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Is household shock a boon or bane to the utilisation of preventive healthcare for children? Evidence from Uganda

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ABSTRACT

A stylised fact in the development literature is that resource-constrained households in low-income countries invest very little in preventive healthcare. This paper investigates how the households trade off investment in their children's preventive healthcare during idiosyncratic shocks when resources are even more limited. By using the incidence of flood or drought as a proxy for negative income shock, and illness of any household member as an indicator for negative health shock, I examine the shocks' effects on the intake of Vitamin A Supplementation (VAS) by children. With four waves of panel data from the Uganda National Panel Survey, results from a household fixed effects analysis show that children under two years of age are significantly more likely to get VAS as a part of their immunisation schedule when the household is under health or income shock. Further investigation shows that this effect of health shock results from the increase in average time spent outside the labour market by the household adults due to illness. On the contrary, an income shock has a positive effect on the average time spent in the labour market. However, a negative interaction effect of the income shock with the household wealth level implies that the relatively wealthier households could be substituting labour hours with the otherwise time-intensive preventive healthcare activities, thus increasing the VAS uptake.

JEL Classification: I12, I30, J13, 012, O15

Keywords: household shocks, preventive healthcare, child immunization, time allocation, Uganda, Africa

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1. Introduction

Although preventive healthcare, such as immunisation, is a proven tool for controlling and eliminating life-threatening diseases, a stylised fact in low-income countries is that households do not invest much in preventive healthcare (Dupas, 2011). According to Dupas, one possible explanation for this could be the high opportunity cost of time for resource-constrained households.[1] Building on this argument, one can expect that in times of negative shocks to the household, when the resources are even more limited, parents would postpone immunisations of their children in order to cater to the bigger crisis at hand. But does this outcome vary with the type of shock suffered? To elucidate, in credit-constrained households, a negative income shock is likely to have a strong income effect on healthcare, especially on preventive healthcare; but on the other hand, if the shock is health-related, e.g. a household member is ill, it could bring awareness in the household about the importance of health. With respect to health shock, it can be argued that if demand for healthcare is a derived demand from that for health (Grossman, 1972), households with reduced health stock will gain higher marginal utility from health, and hence invest more in preventive healthcare. In addition, one could even point out that if a household member has to stay away from work due to illness and/or has to visit the health-centre for remedial care, then the additional cost of taking the child along for preventive healthcare would be lower. This latter argument holds provided that preventive healthcare for children is publicly available for free and that the household only needs to invest time to use that. These various theoretical possibilities justify the need for an empirical investigation into the relationship between different types of shocks faced by resource-constrained households and their preventive healthcare investments. This paper attempts to shed some light on that, and in doing so, also examines the underlying mechanisms of the effects.

With an empirical investigation of Ugandan households, I find that while facing a decrease in total income or a deterioration in health status, low-income households are actually more prone to take their children for immunisation, and this is associated with the increase in time away from the labour market in times of shock.

In the literature of income shock and healthcare for children, the focus, so far, has been mainly on the relative strength of income and substitution effects of aggregate shock, and the evidence on that from developing countries is quite nuanced. Two most relevant studies in this context are by Miller & Urdinola (2010) and Fichera & Savage (2015). However, their evidence are contrasting. By using world coffee price fluctuations as a proxy for aggregate income shock, Miller & Urdinola (2010) find evidence of countercyclical time-intensive child health investments in Columbia, i.e. a stronger substitution effect. They find that when coffee prices are high, parents choose to work and thus do not have time for health investment. On the

[1] While a high opportunity cost of time could be considered to be a consequence of resource/liquidity constraints, other reasons for low investment in preventive healthcare that have been recognised in the literature, are lack of information and behavioural biases (Kremer & Glennerster, 2011).

other hand, Fichera & Savage (2015) who instrument positive income shock with rainfall measurements, find evidence of a stronger income effect in Tanzania, in which a rise in income reduces illness and increases vaccinations for children under six.[2] According to the broader literature of child human capital formation, which follows a similar conceptual framework, most studies based on developing countries have investigated income shock at an aggregate level. Björkman-Nyqvist (2013) finds that negative income shock, measured by reduced rainfall, lowers children's educational hours in Uganda; whereas Shah & Steinberg (2017) find evidence from India that positive aggregate shock measured by rainfall, increases the opportunity cost of schooling and thus increases the school dropout rate. Beegle et al. (2006) conduct one of the very few studies that focus on the effects of an idiosyncratic income shock. They look into children's educational outcomes in Tanzania; findings imply that households, when hit by negative income shock (proxied by sudden crop loss), tend to increase the use of child labour to substitute adult labour in household activities.

The bias in attention on aggregate income shocks in comparison to idiosyncratic ones comes from some strong arguments put forward by the advocates of the former. Ferreira & Schady (2009) argue that an idiosyncratic shock is less interesting because it usually has no substitution effect unlike aggregate shock; Townsend (1994) proposes that an idiosyncratic shock may lack strong manifestation because it can be easily insured away by formal and informal mechanisms. While these arguments are pretty well-founded, one must also consider certain difficulties that arise in estimating the true effect of an aggregate income shock. Hyder et al. (2015) stress that measured aggregate shocks are effectively the average of individual shocks that vary considerably within heterogeneous communities; in that sense, the use of individual idiosyncratic shocks rather than community averages may represent with less measurement error what individual households experience. Another drawback of an aggregate shock is that often it interferes with the supply of services and thus makes it difficult to understand true demand. For example: when the public sector is an important provider, if public spending on health or education is procyclical and if expenditures and service quality are linked, then cuts in public expenditure on these services may reduce the value of schooling and healthcare to households during recessions. Under such circumstances, the income effect gets more pronounced (Ferreira & Schady, 2009). In light of these arguments, studying the effect of idiosyncratic income shock could provide a better and truer understanding of demand by the households.

Moving on to the literature of health shocks, this shock ranks the highest in terms of incidence, idiosyncrasy, costs and impact among the poor (Wagstaff & Lindelow, 2014). However, the literature is quite scarce when it comes to health shock and its effect on healthcare. To date, there is only some evidence on its effects on children's educational outcomes; Bratti & Mendola (2014) in their study based in Bosnia-Herzegovina and Alam (2015) in his study based in Tanzania, confirm that parent's illness affects children's educational

[2] According to Fichera & Savage (2015), this difference in outcomes of the two studies could have been due to insufficient weather-related variations to income compared to that from coffee price variations which in turn did not affect the opportunity cost of time. Furthermore, a stronger income effect than substitution effect in their study could have resulted from the better access to health-centres which also did not affect the opportunity cost of time that heavily.

outcomes to varied extents for different age cohorts.

It can be summarised from the above studies that the literature associating household-level income or health shocks and investment in children's preventive healthcare (or broadly, in child human capital) in developing countries is quite scarce. This sufficiently invigorates our curiosity to empirically examine the effects, if any, of both types of shocks on preventive healthcare for children. Uganda provides an ideal set-up to test the effects of idiosyncratic income and health shocks on household's investment in preventive healthcare for children. It is a financially poor country in Sub-Saharan Africa and currently holds rank 162 out of 189 countries in the Human Development Index. The under-five child mortality rate of the country is 54.6 per 1,000 live births (United Nations Development Programme, 2016). The Ugandan Ministry of Health had already recognized in 2010 that 75% of the disease burden in the country could be averted by immunisation, hygiene and sanitation, nutrition and other preventive healthcare practices and health-promoting activities. The Ugandan National Expanded Programme on Immunisation has been functional for over four decades with a goal that every Ugandan child should be fully vaccinated; and since 2001, the Ugandan National Minimum Healthcare Package entitles every Ugandan a free basic healthcare coverage at public healthcare facilities. In spite of the availability of these programmes, the outcomes on child health are not promising. In 2011, only 52% of children aged 12-23 months were fully vaccinated and only 40% of children aged 12-23 months were immunized before their first birthday (Uganda Bureau of Statistics, 2012). Given this status, it seems logical to investigate if income or health shock at the household-level acts as a demand-side barrier and potentially hinders utilisation of preventive healthcare for children; and also, if the household's trade-off on investment for preventive healthcare varies with the type of shock suffered.

When it comes to preventive healthcare for small children, the best outcome variables to discuss are those related to immunisation.[3] Ugandan Health Ministry and UNICEF strictly recommend that all caretakers of children between 6-59 months should take them to healthcare facilities to receive Vitamin A Supplementation (henceforth, VAS) every six months, as a part of their immunisation and health promotion schedule. In this study, I use the receipt of VAS as the main outcome variable. According to the Uganda Demographic and Health Survey (2011), Vitamin A deficiency is a major public health problem in Uganda with deficiency rate as high as 33% among children under five. With Vitamin A deficiency, the overall immunity of the human body is threatened, and the chances of developing blindness are high. In this paper, I use four waves of panel data from the Uganda National Panel Survey and examine the effect of negative health shock, indicated by illness of any household member, and negative income shock, proxied by the incidence of flood or drought, on the intake of VAS by children under two years.

Primary results from a household fixed effects analysis show that the probability of taking the child to get VAS increases significantly if the household is hit by a negative health shock. Similar evidence is obtained in case of negative income shock too. As mentioned above, no direct cost is incurred by Ugandan households

[3]The words *immunisation* and *vaccination* are often used interchangeably in this context.

in getting their children immunised, however, they could face indirect costs (e.g. from transportation to healthcare facilities) and/or opportunity cost of time which they spend in accessing healthcare services. In the event of health shock, the latter cost (in other words, time spent away from labour market activities) seems to drive my primary findings. Evidence shows that a typical member of a household hit by health shock spends significantly less time in labour market activities than one from a shock-free household. This could mean that the inability to be at work due to illness reduces the opportunity cost of this 'forced' time away from the labour market, which is then used for remedial care and health-promoting activities for their children. In case of an income shock, though it is difficult to pin down the underlying mechanism, the evidence in this study shows that the average effect of income shock on time spent in the labour market is positive; however, an interaction of the shock with the wealth of the household reveals that a relatively wealthier household spends lesser time on average in labour activities during the shock. So the positive effect that I find on the intake of VAS could possibly be driven by the wealthier households substituting preventive healthcare activities for labour (as the opportunity cost of labour hours decreases). Keeping in mind the caveat of health shock confounding with income shock, I put the findings through a battery of robustness checks, and the results remain consistent. Note that most findings of this study are statistically significant at only 10%, and thus calls for further research in similar settings in order to draw a strong conclusion.

This paper is one of the only two works which simultaneously explore effects of both income and non-income shocks on child human capital investment, the other work being by Bandara et al. (2015) which is about child labour in Tanzania. The results obtained in this paper contribute to the line of literature which supports the primacy of time in households for child healthcare (Grossman, 1972; Gronau, 1977; Vistnes & Hamilton, 1995; Miller & Urdinola, 2010). This body of literature agrees that health investment is costly as individuals must trade off time and other resources related to health, and therefore, it affects the optimal demand for health.

From a broader perspective, shocks to health and income are mere identifications of whether they matter for the optimal utilisation of healthcare for children. There is a growing literature on the effect of unconditional and conditional cash transfers in low-income settings on the uptake of vaccinations, and other health and educational outcomes. Works by Barham & Maluccio (2009), Ranganathan & Lagarde (2012), Robertson et al. (2013), etc. identify that the financial barriers to full utilisation of curative and preventive healthcare can be minimised through cash transfer programmes. Among these financial barriers, one is the opportunity cost of time spent on accessing health services instead of being spent on income-generating activities. In this connection, my paper makes a contribution to this body of literature which identifies the demand-side financial barriers in utilising healthcare.

The remainder of the paper is organised as follows: Section 2 introduces the data and the summary statistics; Section 3 consists of the empirical specifications; Section 4 summarises the results, followed by a conclusion in Section 5.

2. Data and summary statistics

2.1. Data

The data consists of four waves of the Uganda National Panel Survey (UNPS) collected in 2009-10, 2010-11, 2011-12 and 2013-14. The UNPS was implemented by the Uganda Bureau of Statistics with financial and technical support from the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) programme of the World Bank. For my analysis, I use data from the household and community modules of the survey.

In the survey, a *household* is defined as a group of people who have been living and eating their meals together for at least 6 of the 12 months preceding the interview. Therefore, the members of the household are defined by their usual place of residence. The first wave of UNPS consists of 2975 such households tracked and interviewed from a nationally and regionally representative sample of 3123 households that were originally interviewed in the Uganda National Household Survey (UNHS), another survey in 2005-06.[4] The 2975 households of the first wave of UNPS include 2607 households retained from those 3123 households after attrition and an additional 368 *split-off* ones.[5] The second and third waves consist of 2716 and 2850 households respectively, after accounting for attrition and tracking of split-off households. The retention rate of the original households between waves 1 and 2 is 89% and that between waves 2 and 3 is 92.4%. In the fourth wave of UNPS, a part of the sample of the third wave was dropped and replaced with a 'fresh' sub-sample of households. This fresh sub-sample was extracted from updated sample frames developed by Ugandan Bureau of Statistics as a part of the 2012 Uganda Population and Housing Census.

As already mentioned, here I use the receipt of VAS by children as the outcome variable on immunisation (or, preventive healthcare). Among other immunisation categories available from the survey, such as measles and DPT-3, I prefer the study variable to be VAS because it is not a one-time dose like the other categories and thus allows me to have a richness of observations by including one child more than once in the analysis. The household questionnaire of UNPS asks the question whether the child had received VAS during the last six months starting from the survey interview date. Since the question concerns intake of VAS in the past six months from the date of the survey interview, only those children who are at or above 12 months of age during the interview, were eligible for VAS intake in the aforementioned time period. In my analysis, I include only the children eligible for VAS. However, this dataset has information on VAS intake by children

[4]The 2009 UNPS is a sub-sample of the 2005-06 UNHS. To select the sample for the UNPS, the UNHS sample was divided into five strata (Kampala, Central, Eastern, Northern and Western). Within each stratum, Enumeration Areas were selected using simple random sampling.

[5]Before the fieldwork of the first wave started in 2009-10, a random sub-sample of 20% from each Enumeration Area, that added up to a total of 643 households, was drawn from the already sampled panel households. If a chosen household indicated that any person who was a member in the 2005-06 survey had left, that 'mover' referred to as split-off would be followed. 430 split-offs were interviewed in the first UNPS and by that time they formed 368 households (from UNPS Reports on waves 1 and 3).

up to the age of 24 months only. Therefore, this analysis is restricted to households that have at least one child between 12-24 months at the time of the survey. Also, since the analysis spans over four annual waves, it is unlikely that one household with only one child between 12-24 months of age would be present in all the four waves unless another child is born in that household. This gives the panel an unbalanced structure. Aiming for a balanced structure of the panel would constrict the dataset to a reduced number of observations.

In this study I identify household shocks of two types - a health shock and an income shock. Throughout the paper, by *shock* I mean a *negative* shock that causes a decrease in the current level of health or income. As a proxy for income shock, I use household-reported shock due to flood or drought/irregular rains in the past six months. Use of agriculture and weather-related variables as proxies for income shock is quite common in the context of developing countries where cultivation is the main livelihood. Some of the proxies used in the literature are accidental crop loss at the household level (Beegle et al., 2006; Bandara et al., 2015), rainfall variation at the district level (Björkman-Nyqvist, 2013; Shah & Steinberg, 2017). In my sample, 50% of the households (having children between 12-24 months), have agriculture as their main income source, with 4% of them doing commercial farming and 96% doing subsistence farming.[6] Therefore, it is reasonable that drought or flood would be ideal candidates for income shock here.

For health shock, I use household-reported information on serious illness or death of any household member in the past six months. In related literature, Bratti & Mendola (2014) focus on self-reported health status of the parents of the child as a measure of health shock, whereas Alam (2015) uses self-reported health status of other household members too; Bandara et al. (2015) use death as a measure of health shock.

The information on shocks is available from the same survey module; the questions being polar, i.e. if the household suffered a shock due to flood or drought/irregular rains in the past year, if the household suffered a shock due to a serious illness/death of a household member in the past year, etc. Last but not the least, I define the incidence of the shock (health/income) as the presence of shock in the household during the last six months from the interview, and this shock could have started even before these last six months but continued into these six months.[7] The reason behind focussing on only the past six months for the experience of shock is due to the fact that the information on VAS dose is available for the prior six months only, and thus, I would get the best possible overlap of the two events.

[6]In Uganda, above 60% of the population, is engaged in agricultural activities and more than 80% of the farming community consists of subsistence or smallholder farmers. These subsistence farmers usually cultivate less than one hectare of land and own a few heads of cattle. They produce crops and/or raise livestock for family consumption with little surplus for the market. Subsistence farming is mostly labour-intensive and is mainly run by household members with no/limited ability to hire outside labour. Usual lack of transport and high transaction costs along value chains often lead them to sell the surplus in local markets and to local traders with negligible profits.

[7] The survey contains information on the start date and the end date of a shock and thus lets me calculate its incidence in the six months prior to the interview.

2.2. Summary statistics

Table 1: Summary statistics of households with and without shock

Variable	Household with no shock		Household with shock	
	Mean	Std. Dev.	Mean	Std. Dev.
Age in years of household-head	39.39	12.83	41.44	13.53
Household-head ever attended school	0.89	0.31	0.83	0.38
Household-head married	0.88	0.32	0.84	0.37
Household members away from household due to work	0.08	0.30	0.07	0.28
Household members living in the household all year round	4.13	2.41	4.36	2.54
Logarithm of total household assets' value (in Ugandan shillings)	14.96	1.77	14.78	1.74
Average number of weeks in the labour market	12.04	13.71	14.20	14.86
Number of children up to five years of age in the household	2.01	0.92	2.21	0.98
Average age of the infants (12-24 mo.) in the household	18.12	3.89	18.02	3.90
Household which faced a health-related shock	0	0	0.26	0.44
Household which faced an income-related shock	0	0	0.83	0.38
Number of observations	1486		553	

Notes: These statistics are obtained by comparing the households with atleast one child of 12-24 months. A household can appear multiple times across the waves.

Table 1 summarises a comparison of the households which faced any shock, health or income, in the past six months with the households that did not. The following statistics pertain to only those households that had at least one child of 12-24 months in at least one survey wave. In **Appendix B Table B1**, I similarly compare the households with at least one child up to five years of age, and the findings do not vary.[8] Typically, the head of a shock-free household is about 40 years old, with about 89% chance of ever attending any school and 88% chance of being married, and the average number of weeks spent in the labour market by a household member is about 12. These figures are slightly different in a household that suffered a shock in the past six months. Among the other variables, the means remain more or less similar across both the groups, with about one person in the household being away from home for work, about four permanent members being present all the year round, about two children in the household being under five and the mean age of children under two being 18 months. Across both the categories of households, the logarithm of the total value of household assets is about 15 Ugandan shillings.[9]

Table 2 provides the means of the variables of interest across all the four waves. On average, 73% of eligible children received VAS in the past six months interval from the interview date. More than 80% of the children are reported to have received their DPT-3 and measles vaccines. Among other child-related variables, 97% of children were breastfed at birth and 92% have their mothers and 73% have fathers living

[8]The comparison with a bigger sample is to ensure that the households with children between 12-24 months are not, in any meaningful way, different from other households with small children (here, under five).

[9]This is equivalent to a total assets value of about 860 USD.

Table 2: Summary statistics by panel waves

Variable	Mean	Std. Dev.
Child related variables:		
Infants (12-24 mo.) who received VAS in last six months from interview date	0.73	0.44
Infants (12-24 mo.) who has received DPT3 vaccine	0.85	0.36
Infants (12-24 mo.) who has received measles vaccine	0.84	0.37
Infants (12-24 mo.) who were breastfed	0.96	0.19
Infants (12-24 mo.) who slept under bednet the prior night	0.60	0.49
Infants (12-24 mo.) whose mother lives in the same household	0.92	0.27
Infants (12-24 mo.) whose father lives in the same household	0.73	0.44
Infants (12-24 mo.) whose mother has no education	0.002	0.05
Infants (12-24 mo.) whose father has no education	0.02	0.14
Household related variables:		
Household with main income source as agriculture	0.52	0.49
Household with main income source as subsistence farming	0.50	0.50
Household members away from household due to work	0.08	0.29
Household members present in household all year round	4.20	2.45
Number of children up to five years present in household	2.06	0.94
Average number of weeks in the labour market	12.61	14.05
Health Shock related variables:		
Households suffering from health shock in the last six mo.	0.07	0.26
Number of months suffered due to health shock	2.83	3.07
Income Shock related variables:		
Households suffering from income shock in the last six mo.	0.22	0.42
Number of months suffered due to income shock	3.54	2.04

Notes: This table provides the mean over all four waves of survey. The household and shock statistics are only for those households which had at least one child between 12 to 24 months in at least one wave, the number of such households being 1604. The child-related statistics span over 2061 children of 12-24 months.

with them in the same household. Compared to these figures, healthy lifestyle measures such as sleeping under a bed net is still not very common - only 60% of children are reported to have slept under bed nets the previous night. Among the health shock related measures, 7% households suffered from a shock in the past six months; the absolute span of health shock i.e. the total number of months of suffering from the shock, was 2.83 months on average (the maximum recorded being 12 months). 22% of the households reportedly suffered from income-related shock in the last six months; the total span of an income shock was 3.54 months on average (the maximum recorded being 12 months). These figures validate that the households in the sample suffered from these shock types only for a few months and hence, the possibility of any related chronic condition can be discarded. Also, the percentage of households suffering from an income shock suggests that the shocks were not all-pervasive to be considered at a large aggregate level (given that it is proxied by flood or drought). Appendix Table **Appendix B Table B2** reports these statistics for the bigger sample of households with children under five years.

3. Identification strategy

I use a linear probability model specification as given below, where I include each shock type as an independent variable.[10]

$$Y_{iht} = \beta_0 + X'_{iht}\beta_1 + \beta_2 HealthShock_{ht} + \beta_3 IncomeShock_{ht} + \alpha_h + \mu_t + \epsilon_{iht} \quad (1)$$

where the subscripts index over child i, household h and survey wave t. Y is the binary outcome variable on the intake of VAS by child i in household h during six months interval before the interview date in survey wave t. *HealthShock* and *IncomeShock* are binary variables denoting experience of negative shock related to health and income, by the household during the same time interval.[11] An income shock is proxied by the incidence of flood or drought; and, health shock is indicated by the illness (or, death) of any household member. X is a set of controls consisting of child and household characteristics that vary over survey wave t. I further include household fixed effects α_h and survey wave fixed effects μ_t. The primary coefficients of interest are β_2 and β_3; they measure the effect of the negative shock experienced by household h in survey wave t on the intake of VAS by child i in the same household in that wave. I use household fixed effects to control for a number of observable and unobservable time-invariant characteristics of the household that could potentially affect shock incidence as well as VAS intake by the eligible children in the household. The use of household fixed effects absorbs all the across-households variation and produces an estimate of the predictor's average effect within households. With the inclusion of household fixed effects, the effect of idiosyncratic risk is investigated and while doing so the time-invariant household risk factors are removed. Finally, the additional use of survey wave fixed effects allows controlling for heterogeneity arising across the survey waves.

I control for individual-level variables for the children, such as quality of care received. These include: if the mother lives in the same household, if the father lives in the same household, if the mother received any education, if the father received any education, if the child had been breastfed at birth.[12] Here, one must use caution while controlling for various individual-level variables on the (quality of) care received, because

[10] A linear probability model specification is clearly preferable here because of the *incidental parameters problem* where the use of non-linear panel data models with fixed effects potentially leads to biased and inconsistent estimates (Greene, 2004; Wooldridge, 2010).

[11] In reality, income and health shocks are bound to confound with each other. Therefore, having both the shocks together in one regression equation could posit multicollinearity challenges. On a positive note, the correlation between the two shock types in my sample is only 0.027, and thus the concern for multicollinearity is minimum. Nevertheless, I again discuss this inseparability issue of the two shocks in greater detail in Section 4.3.2.

[12] Note here, the eligible children within a household do not necessarily belong to the same set of parents.

those variables themselves could potentially be affected by the shock.[13] In this vein of argument, I stress that the control variable on breastfeeding is recorded during the birth hour and is unlikely to be affected by the shock that occurs in the past six months in the household with a child of age 12-24 months. Furthermore, among child-related controls, I use a separate indicator denoting if the child was at the sixth month of its age during the past six months. The reason behind including this indicator is that children start their VAS eligibility schedule at the age of six months, so the parent/caregiver in the household is likely to be more alert about the first schedule.

To further minimise the possibility of omitted variable bias through time-variant household features, I control for the number of children under five years present in the household during survey (this number potentially affects the amount and quality of information which a household has on child healthcare), the total number of permanent[14] members in the household (the more the number of adults in the household the more their cumulative work-free time which could be invested in childcare), the logarithm of the total value of household assets. I further control if the family relocated in the past few years, if the survey interview was being done in a rainy season and if the household lived in a flood-prone region.

In a less-parsimonious version of the model, I also include some health supply-related variables. They are, information on the nearest health facility - whether it provides general outpatient care, whether provides immunisation doses, whether a major limitation of the facility is its remoteness, whether the lack of skilled staff is a major limitation. These health supply-related covariates are likely to be correlated with the income shock as well as VAS uptake; if flood or drought affects a community, the health supply and the demand both are susceptible to getting affected. Note that these are time-variant for the following two reasons, and hence, cannot be absorbed by household fixed effect: the survey design allowed tracking of the sample households or their split-off parts that moved within parishes/communities , and also, in the five-years' span of the four panel waves, many of these health supply facilities expanded.

In another version of the model, by the same reasoning on the time-variance, I control for some variables which indicate the locational advantage and road-networking of the household. I include the distance of the household to the nearest facilities; these are - distances to the public health facility, to the markets selling agricultural inputs, agricultural produce, non-agricultural produce, to the primary market for livestock, to the nearest major roads with gravel and tarmac, to the nearest feeder road.[15]

Regarding the identification strategy, one concern is with the exogeneity of shocks. One could argue that more vulnerable households could more likely be hit by shocks. In addition to having household fixed effects, I address this in the best possible way by including time-variant household features that could

[13] The *bad controls* problem in econometrics.

[14] A *permanent* household member is the one who resides in the household all year round.

[15] To give some perspective, the development of road networks has been on the rise in Uganda; reportedly, from 2009-12 paved roads increased to over 3,500 kilometres with 1,500 kilometres of major roads then under construction. In 2013, construction of over 1,000 kilometres of roads started. So, definitely, the new road networks had quite an impact on the access to all amenities in life.

potentially contribute to its vulnerability in being hit by a shock (e.g. the location of the household in a flood-prone region, the season of the survey interview, and the number of household members present in the past year, relocation of the family in recent years, etc.). Nevertheless, one must bear in mind that time-variant unobserved heterogeneity of the households cannot be entirely wiped out with survey data analysis and hence, leaves some chance for bias in case it drives some of the effects.

As a final note regarding the chosen identification strategy, a better alternative of an income proxy could be to instrument the household income with the reported shock due to drought or flood and proceed with a two-stage least squares (2SLS) model, as, Fichera & Savage (2015) use the weather shock of period $t-1$ as an instrument of income in period t. However, here arises the problem of data limitation of the survey. Information on past year's household income from crop-farming, other agricultural and non-agricultural enterprises is only available for the first three waves, and that too, sparsely. This causes a sample size challenge in 2SLS estimation. As a result, I resort to the currently chosen strategy, given by Equation 1 which can be seen as a reduced-form of the IV strategy.

4. Results

4.1. The effects of shocks on intake of VAS

In **Table 3**, I present the regression estimates of Equation 1. Column (1) depicts the findings for only the two shock types without any controls and Column (2) includes the controls, excluding household fixed effects. It is only in case of income shock that a precise positive effect is found when controls are included (in Column (2)). Columns (3)-(5) include the household fixed effects, but each column differs in the degree of time-varying controls. The R^2 value of Columns (3)-(5) is the *within* value which suggests how much of the variation in the dependent variable within the household units is captured by the model. Note that this value is already higher than the corresponding R^2 values in Columns (1) and (2) which give the overall variation in the dependent variable explained by the models without household fixed effects. This confirms that the models including household fixed effects are more appropriate in this study's analysis. As a result, the discussion of the findings henceforth will be mostly concentrated on the household fixed effects analysis.

Now, in Column (3) are the estimates of the model where I do not include the indicators of health supply and distances to other facilities. We see that an experience of health shock in the household in the last six months increases the probability of VAS intake by the child during the same time interval by 14.4 percentage points (pp.) ($p = 0.067$), while an income shock has an effect of 9.4 pp. ($p = 0.090$) during the same time interval. Column (4) shows that when the health supply indicators are included as controls, these two estimates remain unchanged. With further inclusion of controls on distances to the other facilities, the income shock estimate loses its precision ($p = 0.122$) (Column (5)). Note that the income measure is given by drought or flood which is likely to affect areas within a few kilometres radius alike. Therefore, when I constrict the geographical boundaries by including the distance controls, it is plausible that not too much variation arises in the income shock incidence on households within these cluster areas.

Table 3: Effect of the shock types on intake of VAS by child in the household in last six months

	(1)	(2)	(3)	(4)	(5)
Health Shock	0.026	0.051	0.144*	0.145*	0.147*
	(0.038)	(0.038)	(0.079)	(0.078)	(0.081)
Income Shock	0.018	0.050**	0.094*	0.091*	0.088
	(0.024)	(0.024)	(0.056)	(0.056)	(0.057)
Controls[a]	No	Yes	Yes	Yes	Yes
Health supply covariates	No	Yes	No	Yes	Yes
Distance covariates	No	Yes	No	No	Yes
Households FE	No	No	Yes	Yes	Yes
Surveywave FE	No	Yes	Yes	Yes	Yes
No. of obs.	2109	2109	2109	2109	2109
No.of households	1592	1592	1592	1592	1592
R-sq.	0.001	0.095	0.074	0.081	0.131

Notes: (1) * indicates significance at 10%; (2) [a] includes household level controls - log of total value of household assets, number of children under five, number of permanent members, if the family had moved in recent past, if interviewed in a rainy season, if lived in a flood-prone region; and individual level controls as neonatal care received (breastfed at birth), presence of mother, presence of father, education of mother and father and if attained 6 months of age 6 months ago; (3) Standard errors in parentheses, clustered at household level; (4) The overall mean of VAS intake is 0.73; (5) The R-squared for the household fixed effects models in Columns (3)-(5) is the within-R-squared; (6) Refer to **Appendix B Table B3** for an extended version of this table.

4.2. Investigating the channels of effects

One plausible channel of effect of the shocks on VAS intake (which is available free-of-charge) is the time spent away from the labour market by the household adults. One could reasonably expect that the total labour hours of the household would decrease under health shock, due to hours of illness spent at home and/or due to seeking of remedial healthcare. Under such circumstances, the opportunity cost of getting some preventive healthcare for the child is low, e.g. while visiting the health-centre for remedial purposes, the child is carried along to get immunisation doses. Dillon (2013), for example, find evidence from northern Mali that morbidity shock in the household increases the time spent in childcare. But when it comes to an income shock, it is likely that low-income households would look for ways to smooth the shock, and as a result the average time spent in the labour market would probably increase. However, the result of Table 3 above, that VAS intake increases with incidence of income shock, hints towards a different possibility and thus calls for further investigation.

To examine how the labour participation reacts to the incidence of the shocks, I regress the average labour weeks spent in their main activity in the labour market by a permanent household member on the two shock types after controlling for the usual covariates.[16]

[16]According to the survey questionnaire, *main activity* of an individual is the one in which s/he spent the most time as a

Table 4: Effect of the shock types on the average weeks of labour participation

	(1)	(2)	(3)	(4)	(5)
Health Shock	-0.113	-2.127**	-6.330***	-5.895***	-4.473**
	(1.229)	(0.911)	(2.333)	(2.464)	(1.985)
Income Shock	3.460***	1.133*	3.957**	3.860**	4.368***
	(0.962)	(0.685)	(1.766)	(1.736)	(1.793)
Controls[a]	No	Yes	Yes	Yes	Yes
Health supply covariates	No	Yes	No	Yes	Yes
Distance covariates	No	Yes	No	No	Yes
Households FE	No	No	Yes	Yes	Yes
Surveywave FE	No	Yes	Yes	Yes	Yes
No. of obs.	1518	1518	1518	1518	1518
No.of households	1255	1255	1255	1255	1255
R-sq.	0.011	0.542	0.650	0.653	0.716

Notes: (1) ***,** ,* indicate significance at 1%, 5% and 10% respectively; (2) [a] includes household level controls - log of total value of household assets, number of permanent members, number of members in their prime age, if the family had moved in recent past, if interviewed in a rainy season, if lived in a flood-prone region; (3) Standard errors in parentheses, clustered at household level; (4) This analysis involves only the survey years 2010, 2011 and 2013 since the labour participation hours or weeks cannot be calculated for 2009 due to lack of data; (5) The overall mean of household labour weeks is 12.61; (6) The R-squared for the household fixed effects models in Columns (3)-(5) is the within-R-squared; (7) Refer to **Appendix B Table B4** for an extended version of this table.

In **Table 4**, Column (1) shows the average effects of the two shock types across households without any controls; only the income shock has a positive significant effect. When controls are included, Column (2) shows that the effect of income shock holds, and health shock too has a negative and statistically significant effect on the average labour hours across households. On including household fixed effects in Columns (3)-(5), I find similar results. Column (3) shows that with the experience of a health shock in the household in the past six months, the average labour weeks spent by a permanent household member decreases by 6.3 units ($p = 0.007$). Similar findings seen in Column (4) and Column (5), when further controls are included. This result supports the argument that as productivity gets negatively affected by illness, the opportunity cost of the 'forced' time away from labour market activities due to illness should get lower. So, during this time, taking the child for preventive healthcare is not costly in that sense. Also, it becomes easier for the household members to take the child(ren) along for VAS doses, when they visit the health-centre for remedial care.[17] Note that this finding on the labour force participation also holds for a bigger sample of

labour force participant in the past year; this could be her/his main job (sometimes also a second job or a third job) and it could be any income-generating (in cash/kind) work in agricultural or non-agricultural area, paid domestic work, work in own/household business (sometimes even without being paid), work with/without pay as apprentices, work in a household's farm (tending crops, feeding animals, etc.).

[17]One could be curious about what happens when the health shock in the household is due to the illness of the child itself.

households with children upto the age of five years, and is not just any selection effect. Although due to data limitations it cannot be further verified whether the number of visits to healthcare facilities by the household members also increases or not when struck by health shock, one interesting finding from the coefficients of the health supply covariates can be used to support the mechanism to some extent - the finding being, a stronger positive effect of the availability of general outpatient care at the nearest health facility on VAS uptake (in Column (4) of **Appendix B Table B3**). This hints toward an *economies of scale* approach, i.e. while visiting the health centre for remedial purposes, the additional cost of investing in some preventive healthcare alongside is quite low. In a similar vein, Goldman & Grossman (1978) point out that the time price is a fixed cost since it does not depend on the number of services received per visit. They show that adults with larger fixed cost obtain more services per visit. This reasoning could also be used to appropriately explain my finding.

In **Table 4**, the coefficient of income shock reveals a strong income effect, with the average labour hours increasing by almost 4 units ($p = 0.025$) (Column (3)) from the mean of about 12 weeks in a household facing no income shock. This result is robust to controls on the supply-side variables and distance controls (Columns (4) and (5)). However, this does not reconcile with the main finding of increased VAS intake with income shock in Table 3 Columns (3)-(5).

A further investigation by interacting the shock with the logarithm of household assets' value, provides some explanation for reconciliation of the two findings on income shock in Tables 3 and 4. This specification would help understand how the households with different wealth levels cope with the shock. Focussing on the household fixed effects estimation in Columns (3)-(5) in **Table 5**, we see that in case of income shock, a relatively wealthier household puts lesser time on average in the labour market. The levels of significance on the interaction coefficient are 9.7% and 9.5% in Columns (3) and (4) in case of the basic model and the one where I control for health supply related variables. In Column (5), however, where the distance to other facilities is controlled for, the coefficient of interaction between income shock and household wealth becomes less precise (significant at 14%) even though the magnitude is similar. The coefficient of direct effect of income shock is positive and statistically significant at 10% in all the three columns. Now, the interaction coefficient in say, Column (3) can be interpreted precisely as follows: in times of income shock, with a 10% increase in the household asset value (mean log value being = 12.61), the difference in the the expected mean time spent in labour market decreases by $2.09 * log(1.10) \approx 0.09$ week $\equiv$ 14.5 hours.

A decrease in the slope of wealth level in the time of income shock implies that the more wealth a household has, the less is the urgency to put extra working hours in the labour market. Such an increase in leisure hours is justifiable if the household draws down assets, or borrows credit, or receives transfers to insure away the negative income shock, and in addition, also finds it cheaper to substitute time away

Then it can be argued that an ailing child in the household implies that the closest caregiver is 'forced' to stay away from the labour market. Moreover, if the child is taken to the health-centre for remedial care, then it is more probable that its vaccination doses are updated too. I further discuss this concern in Section 4.3.4.

Table 5: Effect of the shock types on the average weeks of labour participation in households with different wealth levels

	(1)	(2)	(3)	(4)	(5)
log of total assets' value	-0.019	-0.051	-0.029	-0.041	0.157
	(0.216)	(0.191)	(0.664)	(0.679)	(0.710)
Health shock	-3.271	-13.015**	-14.932	-16.229	-24.805*
	(10.122)	(6.408)	(12.227)	(13.078)	(13.889)
Health shock X log of total assets' value	0.208	0.728*	0.622	0.743	1.423
	(0.689)	(0.421)	(0.862)	(0.925)	(0.954)
Income shock	-4.84	-1.368	34.612*	35.089*	32.473*
	(8.795)	(6.921)	(19.130)	(19.305)	(19.574)
Income shock X log of total assets' value	0.563	0.168	-2.092*	-2.133*	-1.921
	(0.596)	(0.464)	(1.261)	(1.278)	(1.301)
Controls[a]	No	Yes	Yes	Yes	Yes
Health supply covariates	No	Yes	No	Yes	Yes
Distance covariates	No	Yes	No	No	Yes
Households FE	No	No	Yes	Yes	Yes
Surveywave FE	No	Yes	Yes	Yes	Yes
No. of obs.	1518	1518	1518	1518	1518
No.of households	1255	1255	1255	1255	1255
R-sq.	0.012	0.542	0.657	0.660	0.722

Notes: (1) **,* indicate significance at 5% and 10%; (2) [a] includes household level controls - log of total value of household assets, number of permanent members, number of members in their prime age, if the family had moved in recent past, if interviewed in a rainy season, if lived in a flood-prone region; (3) The interaction terms gives the difference in slope of *log of total assets* when under a shock to that under no shock; (4) Standard errors in parentheses, clustered at household level; (5) This analysis involves only the survey years 2010, 2011 and 2013 since the labour participation hours or weeks cannot be calculated in 2009 due to lack of data; (6) The overall mean of household labour weeks is 12.61; (7) The R-squared for the household fixed effects models in Columns (3)-(5) is the within-R-squared.

from the labour market. For example, offsetting of transitory income shocks by households with the use of asset-holdings (either as buffer or collateral for credit) has been reported in earlier literature (Deaton, 1992; Beegle et al., 2006). The findings of Table 5 hold true even for a bigger sample of households with children upto five. Note, however, a similar examination of the effect of shock on households at different wealth levels on the uptake of VAS does not provide any precise estimates to directly confirm that relatively wealthier households are more prone to take up VAS for the child during income shock.

4.3. Robustness checks

4.3.1. Attrition and other sample issues

One potential concern regarding the dataset could be that of attrition. Although more than 90% of the households interviewed in the first wave were retained after the end of the third wave, it would be ideal to check if there is any effect of the shock on the probability of exiting the sample. I regress the probability of exiting the sample on the incidence of shock in the household in the previous wave and I find no significant effect. In **Table A1** in **Appendix A**, I report a summary of the findings.

Secondly, since the sample of the fourth wave was 'refreshed' by dropping a substantial number of households and adding new ones, one could argue that the sample loses its originality by the end of the four waves. Therefore, I check the results with a sample which omits the households that were freshly included in the last wave of the survey. The findings as shown in **Appendix A Table A2** remain similar to the main results obtained in Table 3.

4.3.2. (In)separability of health and income shock

The relation between health and income is often interconnected (Weil, 2014). So the possibility of a shock to one being correlated with a shock to the other is difficult to preclude. Here, I try to make the two channels of shock as mutually exclusive as possible and see if the findings change.

The indicator variable for health shock which I have used in the study so far takes value 1 if any household member became ill or died in the past six months from the survey interview date, and this includes even the main income earner of the household. However, one could argue that a health shock to the main income earner could actually interfere as an income shock for the household. Hence, I conduct a robustness check by omitting the health shock of the main income earner from the measure; now, the dummy variable for *HealthShock* takes value 1 if any household member except the main income earner was affected (i.e. got ill or died) in the past six months. **Table A3 Panel A** summarises the results. In all the specifications, we can see that the main finding on VAS intake does not change in any meaningful way. Only in Column (5), the coefficient of *HealthShock* loses precision (significant at 12.6%), but this could be due to the fact that the fraction of households suffering from health shock reduces (from 7% to about 4%) as I revise the dummy variable. (In relation to the health shock measure, one might also argue that *death* does not qualify as a health shock under all circumstances; for example, death due to old age, road accident, etc. Therefore, I conduct the same analysis by considering only the illness of any household member except the main income earner as an indicator of health shock. Now the fraction of households suffering from health shock reduces even further and that is most probably why the precision of the estimates is lost, even though the magnitude remains the same. The findings are summarised in **Table A3 Panel B**.)

In spite of these robustness measures, a caveat remains. Other household members are also likely to have labour force participation and thus contribute to the income pool of the household. As a result, their health shock could also affect the income of the household. An easy solution to this problem could be to examine if the experience of health shock by the household in the past six months has any effect on the household's wealth. By examining this, I do not find any statistically significant effect while using my original proxy of health shock; in contrast, the effect of income shock in the past six months on log of overall asset holdings in the household is negative and statistically significant. This implies that the health shock measure used here does not confound as an income shock. Results reported in **Table A4**.

While these above robustness tests still do not foreclose the possibility of income shock driving health shock, one can (optimistically) deduce from the positive effect of income shock on average labour hours of the household, that this path is unlikely, at least in this sample.

4.3.3. Effect on other child-health measures

As a further interest, I examine how the shocks affect other health measures of the children in the household . Through the following exercise, I also intend to find the shocks' effects on children upto five.[18] Some standard health measures for children under five years, recommended by the World Health Organization, are anthropometric measures such as *weight-for-height, height-for-age*, etc.[19] With the given sample, I measure the *weight-for-height* and its *z-score* for children upto five years in the household, and obtain some meaningful results. This anthropometric measure reflects current body weight relative to the current height of a child of any age. A low measure that indicates malnutrition, can be due to thinness (not due to a pathological process) or wasting (due to acute starvation or disease). On the other hand, a high measure indicates obesity. The measure is recorded for the children during the time of the survey.

By using the same identification strategy used for VAS, I find that under household fixed effects, neither shock has any statistically significant effect on the z-score of *weight-for-height*, but the estimates suggest that the income shock has a negative effect (**Table A5**).[20] This finding is different from that found for VAS intake, but is quite rational (though suggestive). While receiving VAS doses can be thought of as a function of time outside the labour market for the household adults, the *weight-for-height* measure is a direct function of consumption. It is plausible to argue that as a negative income shock hits, the household consumption is directly affected and takes a toll on the nutritional intake of the children, whereas VAS intake could still increase if the time outside the labour market is utilised to get the doses. Similar evidence is found for another anthropometric measure *weight-for-age*.

4.3.4. Other sensitivity checks

In this section, I discuss a variety of robustness examinations *(Results not reported here)*. Firstly, I investigate if the main effects of the shock types differ across different age brackets of children under two. The only noteworthy finding is: the main effect on VAS intake by the children who were between 6-9 months during the shock window, is significantly higher (about 8-9 pp., at 10% level of significance) than among the other children and this effect remains same irrespective of shock incidence. This is justifiable, as the child who is between 6-9 months old is more likely to receive VAS because at this age it is eligible to get other vaccinations too (e.g. for measles), but after that age only a few other vaccines are required. This potentially affects the frequency at which the caregiver in the household visits the health-centre and/or the

[18] Note that the other health(care) measures such as vaccinations on measles, DPT-3, breastfeeding, etc. are mostly available for children under two, with very sparsely available data points for children between 2-5 years.

[19] For children under two years, height is replaced by length.

[20] The findings also hold when the shock window is extended to past one year.

motivation/awareness of household adults to take the child for VAS.

Next moving on to a discussion on the choice of income shock proxy, here I have included incidence of flood or drought as a measure of the shock. Another close candidate for the shock could be erosion as well. However, I leave it out intentionally, as often soil erosion is caused by agricultural practices such as overgrazing of cattle, over-cropping and deforestation. So, this anthropogenic nature of erosion could affect the exogeneity of soil erosion as a proxy for income shock. Nevertheless, even if I include soil erosion in addition to flood or drought in the measure, the effect of income shock on VAS intake does not change. Furthermore, some other potential candidates for income shock measure were available in the survey, such as agricultural crop loss due to disease, livestock loss due to disease, exorbitant price of agricultural inputs, unusually low price of agricultural outputs, etc. However, it makes more sense to choose flood and drought instead, because these natural shocks are often precursors of the others.

Here, I also discuss another issue related to the health shock measure. From the survey, it is not possible to identify if a child who is eligible for VAS itself suffered from illness in the past six months. It could be so that the driver of health shock in the household is the illness of the child itself. With household fixed effects specification, the reported effect of the health shock on VAS intake is the expected mean for the eligible children within one household. But this average estimate for the children in the household would be inaccurate if there are several omitted factors specific to the ailing child who could be actually triggering the health shock. One solution would be to conduct a child fixed effects analysis that basically utilises the variation within a single child over multiple survey waves. The idea of using this estimator is that the household to which the child belongs, could face a health shock (even arising from the illness of the eligible child itself) in one survey wave and could have no health shock in another survey wave, but the child fixed effects will absorb all the observables and unobservables intrinsic to that particular child and will provide an estimate with minimised error. However, the major drawback of using child fixed effects here is the presence of only a few observations[21] and potentially too little within-group variation which could lead to difficulty in assessing the effect. Nevertheless, by using a specification with child fixed effects and controlling for some time-varying child-specific characteristics, I find only suggestive evidence that a child is more likely to get VAS when the household to which it belongs experiences health and income shock compared to when it does not.

On further introspection, I think it is possible to estimate the shock's effect imperfectly if we only consider whether it occurred or not. In this study, I have defined *HealthShock* and *IncomeShock* as experience of a health or income shock by the household in the past six months prior to the interview, which is the same time interval when the household member(s) should have taken the eligible child(ren) in the household for

[21]Only 71 children between 12-24 months appear in multiple waves of the survey (not more than twice). Despite having children of 12-24 months in the analysis and the survey waves being about an year apart, these children appear twice because some households were interviewed at the latter part of say, wave 1 (2009-2010) and they were revisited for wave 2 in the early part of 2010-2011.

VAS; but according to my definition, the onset of this shock could have occurred before the past six months and then continued into these six months. Now suppose, a household faced the shock that had started four months before the last six months and continued for an additional month into these last six months that we are interested in, and a second household faced shock which had started a month before the last six months but continued for three months into these last six months. Clearly, the relative suffering during the last six months by the second household is more than that experienced by the first one. To account for this difference, I control for a measure of 'relative intensity' of shock in the past six months. It is given by the ratio of the number of months of the shock suffered in the last six months to the number of months of suffering before that due to the same.[22] However, the main findings of the study remain robust to the intensity of the shocks. The main and interaction effects of intensity measures are statistically insignificant.

Finally, to briefly comment on seasonal effects, I incorporated the possibility of it by including controls on whether the survey interview took place in a rainy season and whether the household resides in a flood-prone region. But, even if I include interview-month fixed effect, the main findings in Tables 3 and 4 remain unchanged.

5. Conclusion

The aim of this paper was to empirically examine how low-income households trade off investment in their children's preventive healthcare during idiosyncratic shocks when resources get even more limited. Starting with hypotheses that a negative income shock likely has a strong income effect on healthcare, especially preventive healthcare, and that a negative health shock may bring awareness and increase marginal utility from health stock, I examine the effects of both income and health shocks on preventive healthcare utilisation by over 1500 nationally and regionally representative households present in the four waves of Ugandan National Panel Survey. In Uganda, immunisations to small children are publicly provided free-of-cost at public health facilities in the community. So, the only costs that a household can incur while taking the children to get immunised are the indirect costs of transportation and/or the opportunity cost of time spent in accessing that service instead of spending on income-generating activities.

By using incidence of flood or drought as a proxy for negative income shock, and illness of any household member as an indicator for negative health shock, I examine how the receipt of VAS doses by children under two years, as a part of their immunisation schedule, is affected. I find that both health and income shocks have positive effects on VAS take-up, the result of the income shock being contrary to what I expected. Further investigation of the mechanisms shows that the effect of health shock results from the increase in the average time outside the labour market by the members of a shock-hit household. This could mean that

[22]Naturally, this measure only works for those households in which the shock started earlier than the last six months from the interview. Also note, this measure is capable of taking into account the start date of the shock and then accordingly weighing the suffering during the last six months. In that sense, it qualifies as a better measure of the intensity of shock compared to a measure like the total number of months of shock.

the inability to be at work due to illness reduces the opportunity cost of the time away from the labour market which the household adults use in seeking remedial care and other health-promoting activities for their children. This argument should also hold true if a child or an elderly member (who is not a labour force participant) in the household is ill; then some working adult member is 'forced' to stay away from the labour market to take care of the former. In case of income shock, though the average effect on time spent in the labour market is positive, interaction with the wealth level of the household shows the relatively wealthier households allocating lesser time on average in the labour market during income shock. This hints toward the possibility that an income shock in terms of flood or drought reduces the opportunity cost of work for atleast the relatively wealthier who probably are capable of using buffer stocks. As a result, the increase in VAS uptake due to income shock could be driven by them substituting their time with healthcare instead of labour. To summarise, the findings in this study imply the importance of time in child health development, as has been previously shown by Miller & Urdinola (2010) in a developing country setting. Nevertheless, it is worth mentioning here that as the results obtained in this study are not very strong in terms of statistical significance, more research in similar socio-economic settings is necessary before reaching a strong conclusion.[23]

Furthermore, some caveats on the interpretation of the mechanism still remain, and call for further data and research in a similar context. For example, it is crucial to be able to distinguish if the increase in VAS intake during income shock is caused only through leisure hours, or does being in an adverse weather shock such as drought or flood makes the adults more aware of the health of their children? As mentioned earlier, other potential agriculture-based proxies for income shock were available in the survey, but those provide too little number of households exposed to income shock. That would cause an estimation challenge.

Another deeper insight that this paper fails to provide is the household dynamics. The otherwise intriguing results of the paper gives rise to further questions: for example, how is the work division in the household - are the males in the household responsible for all the income-generating work and the women for child-rearing? If so, then why would a change in the time away from the labour market necessarily affect childcare? Also, how much are the elder children in the household involved in the home production? Often multiple nuclear families live in the same household in this context (and that's why the sample often consists of multiple children with different parents across multiple waves within households), then are there multiple main income earners under the same roof? The most that can be answered by exhausting this survey and consulting related literature is that most Ugandan households are engaged in agricultural farming in their own cultivation lands, and the household members, especially women and adolescents, are the main additional labour input providers. So to reconcile the findings of this paper, during health shock, the women are likely to divert time away from those agricultural tasks to look after the ailing. During an income shock, the

[23]To clarify my statement further, the primacy of time in child healthcare is already established in the literature (Grossman, 1972; Gronau, 1977; Vistnes & Hamilton, 1995), but the channels that I study in this paper to reach that conclusion on the primacy of time are not statistically precise. Therefore, the channels need further validation.

household members probably seek out other income-generating activities, but the wealthier the household is the lesser the need for everyone in the household to search work for income smoothing, e.g. the women and adolescents who were working in the household's lands can utilise the 'leisure' to engage in other time-intensive activities. More research is needed to shed light into these gender dynamics within households in times of shock.

All things considered, it can be concluded that in this paper we see an example where even though preventive healthcare for children is available for free, it is the opportunity cost of accessing that which is high. Taking the child to get immunised or investing time in other preventive healthcare practices is something that the adults do during the time outside their labour hours. This indicates that simply providing preventive healthcare services for free is necessarily not enough. Parents and other caregivers in the household should be incentivised through the right channel so that they can easily engage in preventive healthcare activities. However, incentives like a paid day off from work would not be meaningful in the framework of Uganda and other similar countries where the informal labour market has a huge share. Innovative nudges and incentives work; for example, Banerjee et al. (2010) provides evidence from a randomised controlled trial in India, where they found that setting up of immunisation camps increased immunisation rates, but it was more effective when the parents or caregivers were offered an incentive of receiving a kilo of lentils per vaccination. This incentive helped offset the opportunity cost of taking a child to get immunised and thus, was successful.

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Appendix A

Table A1: Effect of shock in one survey wave on the probability of attrition at the end of the wave

Health shock in last one year	-0.004
	(0.014)
Income shock in last one year	0.002
	(0.009)
Households FE	Yes
Surveywave FE	Yes
No. of obs.	11516
No.of households	4520
R-sq. within	0.000

Notes: (1) number of other shocks experienced by the household in the past year is controlled for; (2) Sample includes all households; (3) SE in parentheses, clustered at household level.

Table A2: Effect of the shocks on VAS intake by the child in the household in last six months - checking with only the first three survey waves

	(1)	(2)	(3)	(4)	(5)
Health shock	0.046	0.066*	0.145*	0.146*	0.149*
	(0.040)	(0.040)	(0.079)	(0.078)	(0.081)
Income shock	0.019	0.053**	0.094*	0.091*	0.088
	(0.026)	(0.026)	(0.056)	(0.056)	(0.057)
Controls[a]	No	Yes	Yes	Yes	Yes
Health supply covariates	No	Yes	No	Yes	Yes
Distance covariates	No	Yes	No	No	Yes
Households FE	No	No	Yes	Yes	Yes
Surveywave FE	No	Yes	Yes	Yes	Yes
No. of obs.	1864	1864	1864	1864	1864
No.of households	1357	1357	1357	1357	1357
R-sq.	0.001	0.087	0.075	0.082	0.132

Notes: (1) **,* indicate significance at 5 % and 10%; (2) [a] includes household level controls - log of total value of household assets, number of children under five, number of permanent members, if the family had moved in recent past, if interviewed in a rainy season, if lived in a flood-prone region; and individual level controls as neonatal care received (breastfed at birth), presence of mother, presence of father, education of mother and father and if attained 6 months of age 6 months ago; (3) the regression includes households with children of 12-24 months in the first three survey waves only; (4) Standard errors in parentheses, clustered at household level; (5) The R-squared for the household fixed effects models in Columns (3)-(5) is the within-R-squared.

Table A3: Effect of health shock of any household member except the main income earner on VAS intake of the child

	(1)	(2)	(3)	(4)	(5)
Panel A:					
Health Shock	0.063	0.079*	0.157*	0.145*	0.144
	(0.044)	(0.044)	(0.089)	(0.086)	(0.094)
Income Shock	0.018	0.051**	0.095*	0.093*	0.090
	(0.024)	(0.024)	(0.056)	(0.056)	(0.057)
Controls[a]	No	Yes	Yes	Yes	Yes
Health supply covariates	No	Yes	No	Yes	Yes
Distance covariates	No	Yes	No	No	Yes
Households FE	No	No	Yes	Yes	Yes
Surveywave FE	No	Yes	Yes	Yes	Yes
No. of obs.	2109	2109	2109	2109	2109
No.of households	1592	1592	1592	1592	1592
R-sq.	0.001	0.096	0.072	0.079	0.128
Panel B:					
Health Shock	0.046	0.068	0.102	0.086	0.076
	(0.048)	(0.049)	(0.086)	(0.082)	(0.092)
Income Shock	0.018	0.051**	0.096*	0.093*	0.089
	(0.024)	(0.024)	(0.056)	(0.056)	(0.057)
Controls[a]	No	Yes	Yes	Yes	Yes
Health supply covariates	No	Yes	No	Yes	Yes
Distance covariates	No	Yes	No	No	Yes
Households FE	No	No	Yes	Yes	Yes
Surveywave FE	No	Yes	Yes	Yes	Yes
No. of obs.	2109	2109	2109	2109	2109
No.of households	1592	1592	1592	1592	1592
R-sq.	0.001	0.095	0.070	0.077	0.126

Notes: (1) Panel A reports the estimates of the analysis where health shock is indicated by **illness or death** of any household member except the main income earner, whereas Panel B reports the estimates of the analysis where health shock is indicated by only **illness** of any household member other than the main income earner: (2) * indicates significance at 10%; (3) [a] includes household level controls - log of total value of household assets, number of children under five, number of permanent members, if the family had moved in recent past, if interviewed in a rainy season, if lived in a flood-prone region; and individual level controls as neonatal care received (breastfed at birth), presence of mother, presence of father, education of mother and father and if attained 6 months of age 6 months ago; (4) Standard errors in parentheses, clustered at household level; (5) The R-squared for the household fixed effects models in Columns (3)-(5) is the within-R-squared.

Appendix B

Table A4: Effect of the shocks in the last six months on log of total household wealth

	(1)	(2)	(3)	(4)	(5)
Health shock	0.100	0.065	0.060	0.059	0.047
	(0.102)	(0.099)	(0.079)	(0.080)	(0.079)
Income shock	-0.253***	-0.261***	-0.142***	-0.145***	-0.140***
	(0.059)	(0.056)	(0.046)	(0.046)	(0.046)
Controls[a]	No	Yes	Yes	Yes	Yes
Health supply covariates	No	Yes	No	Yes	Yes
Distance covariates	No	Yes	No	No	Yes
Households FE	No	No	Yes	Yes	Yes
Surveywave FE	No	Yes	Yes	Yes	Yes
No. of obs.	9826	9826	9826	9826	9826
No.of households	3018	3018	3018	3018	3018
R-sq.	0.004	0.067	0.101	0.105	0.118

Notes: (1) *** indicates significance at 1%; (2) [a] includes household level controls - number of permanent members, number of members in prime years of their age, if the family had moved in recent past, if interviewed in a rainy season, if lived in a flood-prone region; (3) the regression includes households with children under five; (4) Standard errors in parentheses, clustered at household level; (5) The overall mean value of logarithm of household's assets is about 15 Ugandan shillings; (6) The R-squared for the household fixed effects models in Columns (3)-(5) is the within-R-squared.

Table A5: Effect of shocks in the past six months on the z-score of weight-for-height of children under five in the household

	(1)	(2)	(3)	(4)	(5)
Health Shock	-0.056**	-0.045*	0.007	0.007	0.011
	(0.025)	(0.027)	(0.037)	(0.037)	(0.035)
Income Shock	-0.006	0.003	-0.044	-0.042	-0.038
	(0.030)	(0.029)	(0.038)	(0.038)	(0.036)
Controls[a]	No	Yes	Yes	Yes	Yes
Health supply covariates	No	Yes	No	Yes	Yes
Distance covariates	No	Yes	No	No	Yes
Households FE	No	No	Yes	Yes	Yes
Surveywave FE	No	Yes	Yes	Yes	Yes
No. of obs.	7033	7033	7033	7033	7033
No.of households	2556	2556	2556	2556	2556
R-sq.	0.001	0.008	0.006	0.007	0.014

Notes: (1) [a] includes household level controls - log of total value of household assets, number of children under five years, number of permanent members, if the family had moved in recent past, if interviewed in a rainy season, if lived in a flood-prone region; and individual level controls as neonatal care received (breastfed at birth), presence of mother, presence of father, education of mother and father and if under two years of age interacted with whether received relevant vaccines on measles and DPT-3; (2) Standard errors in parentheses, clustered at household level; (3) The R-squared for the household fixed effects models in Columns (3)-(5) is the within-R-squared.

Table B1: Summary statistics of households with and without shock

Variable	Household with no shock		Household with shock	
	Mean	Std. Dev.	Mean	Std. Dev.
Age in years of household-head	40.88	13.22	42.96	13.79
Household-head ever attended school	0.89	0.32	0.82	0.39
Household-head married	0.86	0.35	0.83	0.38
Household members away from household due to work	0.07	0.28	0.07	0.28
Household members living in the household all year round	4.08	2.32	4.43	2.40
Logarithm of total household assets' value (in Ugandan shillings)	14.98	1.74	14.79	1.75
Average number of weeks in the labour market	12.55	14.00	13.98	14.53
Number of children up to five years of age in the household	1.70	0.90	1.86	0.95
Average age of under-five children in the household (in months)	30.51	16.35	30.79	16.10
Household which faced a health-related shock	0	0	0.28	0.45
Household which faced an income-related shock	0	0	0.79	0.41
Number of observations	4748		1677	

Notes: These statistics are obtained by comparing the households with atleast one child under five. A household can appear multiple times across the waves.

Table B2: Summary statistics by panel waves

Variable	Mean	Std. Dev.
Household related variables:		
Household with main income source as agriculture	0.50	0.50
Household with main income source as subsistence farming	0.49	0.50
Household members away from household due to work	0.07	0.28
Household members present in household all year round	4.17	2.35
Number of children up to five years present in household	1.74	0.91
Average number of weeks in the labour market	12.89	14.14
Health Shock related variables:		
Households suffering from health shock in the last six mo.	0.07	0.26
Number of months suffered due to health shock	2.82	3.09
Income Shock related variables:		
Households suffering from income shock in the last six mo.	0.21	0.40
Number of months suffered due to income shock	3.63	2.04

Notes: (1) This table provides the mean over four waves of survey. The household and shock statistics are only for those households which had at least one child under five years in at least one wave, the number of such households being 3022 ; (2) The child statistics are not shown here as they are only available for children under two and thus can be found in Table 2.

Table B3: Effect of the shock types on intake of VAS by child in the household in last six months

	(1)	(2)	(3)	(4)	(5)
Health Shock	0.026	0.051	0.144*	0.145*	0.147*
	(0.038)	(0.038)	(0.079)	(0.078)	(0.081)
Income Shock	0.018	0.050**	0.094*	0.091*	0.088
	(0.024)	(0.024)	(0.056)	(0.056)	(0.057)
Individual-specific controls:					
Breastfed at birth		0.056	0.008	0.008	0.008
		(0.052)	(0.13)	(0.13)	(0.120)
At 12th month now		-0.013	-0.032	-0.034	-0.037
		(0.033)	(0.060)	(0.059)	(0.062)
Mother in same household		0.052	0.092	0.096	0.125
		(0.042)	(0.090)	(0.087)	(0.091)
Father in same household		0.050**	0.103	0.091	0.087
		(0.026)	(0.066)	(0.067)	(0.067)
Mother with no education		-0.400***	0.061	0.072	0.097
		(0.151)	(0.238)	(0.234)	(0.226)
Father with no education		0.007	0.256	0.251	0.199
		(0.081)	(0.173)	(0.171)	(0.153)
Household-specific time-variant controls:					
Log of total household assets		0.008	0.017	0.019	0.014
		(0.006)	(0.18)	(0.018)	(0.019)
Total permanent members		-0.002	0.015	0.014	0.016
		(0.004)	(0.017)	(0.017)	(0.017)
Total children under five		-0.009	-0.003	-0.005	-0.014
		(0.011)	(0.031)	(0.030)	(0.030)
If relocated		-0.031	-0.061	-0.002	0.011
		(0.035)	(0.075)	(0.074)	(0.073)
If lives in flood-prone region		0.157***	0.905***	0.899***	0.960***
		(0.022)	(0.124)	(0.143)	(0.152)
If interviewed in rainy season		-0.038**	-0.033	-0.030	-0.025
		(0.019)	(0.040)	(0.041)	(0.041)
Health supply covariates:					
General outpatient care offered		-0.195***		0.397**	0.188
		(0.055)		(0.175)	(0.223)
Immunisation offered		-0.066		-0.316*	-0.156
		(0.048)		(0.166)	(0.209)
If too far		0.006		-0.045	-0.073
		(0.044)		(0.099)	(0.104)
If no skilled staff		-0.082		-0.039	-0.001
		(0.052)		(0.099)	(0.100)
Distance covariates	No	Yes	No	No	Yes
Households FE	No	No	Yes	Yes	Yes
Surveywave FE	No	Yes	Yes	Yes	Yes
No. of obs.	2109	2109	2109	2109	2109
No.of households	1592	1592	1592	1592	1592
R-sq.	0.001	0.095	0.074	0.081	0.131

Notes: (1) ***,** and * indicates significance at 1%, 5% and 10%; (2) Standard errors in parentheses, clustered at household level; (3) The R-squared for the household fixed effects models in Columns (3)-(5) is the within-R-squared.

Table B4: Effect of the shock types on average weeks of labour participation

	(1)	(2)	(3)	(4)	(5)
Health Shock	-0.113	-2.13**	-6.330***	-5.895***	-4.473**
	(1.23)	(0.911)	(2.333)	(2.464)	(1.985)
Income Shock	3.46***	1.133*	3.957**	3.860**	4.368***
	(0.962)	(0.685)	(1.766)	(1.736)	(1.793)
Household-specific time-variant controls:					
Log of total household assets		0.030	-0.381	-0.397	-0.086
		(0.174)	(0.621)	(0.630)	(0.640)
Total permanent members		-0.668***	-0.326	-0.352	-0.218
		(0.115)	(0.482)	(0.492)	(0.512)
Total members in prime years		0.608***	0.111	0.398	0.324
		(0.201)	(0.839)	(0.850)	(0.832)
If relocated		-0.569	-0.749	-1.052	-1.522
		(0.835)	(1.975)	(2.011)	(1.874)
If lives in flood-prone region		-0.327	-20.159***	-18.981***	-19.943***
		(0.522)	(5.206)	(5.917)	(6.618)
If interviewed in rainy season		1.027**	-0.511	-0.614	-1.074
		(0.473)	(1.228)	(1.250)	(1.192)
Health supply covariates:					
General outpatient care offered		7.887**		-8.039	-5.115
		(3.405)		(8.847)	(6.984)
Immunisation offered		-1.166		8.460	6.662
		(1.472)		(8.532)	(6.228)
If too far		-0.780		-2.345	-2.882
		(1.211)		(4.464)	(5.012)
If no skilled staff		1.404		3.657	4.747
		(1.397)		(4.691)	(5.165)
Distance covariates	No	Yes	No	No	Yes
Households FE	No	No	Yes	Yes	Yes
Surveywave FE	No	Yes	Yes	Yes	Yes
No. of obs.	1518	1518	1518	1518	1518
No.of households	1255	1255	1255	1255	1255
R-sq.	0.011	0.542	0.650	0.652	0.716

Notes: (1) ***,** indicate significance at 1% and 5% respectively; (2) Standard errors in parentheses, clustered at household level; (3) This analysis involves only the survey years 2010, 2011 and 2013 since the labour participation hours or weeks cannot be calculated for 2009 due to lack of data; (4) The R-squared for the household fixed effects models in Columns (3)-(5) is the within-R-squared.

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