the seasonal patterns in North Ghana.

[3] In fact, the MV adult surveys designed by the Earth Institute were modeled on the DHS surveys and contain the same type of questions.

Table 1. Characteristics of DHS surveys in Ghana

Year	Months	Sample size (households)	North Region (households)	Malaria/fever reporting	Anthropometrics	Iron/anaemia
1988	Feb-May	4,966	571	Yes	Yes	No
1993	Oct-Jan	5,822	952	Yes	Yes	No
1999	Nov-Feb	6,003	1,395	Yes	Yes	No
2003	Aug-Oct	6,251	1,428	Yes	Yes	Yes
2008	Sep-Nov	11,778	2,750	Yes	Yes	Yes

Anthropometric data

We used the DHS data to calculate mean Z-scores for the months that data are available (see Tables 2-4). Based on these tables, the main conclusions that can be drawn are the following:

- There appear to be month-to-month differences in all three anthropometric indices for almost all periods considered. However, regressions of anthropometric indicators over seasonal dummies rarely find significant coefficients and an F-test of the joint significance of the seasonal coefficients (reported at the bottom of each table) reveals statistically significant differences only in one case. The lack of significance may be due to the small number of observations in each cell.

- The point estimates in the table do not present a clear pattern on how anthropometric measures change over the year: weight-for-age is not steadily decreasing until the height of the dry season for instance. Furthermore, the time period where the differences in the MVs and CVs took place is rarely covered in the datasets.

- We would expect short-term indicators of malnutrition, such as weight-for-age, to be more sensitive to seasonal fluctuations. However, the data do not show higher seasonal variability in weights compared to heights.

Table 2. Average weight-for-age Z-scores among rural children under 5 in Northern Ghana

	DHS 88			DHS 93			DHS 99			DHS 03			DHS 08		
	Av.	sd	ob	Av.	sd	ob	Av.	sd	ob	Av.	sd	ob	Av.	sd	ob
Jan				-1.66	1.21	15	-1.48	1.29	280						
Feb	-0.95	1.38	28				-1.42	1.27	66						
Mar	-1.44	1.17	42												
Apr	-1.54	1.18	47												
May	-1.47	1.37	63												
Jun															
Jul															
Aug										-1.38	1.23	362			
Sep										-1.33	1.24	356	-1.11	1.23	238
Oct				-1.33	1.50	118				-1.47	1.26	131	-1.23	1.20	222
Nov				-1.63	1.31	165	-1.55	1.21	183				-1.23	1.07	175
Dec				-1.57	1.16	33	-1.44	1.23	180						
Ft			0.07			1.71			0.47			1.19			0.00
Pv			0.933			0.182			0.623			0.276			0.991

Note: Ft and Pv are values of an F-test and the P-value of the joint significance of seasonal dummies.

Table 3. Average height-for-age Z-scores among rural children under 5 in Northern Ghana

	DHS 88			DHS 93			DHS 99			DHS 03			DHS 08		
	Av.	sd	ob	Av.	sd	ob	Av.	sd	obs	Av.	sd	ob	Av.	sd	ob
Jan				-1.74	1.54	15	-1.49	1.66	274						
Feb	-1.52	1.54	27				-1.28	1.73	63						
Mar	-1.64	1.33	41												
Apr	-1.73	1.64	47												
May	-1.83	1.44	61												
Jun															
Jul															
Aug										-1.55	1.39	362			
Sep										-1.51	1.50	358	-0.99	1.62	237
Oct				-1.34	1.55	117				-1.96	1.44	131	-0.94	1.72	224
Nov				-1.60	1.44	160	-1.45	1.62	181				-1.14	1.43	173
Dec				-1.75	1.62	33	-1.49	1.49	179						
Ft			0.19			1.37			0.44			8.91**			1.53
Pv			0.826			0.256			0.646			0.003			0.21

Note: Ft and Pv are values of an F-test and the P-value of the joint significance of seasonal dummies.

Table 4. Average weight-for-height Z-scores among rural children under 5 in Northern Ghana

	DHS 88			DHS 93			DHS 99			DHS 03			DHS 08		
	Av.	sd	ob	Av.	sd	ob	Av.	sd	obs	Av.	sd	ob	Av.	sd	ob
Jan				-0.58	1.31	14	-0.66	0.99	298						
Feb	-0.17	1.31	29				-0.70	1.06	72						
Mar	-0.74	1.14	42												
Apr	-0.81	1.06	47												
May	-0.56	1.17	63												
Jun															
Jul															
Aug										-0.48	1.28	365			
Sep										-0.38	1.31	361	-0.61	1.14	238
Oct				-0.82	1.33	116				-0.36	1.21	131	-0.75	1.22	225
Nov				-0.90	1.21	164	-0.82	1.09	192				-0.74	1.01	175
Dec				-0.85	1.01	33	-0.63	1.08	190						
Ft			0.68			0.13			1.66			0.04			0.02
Pv			0.501			0.888			0.191			0.847			0.876

Note: Ft and Pv are values of an F-test and the P-value of the joint significance of seasonal dummies.

Anaemia

Anaemia in children is associated with impaired mental and physical development and increased morbidity and mortality. Determinants of anaemia in children include a nutrition-related poor iron intake, iron absorption for physical growth, parasitic infections, and malaria (DHS 2008). Given that diets vary during the rainy and dry season it is expected that levels of anaemia and haemoglobin will vary with seasonality.

The DHS collected blood samples only in 2003 and 2008 and did not cover the period of the MV baseline survey (April to June 2012).

Table 5. Haemoglobin and prevalence of severe anaemia in rural children of Northern Ghana (DHS)

	DHS 2003					DHS 2008				
	Haemoglobin[a]		Severe anaemia[b]		Obs.	Haemoglobin[a]		Severe anaemia[b]		Obs.
	Av.	SD	Av.	SD		Av.	SD	Av.	SD	
Aug	9.8	2.1	0.061	0.24	423					
Sep	9.5	1.9	0.042	0.20	378	9.2	1.7	0.10	0.31	223
Oct	9.2	1.8	0.099	0.30	131	8.8	1.9	0.14	0.34	216
Nov						8.9	1.5	0.09	0.29	155
F-test		2.96*		5.69**			0.93		1.56	
P-value		0.085		0.017			0.337		0.213	

[a] Haemoglobin is a protein in blood cells carrying oxygen and is measured in grams per decilitre (g/dL).
[b] Prevalence rates. The DHS classifies anaemia as mild (<11 g/dL), moderate (<10 g/dL), and severe (<7 g/dL).

A regression of haemoglobin and severe anaemia on seasonal (monthly dummies) finds statistically significant coefficients (at 5%) in 2003 but not in 2008, though the 2008 sample has over 30% fewer observations. Similarly, the F-tests show that the seasonal averages are jointly different in 2003 but not in 2008. It hard to discern a pattern based on the data of Table 5.

- As the month approaches the height of the rainy season, average haemoglobin levels decrease slightly.
- There is no clear pattern in severe anaemia.
    - In 2003, the per cent of the population with severe anaemia decreases from August to September (height of the rainy season) then increases again. In 2008, it increases from September to October (as in 2003) but then decreases.
    - In 2003, as average levels of haemoglobin decrease, severe anaemia *increases* whilst in 2008 as average levels of haemoglobin decrease, severe anaemia *decreases*.

Secondary Sources: Anaemia and Malaria

The work of Koram et al. (2000) provides insight on patterns we might have expected to find in the data if we had more observations, at least in regards to anaemia. Koram et al. (2000) measured haemoglobin levels, prevalence of fever, and malaria parasite infection among children aged 6 to 24 months in the Kasena-Nangana District of the Upper East Region in Northern Ghana. Data were collected from two random cross-sectional samples of 347 and 286 children. The two samples were collected six months apart: at the end of the low malaria season (May 1997) and at the end of the high malaria season (November 1996). Significant differences were found and are displayed in Table 6 below.

Table 6. Haemoglobin, Malaria, and Anaemia reported in Koram et al. (2000)

	May	November	P-value
Haemoglobin	8.9	7.2	0.000
Severe anaemia HG <6.0	1.4	22.1	0.000
Malaria parasite rate	54.3	70.0	0.001
Proportion with fever	3.3	10.8	0.000

Koram et al. (2003) in another study randomly sampled 2,286 individuals of all ages in May 2001 and 1,673 individuals in November 2001. The seasonal differences found in anaemia prevalence and malaria infection are less dramatic but still large and statistically significant. Results on haemoglobin are reported by age group in Figure 1. Interestingly, the seasonal effect seems to only affect children under the age of five, particularly infants. There is no visible difference between high and low season for adults. Given that the baseline data for the MVs and CVs were collected only for children under the age of five, this suggests that there are likely to be differences due to seasonality.

Figure 1. Seasonal pattern of haemoglobin in Koram et al. (2003)

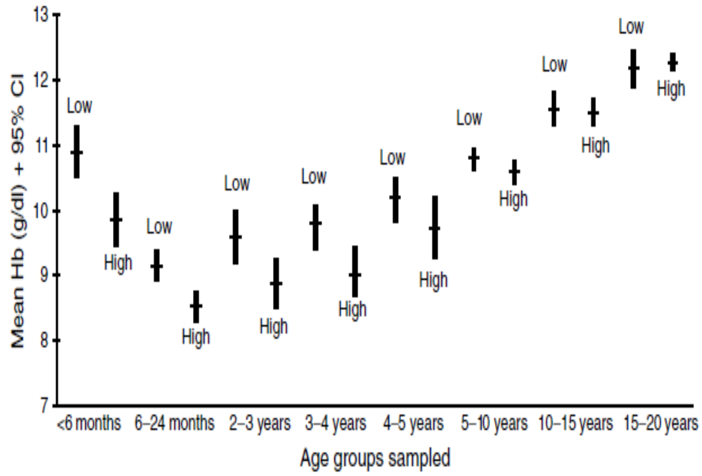


Figure 1 Paired comparison by age group of haemoglobin levels (mean, 95% CI) measured at the end of low (May 2001) and high (November 2001) malaria transmission seasons.

Cairns et al. (2011) used data from Kasena-Nangana District to analyse seasonal patterns of clinical malaria among infants and one-year-olds. The results are in Figure 2, which shows incidence rates close to zero in the month of May and reaching a peak from July-October.

Figure 2. Seasonal pattern in malaria incidence in Cairns et al. (2011)

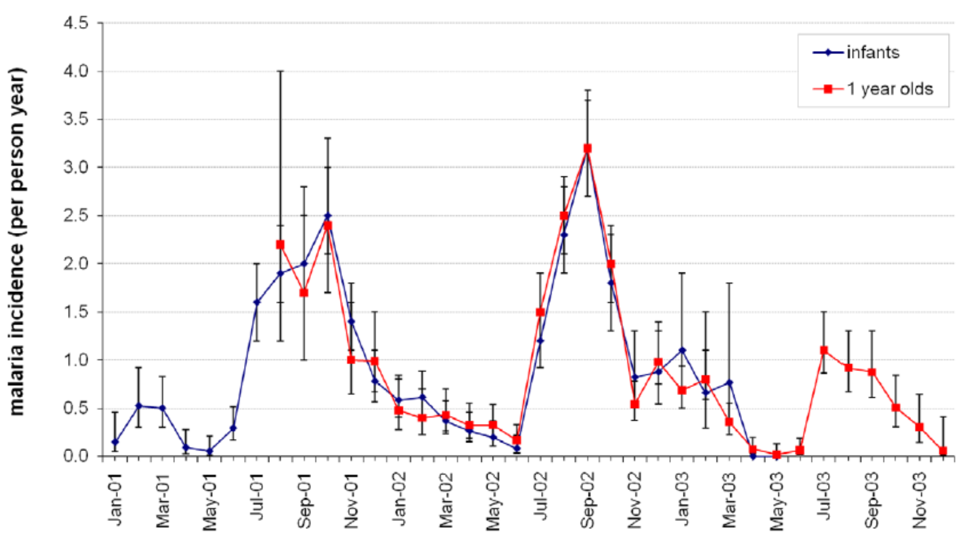
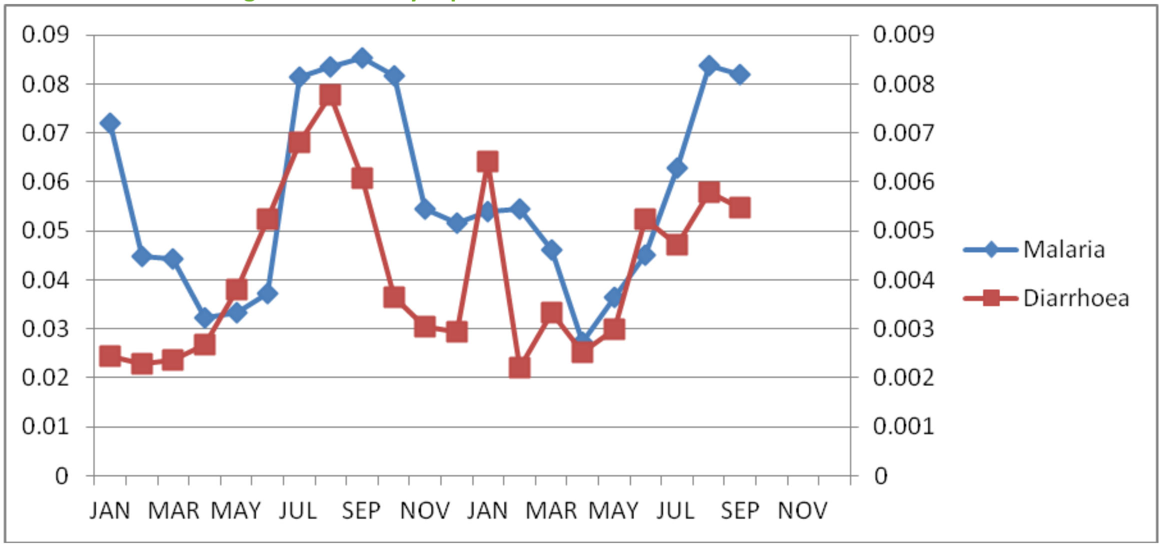


Figure 3. Incidence of clinical malaria in the Navrongo IPTi trial. Incidence of clinical malaria between January 2001 and December 2003 is shown for infants and children 12–23 months of age in the placebo group of the IPTi trial. Error bars indicate 95% confidence interval. Children were enrolled between September 2000– June 2002. Completion of 24 months follow-up ended in June 2004.
doi:10.1371/journal.pone.0018947.g003

Figure 3 is based on data of malaria cases (population level prevalence rates) reported to clinics in the Builsa District between January 2011 and September 2012. Data are from reported cases and do not represent real prevalence. Reporting could be correlated with seasonality, for example if in the rainy season clinics become inaccessible thus reducing the number of reported cases. The change in prevalence before and after the rainy season however is clear.

Figure 3. Monthly reported cases of malaria in the Builsa District



From the secondary analysis we are able to conclude the following:

- Malaria and anaemia incidence are highly seasonal.
    - Malaria and anaemia levels are likely to be highly correlated with rainfall levels.
    - The seasonality effects are especially acute for our group of interest, children under the age of five.
- Over the period of the MV and CV baseline surveys, malaria incidence has a clear pattern, at least for children.
    - The incidence of malaria increases rapidly from April to September.
- Differences in reported fever and haemoglobin levels between May (before rains) and September (after rains) are likely to be large.
    - There appears to be a clear pattern of average haemoglobin levels though decreasing until November.
    - Average haemoglobin levels and severe anaemia appear not to be strongly correlated.
    - There does not appear to be a clear pattern in the proportion of severe anaemia cases over time within a year.
- Seasonal differences are larger among children compared to adults and the gap decreases with age among children.

Income and consumption

In this section we analyse seasonal patterns of income and consumption of Ghanaian households. The goal of this exercise is to assess whether income and expenditure vary across seasons. The MVP survey collected data in MV and CV communities at different times of the year (Table 7) and there is a risk that the comparison is biased by seasonal patterns.

We find that there are substantial seasonal patterns in income and consumption but we conclude that seasonality will not affect the measurement of poverty and income, with the possible exception of a minor bias produced by recall effects. However, we observe a risk of bias in the measurement of health-related outcomes that are affected by food intake, such as anthropometric measurements, anaemia, and reported fever.

Table 7. Percentage of surveys conducted in project and control villages by month

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
MV Households					66%	25%	5%	4%				
CV households								22%	77%	1%		

Income and consumption seasonality

In Northern Ghana there is only one cropping season for main staples (such as rice and maize) and the majority of households obtain their largest income share from agriculture. Harvesting occurs in the months following the rainy season for staple crops (September to November) and agricultural incomes are likely to be highly seasonal with a peak in the post-harvest months. Total household income can be less dependent on the agricultural cycle depending on the share of non-agricultural income sources on total income.

In principle, expenditure should not be affected by seasonality. Lean and harvest seasons are highly predictable and households are well aware of their occurrence every year. Standard economic theory predicts that households smooth consumption by saving in good times and dis-saving in poor times. However, households may be prevented from doing so by a number of constraints. First, households can be desperately poor and consume all their income at any time. Second, households may be unable to borrow in the lean season and repay in the harvest seasons because of the way rural financial markets operate. Finally, households might be unable to save at harvest time either in-kind or cash because of backwardness of storage and financial systems. We can therefore expect some seasonality in consumption though the seasonal pattern of expenditure should be smoother than the seasonal pattern of income.

In addition, seasonal patterns in the data may emerge as a result of how the questionnaire is structured and how questions are phrased, particularly with respect to the recall period of items produced and consumed. We observe that the following biases can emerge when interviews are conducted at different times of the year:

- **Time shift bias.** Real incomes and expenditure tend to increase over time.
- **Projection bias.** People tend to forget past events or extrapolate the present to the past. For example: 'How many ice creams did you consume in the last 12 months?' will produce different answers in August and January.
- **Recall bias.** In contexts of high seasonality, short recall questions are biased. For example: 'How many ice creams did you consume in the last 30 days?' will produce very different answers in August and January.

Data and methods

We use data from three rounds of the Ghana Living Standards Surveys (GLSS) collected by the Ghanaian Statistical Service (GSS) in 1991/92 (GLSS3), 1997/98 (GLSS4), and 2005/06 (GLSS5). We only use data on rural households residing in the Northern region, the Upper East, and the Upper West in order to work on a sample that is comparable to the MVP sample.

We use the data to construct the following variables: agricultural incomes, total household incomes, food expenditure, and total household expenditure. Expenditures were collected by GSS over one years' time in each survey with the use of diaries and repeated visits to each household by enumerators over a two-week period. Income was collected on an annual basis (within the previous 12 months) at the time of the interview, with the exception of income for own consumption, which was collected in the same way as expenditures using diaries.

Data were deflated by the monthly consumer price index (CPI) in order to remove price effects from monthly variations in expenditure. Note that we used the national CPI for food items because no other CPI was available at a more disaggregated level.

In order to detect seasonal patterns, we ran the following regressions using the pooled three datasets together:

$$\ln x_i = a + \sum_{i=2}^{12} b_i M_i + \sum_{j}^{n} c_j x_{ji} + e_i$$

M_i are seasonal dummies for each month of the year (with January as the base year). The dependent variable is household per capita expenditure and it is expressed in logs so that the *b* coefficients of the seasonal dummies represent percentage changes in consumption with respect to the base month (January). X_i are control variables. For simplicity we only included household size, age of the head of household, and survey dummies.

Results

Regression results are presented in Table 8 and displayed again in the charts of Figure 4. We observe the following:

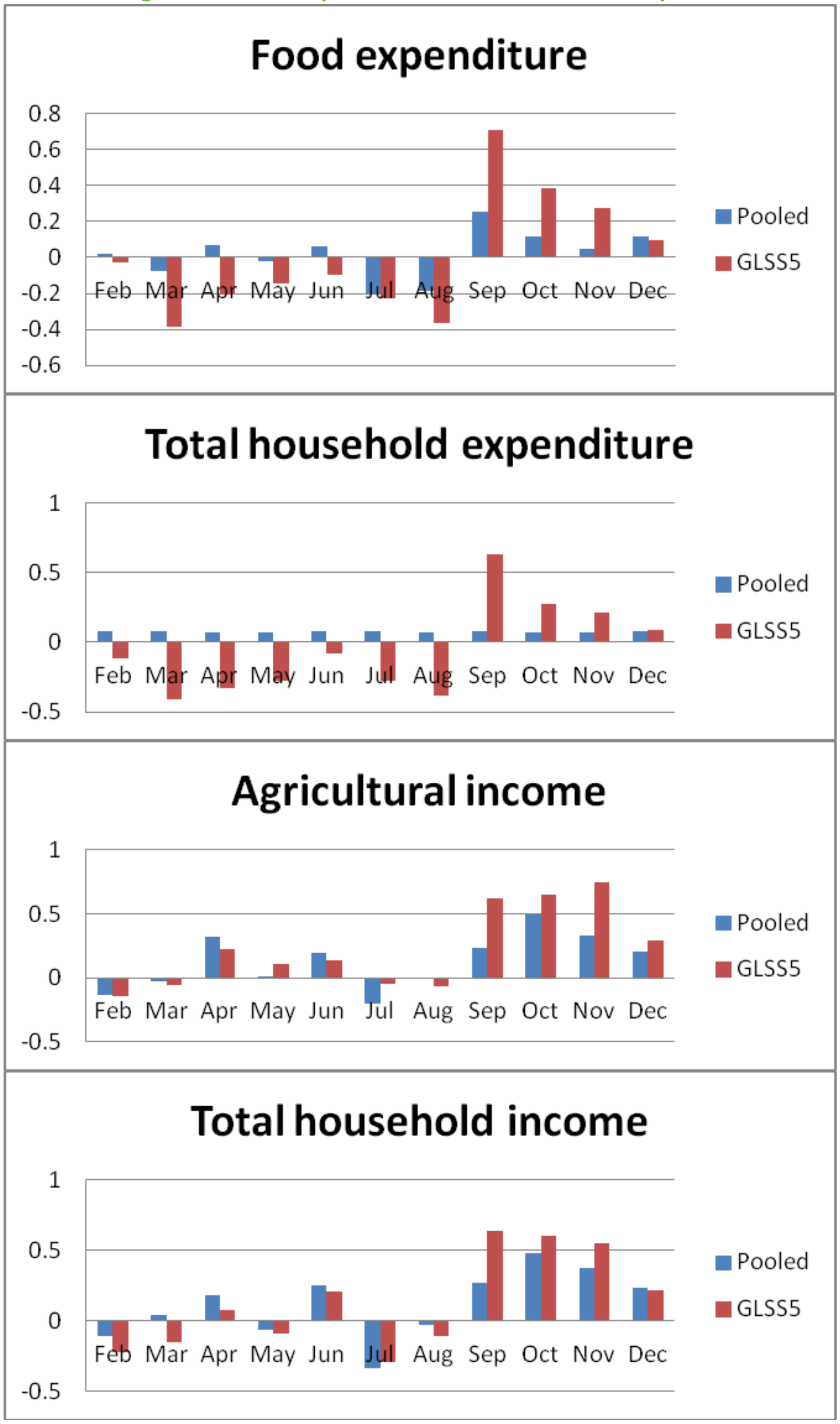
- There is seasonality in income and expenditure, which is clearly related to the agricultural cycle. Incomes and consumption increase in the harvest and post-harvest season in the months of September, October, and November.
- Seasonal fluctuations are stronger for income than for consumption consistently with households' ability to smooth part of the agricultural cycle by saving and dis-saving.
- The monthly expenditure coefficients are quite large (above 20% change in monthly expenditure) suggesting a very limited ability to smooth consumption. This is probably a consequence of extreme poverty and inability to borrow or store food. For these households, consumption follows income very closely and there is limited opportunity to borrow or save.

The largest seasonal effect is observed in September after which expenditure decreases slowly but steadily until March. After March, expenditure becomes more stable before increasing again in September.

Table 8. Seasonal income and expenditure models

	Food expenditure		Total expenditure		Agricultural income		Total income	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
February	0.02	0.804	-0.01	0.944	-0.13	0.440	-0.11	0.436
March	-0.08	0.379	-0.07	0.390	-0.03	0.854	0.04	0.772
April	0.07	0.382	0.00	0.966	0.32**	0.028	0.18	0.138
May	-0.02	0.818	-0.08	0.255	0.00	0.991	-0.06	0.613
June	0.06	0.466	0.10	0.204	0.20	0.227	0.25*	0.057
July	-0.21**	0.013	-0.20*	0.009	-0.20	0.218	-0.33**	0.010
August	-0.19**	0.016	-0.15**	0.035	0.00	0.983	-0.03	0.799
September	0.26**	0.004	0.30***	0.000	0.23	0.186	0.27*	0.056
October	0.11	0.154	0.12	0.111	0.50**	0.001	0.48***	0.000
November	0.05	0.518	0.08	0.266	0.33**	0.025	0.38**	0.002
December	0.12	0.163	0.11	0.171	0.20	0.211	0.23*	0.078
Household size	-0.07***	0.000	-0.07	0.000	-0.04	0.000	-0.05***	0.000
GLSS4	-0.07	0.125	-0.01	0.851	0.01	0.944	0.07	0.330
GLSS5	0.05	0.187	0.14***	0.000	0.39***	0.000	0.43***	0.000
Age of household head	0.00**	0.029	0.00**	0.001	-0.01***	0.000	-0.01***	0.000
Constant	13.69***	0.000	14.05***	0.000	12.6***	0.000	13.1***	0.000
R-square		0.12		0.15		0.05		0.08
Observations		2,681		2,682		2,383		2,635

Figure 4. Seasonal patterns of income and consumption



What are the main implications of these seasonal patterns for the analysis of the MVP survey data? We observe the following:

- Most of the MV baseline data were collected in May 2012, when consumption is at its lowest point in the year. On the other hand, the CV data were collected mostly in September, which is the month of the year in which consumption is at its peak and the peak is quite high.
- It would have been disastrous for the study if the survey had adopted a monthly recall for food expenditure. Luckily, we designed an expenditure questionnaire employing an unusual 12-month recall precisely with the goal of de-seasonalising the data. A 12-month recall is less precise than a one-month recall, but is not affected by seasonal patterns.
- Similarly, the agricultural income data were collected with reference to a 12-month period from harvest-to-harvest and therefore shielded against seasonality effects.
- It is likely that data are affected by the three types of recall bias outlined above. However, because of the way in which the questionnaire was designed we expect this bias to be small.
- The largest levels of food expenditure in the month of data collection in the CVs may have a negative impact on variables whose values are affected by food intake. Weight-for-age and weight-for-height are clearly sensitive to level of food intake and to the composition of the diet. But also anaemia and other health-related indicators such as the occurrence of fever may be affected by food intake because a better nourished body is more likely to overcome the stress caused by infectious diseases.

Our analysis concludes that money metric measurements of welfare, such as poverty and household income and consumption, are unlikely to be affected by seasonal patterns because of the peculiar way in which the survey was designed. However, there is a risk that variables correlated with food intake, such as anthropometrics and anaemia, will show more positive values in the CVs because data were collected in these villages at a time when food intake reaches its peak. Methods to test and adjust for this type of difference are discussed in another note on seasonality of health-related outcomes.

Options for adjusting the seasonal bias

Modelling anaemia using rainfall data

One possible solution would be testing how strongly malaria, diarrhoea, and anaemia are correlated with rainfall in the area. If the relationship is strong and can be modelled with existing data, then rainfall data could be used to predict the required seasonal adjustment. This approach requires time series data on anaemia and rainfall in the project area. The only longitudinal data on anaemia available from the area are those collected by the London School of Hygiene & Tropical Medicine (LSHTM) in the Navrongo experiment funded by DFID. Rainfall data could be obtained from local weather stations. The strengths of this option would depend on the available data and the strength of the correlation between rainfall and anaemia/malaria.

Using a Blinder-Oaxaca decomposition approach

Once the baseline data of the project and control groups become available, the question will arise whether the observed differences in haemoglobin levels, anaemia prevalence, or any of the four groups of variables discussed above are the result of underlying differences between the project and control groups or a result of having interviewed the two groups in different seasons.

One way of addressing this question is by using the standard Blinder-Oaxaca decomposition that has been widely used in labour economics to decompose wage differences between, for example, unionised and non-unionised workers, in differences resulting from characteristics of members of the two groups and unexplained characteristics. The latter is also called the 'union effect' which in our case is the 'season effect.'

One way to accomplish this is by estimating two different equations explaining haemoglobin (*h*) for the project (*p*) and the control (*c*) groups, respectively (J. Johnston and John DiNardo, 1997):

$$h_p = X_p\beta_p + \epsilon_p$$
$$h_c = X_c\beta_c + \epsilon_c$$

The estimated parameter of the first equation can be used to generate the counterfactual:

$$\widehat{h_c^p},$$

The haemoglobin level of control individuals had they not been exposed to the seasonal shock (had the interviews been carried out in May):

$$\widehat{h_c^p} = X_c\widehat{\beta_p}$$

The seasonal effect on the mean haemoglobin in the control group can thus be calculated as:

$$Season\ effect = \overline{h_c} - \widehat{h_c^p}$$

The advantage of this formulation is that it allows the decomposition of the difference in the mean haemoglobin levels in the project and control groups into differences in characteristics and in unexplained (seasonal) differences:

$$\overline{h_c} - \overline{h_p} = (\widehat{\alpha_c} - \widehat{\alpha_a}) + \overline{X_c}(\widehat{\beta_c} - \widehat{\beta_a}) + (\overline{X_c} - \overline{X_p})\widehat{\beta_p}$$

The last term is the difference in haemoglobin explained by differences in characteristics whilst the first two terms represent the difference resulting from a seasonal effect. This seasonal effect can be given a causal interpretation after imposing a number of strong assumptions that are very similar to the assumptions normally imposed in the evaluation literature for the estimation of treatment effects by using, for example, matching methods (N Fortin et al. 2011).

The overall difference in the means of the two samples can be attributed to four differences:

a) **D1.** Differences in returns to the observables

b) **D2.** Differences in returns to the unobservables

c) **D3.** Differences in the distribution of observables

d) **D4.** Differences in the distribution of unobservables

D1 and D2 must be collapsed in a single term because they cannot be separated out. Suppose, for example, that haemoglobin is explained by education (observable) and access to media messages (unobservable). Returns to media messages are likely to be higher for highly educated individuals. This means that an interaction term between *X* and *e* is needed that make the separation of D1 and D2 hard.

The difference in D4 is ignored by adopting the usual *unconfoundness* (or *ignorability* or *conditional independence*) assumption. We assume that unobservables other than the seasonal effect are equally distributed in the two groups. This is the standard assumption adopted in PSM methods. The Oaxaca method clearly fails if there are unobservable determinants of haemoglobin that are differently distributed in the two samples.

Two more adjustments to calculations are needed that are again similar to those adopted in standard PSM approaches. First, the vectors of covariates in the project and control equations should overlap. There should be no covariate (or value of the covariate) that is observed in one group but not in the other. This could be obtained by dropping communities or individuals outside the region of common support. Second, covariates and unobservables can be functions of seasonal factors. The unobservables are assumed to be equally distributed and equally affected by seasonal factors. However, if the covariates are affected by seasonal factors the seasonal effect is no longer identified. The covariates *X* therefore have to be chosen among those that are not affected by seasonal factors.

Conclusions and recommendations

The analysis above suggests that there are likely to be strong seasonal effects for three of the variables of concern: anthropometric data, malaria, and anaemia. However, that is based on secondary data so we would like to suggest that the PRG consider a two pronged approach when considering what to do with the issues of seasonality in the MV baseline data: (i) analyse the data to see if seasonality is present; and (ii) consider correcting the data to adjust for seasonality concerns. With regards to point (ii) we would suggest that the Oaxaca method be used in combination with focusing on specific subgroups for specific variables of interest.

Examining seasonality concerns in MV data

The secondary analysis above suggests one might be able to find effects of seasonality in the MV baseline data if specific subgroups are considered.

- The malaria prevalence amongst infants changes rapidly from April to September, the period when the MV baseline data was collected. Therefore, one could examine how correlated the prevalence of malaria is for infants (or young children) with the date of collection. If seasonality is present then there should be a strong linear trend for both MV and CV data.

- Average levels of haemoglobin seem to decrease linearly from the dry season to end of the rainy season. Therefore, we can see if there is a trend in the average level of haemoglobin with the date the data was collected.
- Despite the lack of a clear pattern for anthropometric data based on the analysis above, it could be examined if there are significant differences in the data based on the collection date. However, there is no hypothesis on what pattern should be seen.

The ability of the three suggested approaches to enlighten discussions on whether there are seasonality concerns in the baseline data will depend on how the sample was collected over time (i.e. were data collected uniformly over the period or primarily on one or two days).

With the analysis of seasonality conducted on the baseline data, we propose that the PRG consider four approaches to deal with correcting for seasonality or examining how big of a bias seasonality might have on the regression results.

Anthropometric analysis

Once two waves of data have been collected, we suggest that the following set of regressions be considered together:

a) DD regression results on weight-for-height (WFH), height-for-age (HFA), and weight-for-age (WFA).

b) DD regression results on subset of samples selected using standard PSM techniques:

    I. Make sure the underlying sample is as similar based on observables.[4]

c) DD regression on data where the Oaxaca estimated seasonality effect[5] has been removed.

d) DD regressions on the subset sampled in April in the MV and September in the CVs:

    I. This sample will have the largest difference in time between data collection.

Under ideal conditions the estimate from (a) would be 'correct.' Therefore, comparing the results of (a) to the other sets of regressions will allow the researchers to determine how much of an issue baseline differences might be when estimating the effect of the MV. For instance, conditional on observables, the estimates from (a) and (b) should be similar, if they are not that suggests that underlying difference – such as timing – might affect the estimate. The estimate from (c) should be corrected based on the discussion above. This method primarily corrects for observable differences in the distribution just as in (b). Therefore, comparing (a) to (c) should provide an indication regarding how potentially biased (a) is. Note that one needs to consider issues of standard errors in any regression where data has been corrected; the bootstrap method would be appropriate to use here.

The estimate from (d) should be 'most biased' due to seasonality. Therefore, comparing the estimate from (a) to that of (b), (c), and (d) should provide some estimate on the size of the bias.

[4] One would have to be careful to make sure variables used in matching are not also affected by seasonality.

[5] One would have to assume the entire effect due to unobservables estimated under Oaxaca was because of seasonality for the data to be corrected in this manner.

Anaemia and malaria

Given that anaemia and malaria data are collected only for children under five years of age, we suggest the following set of regressions be considered together:

a) DD regression results on malaria and anaemia.

b) DD regression results on subset of sample selected using standard PSM techniques:

    I. Ensure the underlying sample is as similar based on observables.

c) DD regression on data where the Oaxaca estimated seasonality effect has been removed.

d) DD regressions on the subset sampled in April in the MV and September in the CVs:

    I. This sample will have the largest difference in time between data collection.

e) DD regressions for malaria on the subset sampled in June in the MV and August in the CVs because this sample will have the smallest difference in time between data collection.

f) Calculate the difference in anaemia for children under one year of age and children who are four or five in the:

    I. MV area

    II. CV area

The estimates in (a), (b), (c), and (d) can all be compared as above.

Malaria is particularly sensitive to seasonal considerations and has a clear pattern, at least for children, as time moves towards the rainy season (refer to the table from Cairns et al. (2011) above), therefore the estimates in (d) should be 'very' different from those in (e) if seasonality is causing large differences. In fact, the estimate from (e) should be the minimal seasonal effect and those from (d) should be the largest seasonal effect. The data can then be corrected appropriately.

The difference in the level of anaemia between infants is larger than for children. Therefore if the estimated difference in (f)(i) is significantly different than (f)(ii), that would suggest that there is an effect of seasonality. Under strong assumptions, one could then correct the data based on the difference in the difference of (f)(i) and (f)(ii).

Please note that when data is corrected for potential seasonality effects it is not immediately clear how the standard errors of the regressions should be corrected.

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