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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

This paper investigates how poor households in low-income countries trade off time investment in their children's preventive healthcare vis-à-vis labour force participation during household-level health shocks. By using the reported illness or death of any household member as the indicator for an adverse health shock, I examine its effect on the intake of Vitamin A Supplementation (VAS) by children. Using four waves of the Uganda National Panel Survey, I find that children between 12-24 months are significantly more likely to get VAS when the household is under a health shock. I argue that this effect works through an *economies of scale* mechanism, by which the household adult(s) utilise the released time from the labour force during the shock to access remedial care from the healthcare facility and simultaneously obtain VAS for their children during the same visit. This arguably results from the high opportunity cost of time-constrained households, which is exacerbated by a mediocre service delivery side. To distinguish the unique mechanism of the health shock in this context, the effect and channels of an income shock are also explored. By proxying a negative income shock with the household-reported incidence of flood or drought, the study cautiously hints that VAS adoption may increase among the relatively wealthy who experience a dominating substitution effect of the income shock.

Keywords: household shocks, preventive child healthcare, Vitamin A supplementation, time allocation, Uganda
JEL: I12, J13, J22, O12, O15

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1. Introduction

Shocks are events manifested through risks and cause significant negative welfare effects to a group or an individual. In the form of illness, unemployment, or natural calamities, shocks may themselves cause or compound poverty (Canagarajah et al., 2002; Marques, 2003). Vulnerability to such risks is especially acute for impoverished households in developing nations; limited savings and insurance options contribute to persistent poverty risk (Dercon, 2002). In incidence, idiosyncrasy, costs and impact among the poor, health shock ranks the highest (Wagstaff and Lindelow, 2014); in the absence of formal insurance, these health shocks can have dire economic consequences (Mitra et al., 2016), often impeding investments in child human capital development (Bratti and Mendola, 2014; Alam, 2015; Dhanaraj, 2016).

With shocks so widespread among poor households, this study aims to examine how these adversities affect their utilisation of preventive healthcare for children. Given the scarcity of resources and the struggle for coping mechanisms, to what extent do the households trade off investments in their children's preventive healthcare? *Preventive* healthcare (e.g. vaccinations, treating drinking water, taking deworming pills) is of particular interest because, despite its efficacy, a stylised fact in low-income countries is that poor households invest minimally 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 premise, one might hypothesize that during adverse household shocks, when resources are even scarcer, parents potentially divert their attention and resources away from children's preventive healthcare in favour of addressing more immediate crises. However, this paper argues that the ramifications of this trade-off may not be straightforward; the intricate mechanisms at play likely hinge on the type of shock experienced by the household. Therefore, this study aims to validate this hypothesis empirically.

Given how common and concentrated *health shocks* are among the poor, this study primarily focuses on them.[2] In terms of how a health shock affects preventive healthcare, one can argue with a number of ways by which it may unexpectedly have a positive impact. For example, a health shock within the household could simply heighten health awareness (equivalent to the concept of *salience* (Kahneman and Thaler, 2006; Seymour et al., 2007)) thereby increasing the use of preventive healthcare. The second argument stems from basic economics: if demand for healthcare is a *derived* demand from that for health (Grossman, 1972), households with diminished health stock might derive higher marginal utility from health, and hence invest more in preventive healthcare. Finally, an *economies of scale* approach could come into play. If an ill household member needs to visit a health centre for remedial care, the additional cost of bringing a child along for preventive healthcare could be relatively low. This is particularly relevant for obtaining vaccinations

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

[2] Moreover, considering the global commitment to achieving universal health coverage - central to the Sustainable Development Goals on health - an understanding of health shocks is crucial for designing effective health policies (Giedion et al., 2013).

and supplementary medicines during visits to healthcare facilities; furthermore, it requires this type of preventive healthcare to be publicly available for free, requiring only time investment from the household. Now, if one of these argued mechanisms is functional, a health shock could lead to unanticipated positive effects on the take-up of preventive healthcare practices. These various theoretical arguments justify the need for an empirical investigation into the relationship between health shock faced by households and their preventive healthcare adoption. This paper attempts to shed light on that and, in doing so, also explores some underlying mechanisms.

In the development economics literature, a health shock is often regarded as an economic shock (Atake, 2018) due to their complex inter-connectedness (Weil, 2014). Existing studies on household health shock in the context of developing economies have primarily focused on its effects on health expenditure, due to the absence of formal insurance mechanisms (Ahmad and Aggarwal, 2017) and welfare outcomes such as consumption (Mitra et al., 2016). However, the literature addressing the impact of health shocks on household (preventive) healthcare practices and outcomes remains scarce. Expanding our scope to the sphere of child human capital formation adds to the body of evidence on the impact of household health shocks. Studies by Bratti and Mendola (2014), Alam (2015) and Dhanaraj (2016) based on low-income settings confirm that parent's illness negatively affects the educational outcomes of children of different age cohorts to varying extents.

The scarcity of literature linking household-level/idiosyncratic health shock with investments in children's preventive healthcare in developing countries thus invigorates our curiosity to empirically investigate the effect, if any, of health shock on preventive healthcare for children. In this empirical study, my focus centres on Uganda - a nation struggling with persistently poor child health indicators. Over decades, child health progress has been slow, with an under-five child mortality rate of 139 per 1,000 live births in 2001, gradually reducing to ∼70 in the first half of the 2010s.[3]. Full immunisation for children aged 12-23 months remained around 50% in the 2010s, with large regional disparities (Okello et al., 2022). Simple and cost-effective child health practices, such as boiling drinking water, exclusive breastfeeding, and birth spacing, continue to witness low adoption rates (Bhutta et al., 2013). In the economic landscape, 41% of the population survived on less than $1.90/day (PPP), while 91% managed with less than $5.50/day (PPP) in recent years like 2019[4] that was similar or even worse during the study period of 2009-14. Most Ugandan population works in the informal sector, particularly in agriculture. Households often rely on multiple income sources to meet their needs (Khan and Morrissey, 2023), and they usually substitute time from the labour market to perform household chores or contribute to (preventive) healthcare for children. (Miller and Urdinola (2010) provide an overview of child health investment patterns which is quite consistent across the developing nations).

In studying preventive healthcare for children, I focus on the take-up of Vitamin A Supplementation (VAS) - a health supplement included in the routine immunisation and health promotion programme recom-

[3] `https://data.unicef.org/country/uga/` [accessed May 2023]
[4] `https://www.macrotrends.net/countries/UGA/uganda/poverty-rate`[accessed May 2023]

mended by the World Health Organization and Ugandan Health Ministry for children aged 6-59 months.[5] Using four waves from the Uganda National Panel Survey spanning 2009-14, I investigate the impact of adverse health shocks on the recommended VAS take-up for children aged 12-24 months. To identify a negative health shock, I use any household member's reported illness as an indicator.

Through household fixed effects (FE) analysis, I find that a negative health shock substantially raises the likelihood of children receiving VAS. Additional evidence indicates that, when a household experiences a health shock, the average time a household member dedicates to labour market activities significantly decreases compared to a shock-free scenario. In this study sample, the healthcare facilities that the households mostly access are about 90% likely to offer immunisation services besides general outpatient care (GOP), the latter being offered by most. I find a strong positive association between VAS take-up and the availability of GOP in the accessed facility by the household during no shock, and the association is suggestively larger during a health shock (whereas the association between VAS take-up and availability of immunisation services in the accessed facility is strongly negative under no shock). With the decrease in average time spent by a household member in the labour force in the event of a health shock, it is plausible that they stay home and/or access a healthcare facility for remedial care. The significant correlation between VAS adoption and the presence of GOP services in the most-accessed healthcare facility, together with the higher take-up rate of VAS during a health shock suggest that adults typically seek remedial care at health centres when facing a health shock, and these visits likely also serve as an opportunity to administer their children's (pending) VAS. This argues for an *economies of scale* approach, where the added cost of accessing other healthcare services, such as supplementary medication for children, is relatively low when seeking care for health emergencies.

In Uganda, with user fees abolished since 2001 (Nabyonga Orem et al., 2011), households incur no direct cost in getting their children immunised; however, they could face indirect costs like transportation and significant opportunity costs from time spent accessing healthcare services. The situation is further complicated by accessibility issues, where simply reaching the so-called "nearest" health centre can require hours of travel, with no assurance of availability of services. Under these circumstances, households might defer their children's routine immunisations, obtaining them only when compelled to visit for shock-related remedial care. This reasoning aligns with a theoretical healthcare model proposed by Goldman and Grossman (1978), where visiting a health centre entails a fixed cost encompassing transportation, opportunity costs of travel, and waiting time. This fixed cost is independent of the number of services received per visit. Consequently, it is optimal for the healthcare seeker to maximise the number or quality of services per visit, given the fixed cost. In fact, the data depicts a pattern where most of my sample households access larger

[5] As per the Centers for Disease Control and Prevention's definitions (`https://www.cdc.gov/vaccines/vac-gen/imz-basics.htm` [accessed September 2023]), *vaccination* is the act of introducing a vaccine into the body to produce protection from a specific disease, and *immunisation* describes the overall process by which a person gains immunity to a disease through vaccination. The term immunisation is often used interchangeably with vaccination or inoculation. I acknowledge that VAS is not a vaccine per se like the ones obtained for measles, polio or tuberculosis; VAS is more of a supplement. However, since it is included in the official immunisation guidelines for small children in developing countries, I assume that it is treated on par with traditional vaccines in terms of its acceptance, adoption and delivery.

and more distant health centres that have more facilities but impose a higher fixed cost of travelling and waiting time.

Now, it is true that a debilitating health shock may often culminate into an income shock (e.g. severe and prolonged illness of a primary earner for many months or their demise), rendering it hard to disentangle the effects of the two; yet, in this study, I attempt to separate the two shock types. It is feasible because, firstly, the survey data permits the identification of a shock's source, and secondly, the health shocks observed in my sample are typically brief in duration, meaning they rarely result in a subsequent economic shock. This separation aims to discern whether an adverse income shock impacts Vitamin A Supplementation (VAS) take-up differently than a health shock. Given that a negative income shock is likely to exert a stronger income effect counteracting a substitution effect, thereby lowering VAS take-up (because childcare presumably happens in time away from work), I delve into the complexities of this relationship.[6], [7] However, by proxying a negative income shock with the incidence of flood or drought, I find an average positive effect on VAS take-up. Additionally, the average effect of the income shock on labour market time is positive. The reconciliation of these two seemingly contradictory findings reveals that wealthier households experience a stronger substitution effect during negative income shocks. Such households tend to substitute labour hours with activities like childcare (Miller and Urdinola, 2010) due to their capacity to utilise consumption-smoothing tools such as asset draw-downs or credit borrowing (Beegle et al., 2006). However, in this study, with the limitation of being able to confirm the effect on VAS take-up directly, I can only suggest with some descriptive evidence that the average positive effect found on VAS adoption is likely coming from the wealthier households substituting preventive healthcare activities for labour (as their opportunity cost of time away from work falls). Absent robust analysis to justify this claim, I do not stress the mechanisms of the income shock in this study. Nevertheless, it offers some direction to our understanding of how VAS take-up can be affected by different shock types, probably through different pathways.[8]

Finally, shifting our attention back to the health shock, its key findings are put through a battery of robustness checks, and the results remain consistent. However, it is acknowledged that studying the effect of household health shocks on their health decisions is challenging due to endogeneity. To address this, an instrumental variable approach is adopted as a robustness check. Furthermore, since the shock's effect in this study is statistically significant at the 10% level, there is a need for further research in similar settings

[6] Households in developing countries with informal work opportunities depend on various income sources to spread the risk of shocks (Heumesser and Kray, 2019). Therefore, a negative income shock to their agricultural activities (through floods or droughts), which is usually their primary income source, leads them to compensate by spending more hours in their secondary or tertiary jobs (Dimova et al., 2021; Khan and Morrissey, 2023).

[7] Existing literature exploring income shocks and healthcare, especially for children, concentrates on deciphering the interplay between income and substitution effects of shocks, yielding nuanced evidence from developing nations. Two pertinent studies in this sphere are by Miller and Urdinola (2010) and Fichera and Savage (2015), which yield contrasting findings. Using coffee price fluctuations as a proxy for aggregate income shocks, Miller and Urdinola (2010) uncovers evidence of counter-cyclical, time-intensive child health investments in Colombia - a stronger substitution effect. On the other hand, Fichera and Savage (2015), instrumenting a positive income shock with rainfall measures, finds a stronger income effect in Tanzania, with increased income reducing illness and boosting child vaccinations.

[8] Another study that investigates the effects of both income and non-income shocks on child human capital investment is by Bandara et al. (2015) in the context of child labour in Tanzania.

to draw stronger and more definitive conclusions.

All things considered, this study's primary contribution lies in shedding light on how an adverse health shock might unexpectedly enhance the take-up of preventive healthcare for children, specifically in the case of Vitamin A Supplementation. These findings hold implications for understanding how time constraints shape households' actions in developing nations. The study suggests that even time freed up due to shocks can lead to improved child preventive healthcare, implying that underutilisation of social policies may be partially attributed to time constraints. Simultaneously, the study underscores how an inadequate and inequitable health supply side can exacerbate these time constraints. Furthermore, if the weaker evidence from the income shock is to be considered too, the ultimate implication from that is also the time constraint of the poor. The finding on the income shock does not diminish the fact that the shock potentially has a stronger income effect on poorer households who increase their labour supply for consumption smoothing, which in turn likely reduces their time for child healthcare activities.

Among its other contributions, the results in this paper add to the literature that supports the primacy of time in households for healthcare (Grossman, 1972; Gronau, 1977; Vistnes and Hamilton, 1995; Miller and Urdinola, 2010). These studies recognise that health investment is costly since individuals must trade off time and other resources related to health; therefore, it affects the optimal demand for health. Furthermore, I note that a shock is merely an identification of the dimensions along which the household is constrained ex-ante. In this context, a growing literature exploring the impact of both unconditional and conditional cash transfers in low-income environments on the adoption of preventative healthcare measures, such as vaccinations (Barham and Maluccio, 2009; Robertson et al., 2013), regular cancer screening and HIV tests (Ranganathan and Lagarde, 2012), and other health and nutritional outcomes like stunting and obesity (Behram and Hoddinott, 2005; Fernald et al., 2008a,b), identifies that financial barriers are primarily responsible for the underutilisation of preventive healthcare. Among these barriers, one is the opportunity cost of time allocated to accessing healthcare services instead of income-generating activities. In this vein, my paper further enriches the understanding of demand-side financial obstacles to healthcare utilisation. Finally, this paper extends the literature exploring various factors associated with health and healthcare in Uganda, some being: the production and consumption of beta-carotene-rich orange sweet potatoes leading to increased Vitamin A intake in children and women (Hotz et al., 2012); improved water supply and reduction in water-borne diseases (Frempong et al., 2021); increased utilisation of healthcare and improved child health outcomes due to health-promotional home-visits by healthcare promoters (Björkman Nyqvist et al., 2019) and community-based monitoring of primary healthcare providers (Björkman and Svensson, 2009).

The remainder of the paper is organised as follows: Section 2 gives an overview of child health and healthcare status in Uganda and motivates its suitability in studying my research questions. Section 3 introduces the data, study variables and the summary statistics; Section 4 consists of the empirical specification; Section 5 discusses the primary results, followed by Section 6 that investigates the reliability of the results. Finally, a discussion and conclusion follows in Section 7.

2. The Ugandan context

Uganda is a developing country in sub-Saharan Africa, ranking 160/187 on the Human Development Index (HDI) in 2011 and 166/191 in 2021. The under-five child mortality rate of the country was ∼70 per 1,000 live births in the early 2010s and 42.1 in 2021.[9] Although the child mortality rate has reduced over time, the relative drop in HDI ranking suggests that the country has done worse than others on overall human development fronts. The Ugandan Ministry of Health had already recognised in 2010 that 75% 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 the goal that every Ugandan child should be fully vaccinated. Also, since 2001, the *Ugandan National Minimum Healthcare Package* (UNMHCP) entitles every Ugandan to free basic healthcare coverage at public healthcare facilities.[10] Furthermore, since 2001, the Ugandan government has abolished user fees in the form of out-of-pocket payments at public healthcare facilities and hospitals (Nabyonga Orem et al., 2011).

The health system in Uganda is decentralised, in which the central (=national) level takes a role in policy formulation and oversight, and the decentralised units at district levels handle service delivery. The district takes charge of primary healthcare through the UNMHCP with the help of a tiered system of healthcare facilities. The first healthcare contact for a Ugandan patient in rural areas is the village health team/ primary health centre, which can only advise and refer the patient to the upper-tier health centres. While this primary health centre serves a population of ∼1,000, the next ones in the hierarchy are Health Centres II and III at the parish- and sub-county- levels. A Health Centre II provides to a cluster of villages (∼5,000 people) general outpatient care, immunisations, antenatal care and emergency deliveries and treats common diseases. Health Centre III serves a cluster of parishes (∼20,000 people) and provides inpatient care and surgeries in the presence of more trained healthcare staff and laboratories, in addition to the services also provided in the lower-tier Health Centre II. The ownership of these health centres could be public, not-for-profit-private/NGOs or private, with the public alone having a share of more than half. The private-owned centres are licensed and supervised by regulatory bodies, and the government subsidises them to lower user fees. Higher in the tier are Health Centre IV at the county level and a general hospital for each district. The regional referral hospital and the national hospital are under the direct administration of the national health ministry (Kadowa, 2017).

Despite the availability of these health policies and the primary healthcare system for decades, improvement is far from universal. Among the child health and immunisation indicators, only 52% of children aged

[9]Child health statistics obtained from `https://data.unicef.org/country/uga/` [accessed May 2023].

[10]The UNMHCP was introduced in 1999/2000 National Health Policy, accompanied by the countrys first Health Sector Strategic Plan. Since then, health sector policy discourse has continued to centre around the concept of the UNMHCP. The programme prioritised an efficient use of available health resources (both public and not-for-profit-private) in facilitating primary healthcare, including preventive care and combating diseases and conditions that are widely prevalent in the county. See Kadowa (2017) for an overview.

12-23 months were fully immunised, and only 40% of children aged 12-23 months were immunised before their first birthday in 2011 (UBoS, 2012). According to the Uganda Demographic and Health Survey (2011), the rate of Vitamin A deficiency, which can threaten overall immunity and cause blindness, was as high as 33% among under-five children, despite the availability of Vitamin A doses in the immunisation programme.

While, in theory, the health service delivery system sounds well-planned, it is quite inequitable in practice. Though public institutions remain a preferred source of healthcare by the poorer income quintiles, the rural population, which constitutes the majority of the poor, is constrained in their access to healthcare by distance and geographically challenging terrains (Nabyonga Orem et al., 2011). While an estimated 49% of the population lived within five kilometres of a health service unit and only 42.7% of parishes had access to any form of healthcare facility in the 1990s, Health Centres II were typically about 35 kilometres away around 2010. They were within one-hour walking distance for 72% of the population and Health Centres III to about 50% (Dowhaniuk, 2021). In the 2010s, 20% population lived at > two-hour walking distance from a public hospital (Ouma et al., 2018). However, this travel duration neither necessarily reflects the availability of services nor the potential waiting time if services were indeed available. (For example, Chaudhury et al. (2006) document a > 35% absence rate of healthcare providers in Ugandan health centres.) It implies that heterogeneity exists in the availability of services even within the same tiers (Kadowa, 2017; WHO, 2017). While the geographical access gap has reduced over the decades, the availability of services remains the next challenge to be overcome in public healthcare (WHO, 2007).

While it is indisputable that substantial improvements in infrastructure and actual service delivery are needed on the supply side to truly promote and facilitate the take-up of services, the reality remains that until these improvements are realised, individuals in need will continue to bear additional direct and indirect expenses related to travelling and waiting (Kremer and Glennerster, 2011), and these costs could be equivalent to losing a day's wages for a poor household.[11]

3. Data and summary statistics

3.1. 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 Uganda Bureau of Statistics implemented the UNPS in collaboration with the *Living Standards Measurement Study-Integrated Surveys on Agriculture* (LSMS-ISA) programme of the World Bank. For the analysis, I obtain data from the household and community modules of the survey.

[11] In the late 2010s, in most of the sub-Saharan African countries, smallholder families with a small farm ($\equiv$ 0.9 hectares) generated income of about 0.8 USD per person per day, whereas those with large farms ($\equiv$ 3.5 hectares) about twice per person per day. With this meagre amount, the household met a range of expenses - from buying food, agricultural inputs and clothes to paying for housing, education and health services (Rapsomanikis, 2015). (See more on smallholder farmers in Footnote 45.) Typically, the daily wage rate in the agricultural sector in Uganda was 0.55 USD and could only rarely reach a higher 1.4 USD in the construction sector (`https://pdf.usaid.gov/pdf_docs/PA00MJZ6.pdf`) [accessed May 2023].

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 out of 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 initially interviewed in the Uganda National Household Survey (UNHS), another survey in 2005-06.[12] 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.[13] 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 between waves 2 and 3 is 92.4%. In the fourth wave of UNPS, a part of the third wave sample was dropped and replaced with a 'fresh' sub-sample of households. This fresh sub-sample was extracted from updated sample frames developed by the Ugandan Bureau of Statistics as a part of the 2012 Uganda Population and Housing Census.[14]

3.2. Variables

As the outcome variable on preventive healthcare for children, I use the receipt of Vitamin A Supplementation (VAS). The Ugandan Health Ministry strictly recommends that caretakers of children of 6-59 months should take them to healthcare facilities to receive VAS every six months as a part of their routine immunisation and health promotion programme. As noted earlier in Section 1, though VAS is a supplement as opposed to a traditional vaccine, it is a part of the official immunisation guidelines for small children, and thus I assume it to have equal implementation, adoption and delivery like other vaccines or immunisation categories.[15]

I choose VAS as the primary study variable due to the survey questionnaire's clear information regarding its receipt, as opposed to other immunisation categories like measles and DPT-3 vaccines. The household questionnaire of each survey wave records whether a child received VAS specifically in the last six months, while the timing for measles or DPT-3 vaccines is less explicit.

VAS is to be implemented from the age of six months, and the survey question on VAS concerns its receipt in the last six months from the survey interview date, meaning that only those children ≥ 12 months of age during the interview were eligible for VAS intake in the past six months. Focusing on only the children *eligible* for VAS, the analysis is limited to children aged 12-24 months and their households because the

[12]The 2009 UNPS is a sub-sample of the 2005-06 UNHS. For the UNPS sample, 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.

[13]Before the fieldwork of the first wave 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 a *split-off* would be followed. 430 split-offs were interviewed in the first UNPS and by that time they formed 368 households (information from UNPS Reports on waves 1 and 3).

[14]More recently, waves from 2015-16, 2018-19 and 2019-20 have been added to UNPS; however, the sample has changed substantially, along with changes in survey questions.

[15]A detailed guideline on immunisation for Ugandan children, with recommendations from the World Health Organization and UNICEF, can be obtained from `https://www.unicef.org/uganda/key-practice-immunization` [accessed May 2023].

dataset only includes VAS information up to 24 months.

Since the analysis spans four annual waves, it is unlikely that one household with only one child between 12-24 months would appear in all four waves unless another child is born in that household. When looking at how the households appear in the end sample, it essentially contains a mix of the following:- (1) households that appear only once when they have only one child between 12-24 months during a given survey wave, (2) households that appear more than once in various survey waves but in each of those waves with a different child between 12-24 months, (3) households that appear at most twice with the same child in two different waves (e.g. when the child is 12 months old and again when 24 months old), and (4) households that appear in one survey wave but as > 1 observations with twins or multiple children (from different parents) of 12-24 months.

In this study, I define a health shock from household-reported information on a severe illness or death of a household member in the past six months. In the development literature, self-reported health status/illness of the parents and/or death in the household are commonly used as health shock proxies in studying outcomes of the child's human capital investment, e.g. Bratti and Mendola (2014) focus on the self-reported health status of the parents of the child as a measure of health shock, whereas Alam (2015) uses the self-reported health status of other household members too. In contrast, Bandara et al. (2015) use death as a measure of health shock, whereas Dhanaraj (2016) uses both severe illness and death as a health shock.

The information on the shock is available from the same survey module as VAS. The relevant question is *if the household faced a shock due to severe illness/death of a household member in the past year*. For this study, I define the incidence of the shock as its presence in the household during the last *six months* from the interview. It is important to note that this shock may have originated prior to this six-month period but extended into it.[16] I limit the shock experience to the past six months because the VAS dose information aligns with this window from each wave's interview date, ensuring the best possible overlap of events. In that regard, using other immunisation measures as outcome variables could, in principle, work; however, to get an overlap of the shock incidence window and the receipt of, say, measles vaccine (which is implemented only once at the age of 9 months), I must limit the age of the child between 9 and some months after (assuming it is obtained with some potential delays). Likewise, receipt of the DPT-3 vaccine (to be implemented at 14 weeks of age) requires limiting the child's age between 3.5 months and some months after. In principle, one can allow the age range to be bigger; however, it reduces the chances of an effective overlap between the shock and the immunisation date. Therefore, the receipt of the measles and DPT-3 vaccines are less likelier than VAS in having this overlap because it is impossible to know from the questionnaire the actual age when the child received these two vaccines.[17]

[16] The survey contains information on the start and end dates of a shock and thus allows to calculate its incidence during six months prior to the interview.

[17] Noting these caveats, I do report my findings on the effect of health shock on these two vaccinations in Section 6.2.

3.3. Summary statistics

Table 1 summarises a comparison of the households that faced a health shock in the past six months with the households that did not. The following statistics pertain only to households with at least one child of 12-24 months in at least one survey wave.[18] The table shows no statistically significant difference in the average VAS take-up rates between these groups; however, it does not dismiss that differences may emerge when controlling for household FE effects. Among other attributes, typically, the head of a shock-free household is 39.75 years old, with about 87% chance of ever attending any school and 88% chance of being married. A member in a shock-free household typically spends 12.34 weeks in the labour market. About four permanent members are present all the year-round, and about two children in the household are under five. The mean age of children between 12-24 months is 18.05 months. The average wealth of a shock-free household falls slightly below the middle of the wealth distribution measured from the valuation of land and housing owned by households.[19] The means of the households that suffer a health shock are not significantly different in most attributes except the age of the household head, their marital status and the household's experience of an income shock in the past.

[Table 1 here]

Table 2 provides the means of the variables of interest across all four waves. On average, 73% of eligible children received VAS in the past six months from the interview date. More than 80% of the children were reported to have received their DPT-3 and measles vaccines; however, the exact age of receipt of the latter two vaccines is unknown. Among other child-related variables, 97% of children were breastfed at birth, 92% had their mothers, and 74% had their fathers living with them in the same household. Compared to these figures, healthy lifestyle measures, such as sleeping under a bed net, were still less prevalent - only 60% children were reported to have slept under bed nets the previous night. Among the health shock-related measures, 7% of the households suffered from a shock in the past six months. The absolute span of health shock, i.e. the mean number of months suffered, was 2.75 months (the maximum recorded being 12 months). 22% of the households reportedly suffered from an income-related shock in the last six months; the mean span of an income shock was 3.52 months (the maximum recorded being 12 months). These statistics indicate that the sample households suffered from these shock types only for a few months, thus discarding the possibility of any related chronic condition.

[Table 2 here]

[18]In Online Appendix B Table B3, a similar summary statistics of households with at least one child up to the age of five years shows the mean values of socio-economic characteristics remain similar to those in Table 1. The comparison with a bigger sample ensures that the households with children between 12-24 months are not, in any particular way, different from other households with small children in general. Similarly, Table B4 in Online Appendix B reports the corresponding statistics of Table 2 for a larger sample of households with children under five years.

[19]The values considered are in nominal terms, having a correlation of 0.99 with the real terms, and considering the latter does not change the study's main findings.

4. Empirical strategy

I use a linear probability model specification as given below, where health shock is the independent variable.[20]

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

Here, 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 the six-month interval before the interview date in survey wave t. *HealthShock* is a binary variable denoting the experience of a negative shock to health by the household h during the same time interval t. A health shock is indicated by the reported 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 (FE) α_h and survey wave FE μ_t. Our primary coefficient of interest is β_2, which measures the effect of the negative health shock experienced by household h in survey wave t on the intake of VAS by child i in the same household in that wave.

Through X, I control for child-level variables, such as the quality of care received. These include: if each parent lived in the same household, if each parent received any education[21] and if the child was breastfed at birth.[22] I further use household FE to control for several observable and unobservable time-invariant household characteristics that potentially affect the VAS intake by the eligible children. Household FE absorbs all the across-household variation and produces an estimate of the shock's average effect within households. Finally, the additional use of survey wave FE allows for controlling heterogeneity across the survey waves.

To further minimise the possibility of *omitted variable bias* through time-variant household features, I control for the number of under-five children present in the household during the survey (this number potentially affects the amount and quality of information which a household has on child healthcare), the total number of permanent members, i.e. those residing in the household all year round (gives an idea of the number of adults present; the more the number of household adults, the more flexibility in time to be invested in childcare), and a wealth measure proxied by percentiles in the valuation of land and housing owned. I further control if the family had relocated in recent years, if the survey interview occurred in a rainy season, and if the household lived in a flood-prone region. The last two controls take into account any possible seasonal effect.[23] Finally, in the set of controls for this econometric specification, I also include the indicator of a negative income shock proxied by a household-reported incidence of flood or drought, which may confound with a health shock.

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

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

[22] The variable on breastfeeding at birth should not be a 'bad control' (Angrist and Pischke, 2009; Wooldridge, 2010), as it is recorded during birth and is unlikely to be affected by a shock that occurs in the past six months in the household when the child is between 12-24 months.

[23] Figure B1 in the Online Appendix B confirms that these household-level variables are time-variant and thus, are not absorbed by household FE.

In a less-parsimonious version of the model, I also include some health supply-related variables. They are information on the healthcare facility accessed by the household; more specifically, whether it provides services on general outpatient care, immunisation, and whether the major limitations of the facility are its remoteness and lack of skilled staff. These health supply-related covariates potentially correlate with health shock and VAS take-up, as the role of the nearest healthcare facility plausibly relates to the health status of the household and their demand for healthcare. These variables are time-varying for two reasons and therefore cannot be accounted for by household FE: (1) the survey design allowed tracking of the sample households or their split-off parts that moved within parishes/communities, and (2) throughout the four survey waves spanning five years, many of these health supply facilities underwent expansions.

In another version, by the same argument of time variability, I control for more variables related to the location and road networking of the household. I include the distance of the household to the nearest facilities; these are - distances to the nearest public health centre, to the markets selling agricultural inputs, agricultural produce, and non-agricultural produce, to the primary market for livestock, to the nearest major trunk road and feeder road.[24], [25]

Finally, regarding the identification strategy, one concern is the exogeneity of the shock. One could argue that shocks are more likely to hit more vulnerable households. In addition to having household FE, I address the issue by including time-variant household features that potentially contribute to its vulnerability to being hit by a shock (discussed above). Later, I also implement the coefficient stability test (Oster, 2019) to quantitatively understand the degree of bias due to the selection on observables and unobservables (in Section 6.1); findings suggest that the estimated effect on VAS take-up is unlikely to be driven by unobservables.

To sum up this section: conditioning on the household FE and the possible time-variant confounders, the household shocks are likely to be orthogonal to any other unobserved determinant of VAS adoption, and thus we can expect that the effects are as good as causal.[26].

5. Results

5.1. The effect of health shock on intake of VAS

In Table 3, I present the regression estimates of Equation 1. Column (1) depicts the finding of health shock without any controls and Column (2) includes the controls, excluding household FE. In both columns, we see no significant effect of the health shock on VAS intake. Columns (3)-(5) include the household FE, but each column differs in the degree of time-varying controls.

[24]Controlling for the distance to markets on agricultural inputs and outputs accounts for the time used by the household adults in their primary agricultural activities, and in turn childcare. Additionally, connectivity to major roads controls for the time and effort required to reach more distant destinations.

[25]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 under construction during that time. In 2013, the construction of over 1,000 kilometres of roads started. So, the new road networks had a substantial impact on access to all amenities in life.

[26]In Online Appendix H, considering a balanced panel of households, I show that the common trends assumption holds for households with and without shocks, which further argues for causal identification.

In the sample, a substantial number of households (1172 out of 1592) appear only in one survey wave (because a household is only considered in a survey wave in which they have a child between 12-24 months) (See Section 3.2 para.4 for a discussion on the sample structure). In that case, ex-ante a pooled OLS may seem like a better model choice than one with household FE. However, a restricted F-test rejects the null hypothesis that the household-specific intercepts are jointly zero. Thus, it supports a household FE model as an appropriate choice, even though the effect then comes from only 420 households that appear in two waves on average. This indicates that the unobserved time-invariant characteristics specific to households are correlated with the shocks, which renders a pooled OLS estimate inconsistent and a household FE regression more reliable (Cameron and Trivedi, 2005).

Now, Column (3) presents the estimates of the model without any indicators of health supply and distances to other amenities. We see that the experience of a 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 14.6 percentage points (pp.) ($p = 0.070$). Compared to the overall sample mean of 73% VAS intake, these increases are about 20% due to health shock.[27] Column (4) shows that when the health supply indicators are included as controls, the coefficient remains similar. With further inclusion of controls on distances to the other facilities, the health shock coefficient is 0.160 ($p = 0.056$).

[Table 3 here]

5.2. Investigating the channels of effect

5.2.1. Time spent in labour force participation

The discussion of the healthcare structure of Uganda in Section 2 reveals that access is costly, not necessarily in user payment, but in terms of actually arriving and waiting at a healthcare facility to receive the services. Travelling to a healthcare facility has a high opportunity cost, especially in poor households whose daily earnings directly translate to only the basic sustenance of the family (Footnote 11). Therefore, it is interesting to examine if the positive effect of the health shock on VAS take-up happens due to the time spent away from the labour market by the household adults. Increasing time allocation in childcare during negative shocks is not uncommon in a poor household setting in developing countries. While Grossman (1972), Gronau (1977), among others, have provided the theoretical foundation to it, empirical studies show that the relative price of healthcare falls as do returns to working, especially in developing countries where child healthcare is more time-consuming (Miller and Urdinola, 2010).

To understand how the labour force participation reacts to the incidence of the shock, I regress the average weeks spent in their main activity in the labour market by a permanent household member on health shock, after controlling for the usual covariates.[28]

[27] Note that the overall means of VAS and other relevant variables do not change considerably in the sample utilised for household FE specification (Online Appendix B Table B2).

[28] According to the survey questionnaire, the *main activity* of individuals is the one in which they spent the most time of their

[Table 4 here]

Table 4 Column (1) shows the average effects of the health shock across households without any controls. With controls, Column (2) shows that the effect of a health shock has a negative and statistically significant on the average labour weeks across households. By including household FE in Columns (3)-(5), I find similar results. Column (3) shows that with the experience of a health shock in the household in the last six months, the average labour weeks spent by a permanent household member decreases by 6.41 units ($p = 0.006$). Similar findings are seen in Column (4) and Column (5) with more controls.[29] I also note that the variable on labour force participation cannot be constructed from the first survey wave due to data limitation, and thus, the analysis in Table 4 considers observations from the last three waves only. To confirm that the result is not specific to only a small sample, I re-run the regression on labour supply by considering households with children under five (Online Appendix B Table B5). The results qualitatively corroborate the earlier findings.

The measure of the household's labour force participation accounts for the time spent by all the permanent household members in their main activities in the recent past and takes an average over that. Now, if any member has to stay away from the labour force due to illness, this average labour time in the household likely decreases. One might argue that a health shock affecting a household member could prompt other members to make up for the former's lost wages by working more, however, the extra hours needed are perhaps not as high (somewhat evident from the summary statistics on average labour time with vs without shock in Table 1 and Online Appendix Table B6). Moreover, a health shock typically affects only 1-2 household members at a time (the sick person and possibly their caregiver), reducing the likelihood of creating a sense of urgency for consumption-smoothing through increased work, unlike e.g. an income shock resulting from a weather-related event that can impact the income of multiple household members simultaneously.

5.2.2. "Economies of scale" in seeking healthcare

The combined findings of Tables 3 and 4 hint at the possibility that VAS adoption happens while seeking remedial care from health shock. In Section 2, it becomes apparent that accessing healthcare is costly in terms of distance and time. In a typical case, a healthcare facility is accessible within 3-5 km of walking distance; however, it does not guarantee that the service sought will actually be obtained given the lack of available services (Chaudhury et al., 2006; WHO, 2017). Therefore, this may result in travelling to other healthcare facilities farther away, thus prolonging the travelling and waiting time. By definition, Health Centre II at the parish level should provide both general outpatient (GOP) care and immunisation services

labour force participation during the previous year. This activity could be their primary job (sometimes also a second/third job), and it could be any income-generating (in cash/kind) work in the agricultural or non-agricultural area, paid domestic work, work in their own/household business (sometimes even without being paid), work with/without pay as apprentices, work in a household's farm (e.g. tending crops, feeding animals). It implies that domestic work for one's own household e.g. cooking and cleaning, and taking care of household members are excluded from this definition.

[29] Although in this exercise, the restricted F-test does not reject the null hypothesis that the household-specific intercepts are jointly zero (except in Column 5), I opt to focus on the household FE specification since the first set of results on VAS take-up (Table 3) is based on that.

(including VAS). However, a closer look at the data in Table 5 shows that although all Health Centres II, which the households in my sample have access to, are equipped to provide GOP, there is an 11% chance that they do not provide immunisation.[30] More striking is the statistics that there is only a 59% chance that when they do provide immunisation, they would have suitable conditions (e.g. refrigerators) to store vaccines.[31] It also appears from the number of observations in the table that, in more than 50% cases, households are primarily dependent on Health Centre III (located at a higher aggregate, i.e. sub-county level), and the chances for them to be located quite far is as high as 36%. In summary, these statistics highlight two facets of the Ugandan healthcare reality: (1) immunisation services may not be as *easily* and as *successfully* accessible as GOP services at the "closer" Health Centre II and thus may discourage take-up in general; (2) most of the households in the sample may have to travel far to maximise receiving healthcare services (both remedial and preventive) under one roof.

[Table 5 here]

To understand better how the households optimise their visit to the healthcare facility in this context, I resort to the theoretical foundations provided by Goldman and Grossman (1978).[32] In a framework to study the demand for (paediatric) healthcare where quality in the physician market is distinguishable, it is assumed that (1) the quality of a visit to the physician has a quality-adjusted price per visit (quality being the physician's experience, credentials, etc.) and (2) the price per visit is an increasing function of the quality. The fixed cost covers the transportation cost and the opportunity cost of the time spent by the parent in travelling and waiting (weighted by their hourly wage). This fixed cost per visit is independent of the quality of the service received. The shadow price of quality increases with visits, and that of the number of visits increases with quality. Therefore, in equilibrium, the marginal rate of substitution between quality and visits must equal the price of quality relative to the price of visits. In comparative statics analysis, Goldman and Grossman (1978) show that visits fall and quality per visit rises as fixed cost increases. They also find that quality-adjusted prices have a larger negative effect on the quality sought than the number of visits.

The theoretical arguments of this model validate the findings of my study to a large extent. First, I plausibly argue that the quality of Health Centre III is always better than that of Health Centre II (the former clearly offers better chances of receiving more services successfully than the latter (also in Table 5). (In my case, quality is analogous to the number of services that can be successfully obtained.) Since 90% healthcare

[30]The community questionnaire of the UNPS survey informs about the healthcare centres available (≡ most accessed) for a given community/village. Relevant information on the availability of services (GOP, immunisation, etc.) and other attributes are also available.

[31]Measles, DPT, BCG, etc. vaccines are medically recommended to be stored at cool temperatures of 2-8° Celsius and should be strictly discarded after a few hours of opening the vial. Conversely, VAS, which is available as oral liquid drops for children, can be stored at room temperature; however, they should be stored in a refrigerator until expiry once the vial is opened. Furthermore, I assume that given VAS is part of the children's immunisation and health promotion programme, its availability in healthcare facilities is expected to be comparable to that of other immunisation categories, like measles and DPT vaccines.

[32]They extend the theoretical framework of quality-quantity developed by Becker and Lewis (1973).

facilities in my sample are government-owned, we can assume that the quality-adjusted price per visit does not increase substantially (perhaps nominally, with some additional out-of-pocket expenditure if the patients obtain more healthcare services). However, travelling to a better but more distant facility substantially increases the fixed cost of travelling and waiting.[33] Therefore, in line with the model predictions by Goldman and Grossman (1978), the ratio of quality to visit would increase as the fixed cost per visit increases. With prior experience that the lower-tier Health Centre II may not be well-equipped with immunisation facilities and that they have to travel farther to the Health Centre III for better facilities, the household is likely to postpone the child's routine immunisation and rather receive "quality" healthcare including both remedial and preventive, during the same visit to the higher-tier Health Centre III, with a trade-off of higher fixed cost. While preventive actions (routine immunisations recommended in the child health programme, including VAS) could be postponed, remedial care may not be. As a result, visits to the healthcare facility for multiple services arguably happen during health shocks in the household.[34]

[Table 6 here]

Furthermore, in this sample, more than 90% of the accessed healthcare facilities are also supposed to provide immunisation services besides GOP (Table 5), but there are also those that provide only GOP, or only immunisation services but rarely. Holding constant that immunisation services are provided in a given healthcare facility, Table 6 Column (1) confirms that there is a statistically significant positive association between the provision of GOP and VAS take-up by the household in that facility in a shock-free situation.[35] With the incidence of a health shock, this positive association gets larger in magnitude (increased by 17 pp.); however, the estimate becomes statistically insignificant and only suggestive. Conversely, Column (2) shows that the provision of immunisation services in the facility and VAS take-up are negatively associated and that is statistically significant; during health shock, the effect becomes relatively positive but remains statistically insignificant. Thus, this again somewhat hints that the VAS take-up channel is more functional through the availability of GOP services (along with immunisation services) in healthcare facilities.

Before concluding this section, recall that the health measure used in this study is the self-reported incidence of severe illness or death in the household. While the above mechanism potentially works during illness, it does not work during death. Regardless, it is unlikely to be a major issue in this study as only 12% reported health shocks ($\equiv < 1\%$ in the entire sample) are deaths. Furthermore, some deaths may happen after a period of seeking and obtaining remedial care in healthcare facilities, in which case the argued mechanism would still be valid.

[33] Recall from Section 2 that Health Centre III is at the sub-county level and caters to a population of size ~20,000, as opposed to Health Centre II, meant for ~5,000 people. Naturally, waiting time is longer in the former, which is exacerbated if patients also arrive for services which are supposed to be already obtainable at a lower-tier facility like Health Centre II.

[34] Considering the healthcare facility "Other" in Table 5, they seem to be few, small (perhaps community-owned) units. Although they are closer and thus have reduced fixed costs, the quality of services obtained is lower (only 75% offers immunisation), and the prior knowledge of quality shortage could be a deterrent to visiting them.

[35] I rely on diagnostics to discard any severe concern of multicollinearity when controlling for immunisation services in the same regression model studying GOP services.

To sum up Section 5: the incidence of health shock in the household is found to increase VAS take-up for the child. I show that when health shock hits, the average time in the labour supply decreases within a household. Drawing on the institutional setting and with the support of descriptive evidence, I argue that the underlying mechanism is somewhat an *economies of scale* approach of combining remedial care and VAS take-up in times of health shock, by which the household minimises the fixed cost of travelling to distant health centres by maximising the number or quality of care sought. This is in line with the theoretical foundations provided by Goldman and Grossman (1978). Reflecting further on the summary statistics in Tables 1 and 2, an average household consists of four permanent members, with two being children under five years. Therefore, either one of the adults or children gets a health shock. For instance, if one of the adults - e.g. a parent - falls ill, that adult typically visits a healthcare facility and brings the children along, resulting in the children indirectly receiving their VAS doses. Alternatively, if one of the children falls ill, the primary caregiver, often the mother, may forgo work to take them to the healthcare facility.[36] It is also possible that the very child who is eligible for VAS gets the health shock; however, that too can be explained with the same mechanism: i.e. if the child is taken to the healthcare facility for remedial care, it is likely that the sick child's VAS doses are updated too.[37] Finally, if the one who gets sick is an elderly member (who is not active in the labour force), then the other working adult remains at home and cares for the former; if they visit the healthcare facility for remedial care, it is very plausible that they do not leave the children behind at home, and as a consequence of the visit, the children get their VAS doses. All in all, given the composition of the households with 12-24-month-old children in my sample, it is hard to distinguish whether, in the event of a health shock, the family actively decides to take the child to the healthcare facility to get their VAS (and other immunisation doses) updated while seeking other remedial care, or if it is (passively) obtained as a secondary service from the healthcare provider because leaving behind the small children at home is not an option. Nevertheless, the overarching issue remains that work often takes precedence over timely investments in a child's preventive healthcare; otherwise, VAS would have been administered on schedule regardless of experiencing a health shock.

6. Sensitivity, Validity and Robustness

The findings in Section 5 lead to some intriguing arguments on the unexpected outcomes of adverse health shock on the VAS take-up for children through adults' time released from the labour market. In this section, I first gauge the sensitivity of the main result by implementing the coefficient stability test proposed by Oster (2019). It is followed by an exercise on internal validity test where I explore if the shock's

[36]The mother is a child's primary caregiver, and the literature considers the opportunity cost of child healthcare primarily as the mother's lost daily wages (Goldman and Grossman, 1978; Vistnes and Hamilton, 1995). Furthermore, existing literature acknowledges that women constitute 50% of the workforce in Ugandan agriculture; however, their productivity in agriculture is lowered by their time demand in child- and elderly-care and domestic work (Ali et al., 2016; Guloba et al., 2018).

[37]I further discuss the econometric modelling concern regarding the health shock of the child who is VAS-eligible, in Online Appendix C.

effect is replicated on the take-up of other categories which are part of children's immunisation programme. Subsequently, I conduct a robustness check with an instrument variable approach, followed by an auxiliary investigation to distinguish between the effect and pathway of a health shock versus an income shock.

(Since the econometric models with household FE function better in the main analysis of VAS take-up, I consider only those specifications in the analyses in the following subsections and in the Online Appendices unless stated otherwise.)

6.1. Selection on Observables and Unobservables

In this section, I explore the stability of coefficients using the methodology proposed by Oster (2019), which allows for different assumptions on bias due to the selection on observables and unobservables.

For this exercise, I consider two model specifications - with vs without household FE.[38] To implement this method, I first repeat baseline regressions without any controls (except for the household FE in the model which has it). The baseline coefficients and R^2 are given by $\dot{\beta}$ and $\dot{R}^2$ and that of the regressions with the full set of controls are given by $\tilde{\beta}$ and $\tilde{R}^2$. Following the adjustment strategy proposed by Oster (2019), the bounding values of the coefficient are calculated for R^2_{max} and δ. While calculating the bounding values of the coefficient, I assume equal selection on observables and unobservables i.e. $\delta = 1$ and set R^2_{max} to $min(1, \pi^* \tilde{R}^2)$ with a benchmark rule-of-thumb of $\pi = 1.3$ and a more demanding assumption of $\pi = 2$ (Oster, 2019; Tabellini, 2020). Table A1 Columns (5)-(6) suggest limited movement in the point estimate, especially for $\pi = 1.3$, which in turn implies that there is no potential omitted variable bias in the model.

I also present Oster's *delta*, which indicates the degree of selection on unobservables relative to observables which is required to fully explain my results by omitted variable bias. While a positive delta would imply that the selection in unobservables has to be higher than the selection in observables in order to make the treatment effect null; on the contrary, a negative delta implies if observables are positively correlated with the treatment, then unobservables have to be negatively correlated with the treatment, to have a null treatment effect. I obtain negative values of the delta (Table A1 Columns (7)-(8)). However, since the inclusion of controls actually strengthens the shock's estimated effect on VAS take-up, the test indicates that it is unlikely that omitted variables are driving the observed effect (Graham et al., 2017; Eichengreen et al., 2021).

6.2. Effects on other immunisations for children

This section reports an internal validity test by examining the take-up of other categories recommended in the immunisation and health promotion programme for children, such as measles and DPT-3 vaccines. The primary rationale for my emphasis on VAS in this study thus far lies in the quality of the information available. The survey enumerator asked the household in each wave whether their child (12-24 months) received VAS specifically in the past six months and whether they suffered from a shock in the recent past. From the detailed information available for the shock, it is possible to pin down whether the shock occurred

[38] These are equivalent to specifications in Columns (2) and (5) in Table 3.

during the past six months when the VAS was also due. However, for measles or DPT-3 vaccines, the enumerator only asked if the child (12-24 months) received those vaccines at any time in the past. Ideally, measles immunisation should occur at 9 months of age, but delayed receipt of routine vaccines is common in developing countries. Consequently, it is difficult to know if the measles immunisation timing and the shock in question overlapped in this context. Even if I extend the shock incidence window in the study, several other factors could be driving (no)/take-up.

As a result, in order to optimise the overlap of the shock and immunisation and also be able to say that the shock might have been the driving agent of take-up of the vaccine, I limit the age range of children to 9-15 months in each wave, and I analyse the child's receipt of measles vaccine due to a health shock in the past six months from the survey interview date in their households.[39] Table A2 Panel A indicates that the effect of the health shock is imprecisely estimated at zero, with large standard errors.

The recommended schedule for DPT-3 immunisation is 14 weeks after birth. Limiting the age range e.g. to < 6 months does not provide any meaningful sample size to work with. Therefore, in this case, I limit the child's age between 0-12 months during each survey interview; moreover, I also extend the shock window in their households to the past 12 months from the interview date. With standard errors similar to VAS results (Table 3), it is probable that the estimated effect of health shock on the DPT-3 take-up is precisely zero in Table A2 Panel B.

To summarise: the effect of the health shock is reflected only in VAS take-up and not in the take-up of other more "conventional" immunisation categories, in this context. The measurement error issues discussed above call for more research to conclude on a broader impact on all immunisation categories.

6.3. Endogeneity of health shock

This study is interested in the effect of health shock in the household on the take-up of VAS for their children, where I have used VAS as a representative of preventive healthcare for children. However, studying the effect of health shock on health outcomes is potentially riddled with reverse causation, i.e. in this setting, the take-up of preventive healthcare could affect the probability of facing a health shock. To address this potential channel of endogeneity, I use the instrumental variable (IV) approach. The two candidates used as instruments for health shock in the household are (1) the prevalence of health shocks within the same parish in the same survey wave, weighted by the age group of the household head,[40] and (2) if the household used mosquito-repelling bednets while sleeping at night in the recent past.[41]

[39] While limiting the age range could give a better overlap, it also reduces the sample size, and vice versa if the age range is increased.

[40] The rationale is: the association of prevalence of health shock in the vicinity with household-level shock would be stronger if the household has older adults (proxied by the head's age-group) who, in other words, are more prone to falling ill. (This stronger correlation is also visible in the sample.) A similar instrument of household-level health shock has been used by Mitra et al. (2016).

[41] In 2009-10, malaria was highly endemic in ∼95% of Uganda, representing ∼90% of the population of ∼33 million. The 2009 Uganda Malaria Indicator Survey measured a prevalence of malarial parasitemia, assessed based on microscopy, of ∼3050% in children aged 659 months (UBoS, 2010).

While using only a household FE removes time-invariant heterogeneity and systematic measurement error across households, combining FE with IV could address time-variant heterogeneity and random measurement error. The instruments' validity depends on the following criteria: (1) they must be sufficiently correlated with the endogenous regressor, i.e. in this case, the health shock measure (relevance criteria); (2) they affect VAS take-up only through the channel of the health shock (exclusion restriction); and (3) they should not be correlated with time-variant, household-specific error terms that affect VAS take-up (Wooldridge, 2010).

Concerning the exclusion restriction, one can argue that the instrument of the prevalence of health shock in the parish potentially affects the urgency of healthcare supply in the area, which in turn affects preventive healthcare/VAS take-up. However, my econometric specification already controls for that pathway by conditioning on health supply-side covariates and other distance variables of road networks; thus, in principle, the exclusion restriction should be satisfied. Concerning the second instrument, if the incidence of health shock in the household is to affect the take-up of VAS, then it is plausible that bednet use in the recent past can be linked to VAS only through the health shock in the household.[42] Another potential channel that could directly link bednet use and VAS take-up would be household lifestyle and attitude; however, it should be absorbed by household FE. The further use of relevant time-variant household-level controls ensures the exogeneity of the instrument.

The first-stage estimation is reported for the two instrument variables separately and together (Table A3). In the IV diagnostics, the first instrument - the prevalence of health shock within the same parish weighted by the household head's age - performs the best alone by qualifying all the validity checks of under- and weak-identifications. However, the other instrument of bednet use does not qualify alone as a valid instrument. When considered together, the null hypothesis of zero correlation between the instruments and the error term cannot be rejected through the over-identification test.

Finally, the second stage of the first instrument alone (Column (1)) and the two instruments together (Column (2)) are reported in Table A4. The effect on VAS take-up does not change meaningfully from Table 3; the magnitude is larger. Including the second instrument with the first does not lead to the rejection of weak identification (Kleibergen Paap rk Wald statistic $<$ Stock-Yogo critical value) when standard errors are clustered.[43] Although the first instrument works better alone, it is preferable to keep both as each essentially covers different sources of variation in the health shock in the household.

6.4. Effect of income shock on VAS

In the existing literature, the distinction between health and income shocks often gets unclear, due to their interconnectedness (Weil, 2014). However, in this study, since the mechanism through which health

[42] If the mechanism of VAS take-up due to health shock is indeed through the *scale* approach explained in Section 5.2.2 (i.e. VAS take-up happens when the household adults visit a health centre for remedial care), then it is plausible that sleeping under a bednet is associated with reduced chances of health shocks such as malaria and other diseases from pest- and bug-bites, which in turn would associate with reduced take-up of VAS.

[43] With i.i.d assumption, however, the weak instrument problem is eliminated. However, note that the case of weak instruments for health shock is not uncommon in the related literature (Grimm, 2010; Mitra et al., 2016).

shocks influence VAS take-up is unique, it is interesting to examine the role of an income shock within this context. Given that my sample primarily experiences short-term health shocks (Table 2) with minimal death occurrences (which otherwise may confound as negative income shock), I attempt to assess the two effects separately. Note that all the regressions studying the effect of health shock so far, also control for an income shock suffered by the household during the same time window. Tables 3-4 suppress the coefficients of the income shock; however, here I highlight and discuss the income shock coefficients (see Tables A5-A6 in Appendix A). Essentially, in this section, I discuss an econometric specification as follows:

$$Y_{iht} = \beta_0 + X'_{iht}\beta_1 + \beta_2 HealthShock_{ht} + \beta_3 IncomeShock_{ht} + \alpha_h + \mu_t + \epsilon_{iht} \quad (2)$$

Equation 2 is an extension of Equation 1, where the coefficient β_3 of *IncomeShock* is also of interest.[44] As briefly mentioned earlier in Section 4, *IncomeShock* is a binary variable denoting the experience of a negative income shock proxied by a reported incidence of flood or drought by the household h during the same time interval t when VAS is taken. (The relevant question in the survey questionnaire is *if the household faced a shock due to flood or drought/irregular rains in the past year*, and its incidence in the past six months is obtained in the same way as for the health shock.)

In the context of developing countries where agriculture is the main livelihood, a common practice is to use agriculture-related variables (e.g. accidental crop loss by farming households (Beegle et al., 2006; Bandara et al., 2015)) or weather-related variables (e.g. district-wise rainfall variation (Björkman-Nyqvist, 2013; Shah and Steinberg, 2017)) as proxies for income shocks. In my sample, 50% of the households (having children between 12-24 months) have agriculture as their primary income source, with 4% of them engaging in commercial farming and 96% in subsistence farming.[45] Therefore, drought and flood are ideal candidates for an income shock here.

Table A5, which is merely an extension of Table 3 reporting the estimate of the income shock, shows that it affects VAS intake positively in a household FE specification (except in Column (3)). On the other hand, the average effect of the shock on labour force participation is positive too (Table A6). An income shock likely has a broader impact on households in this setting, which explains the second finding above. In Uganda, many households rely on agricultural activities as their primary income source. Consequently, when a shock affects this income source, it compels them to seek alternative income sources for consumption-

[44]In practice, income and health shocks can often be intertwined, potentially causing multicollinearity issues when considered together in a single regression equation. However, in my sample, the correlation between these two shocks is only 0.027, indicating minimal concern for multicollinearity. Nevertheless, I reiterate this inseparability issue of the two shocks in greater detail later in Section 6.4.1.

[45]In Uganda, over 60% population is involved in agricultural activities, and more than 80% of these individuals are subsistence or smallholder farmers. These subsistence farmers typically cultivate < 1 hectare of land and have a small number of cattle. They grow crops and raise livestock primarily for their own consumption, with a small surplus intended for local markets. Subsistence farming is typically labour-intensive and relies on household members, as these farmers often lack the means to hire external labour. Due to limited transportation options and high transaction costs along the value chains, they often sell their surplus produce to local markets and traders, yielding minimal profits.

smoothing.[46] As a result of this shock, often additional members, especially in poorer households, may also contribute by looking for income-generating activities; evidence supports that adolescents are also sent to work to contribute to the income pool (Beegle et al., 2006) or substitute labour at home production when the adults look for more work (Björkman-Nyqvist, 2013). Thus, given the definition of the *main activity* used in the survey questionnaire (Footnote 28), it is likely that during income shock, all the working adults spend their maximum time in their second or other jobs and adolescents are probably sent to work too, thus increasing the average weeks spent in the labour force.

While it is valid to have a dominant income effect of the shock in this context, it is also necessary to reconcile this with the contradictory increase in VAS take-up (which could plausibly happen through a dominant substitution effect). To investigate further if the two findings in Tables A5 and A6 can be reconciled, I interact the shock with the wealth percentiles of the household. This specification helps us understand how households with different wealth levels cope with the income shock. Focusing on the household FE estimation in Table A7 Panel A, we see that during an income shock, a relatively wealthy household allocates less time on average to the labour market (with the interaction coefficients becoming more negative higher up in the wealth percentile). However, these findings are not statistically significant.

As noted earlier, the variable on labour force participation suffers from data issues and thus the finding in Panel A may be riddled with a statistical power challenge. On repeating the same exercise with a bigger sample of households with at least a child under five years in each wave (Panel B), the interaction coefficients across the wealth percentiles confirm the pattern, i.e. as the wealth percentile increases, the average weeks spent in the labour force decreases during an adverse income shock. This sufficiently confirms how households with different wealth levels react to an income shock in their labour supply.

A decrease in the slope of wealth level during an income shock implies a stronger substitution effect for the relatively wealthy. If the household is capable of insuring away the shock by buffer stocks, the opportunity cost of being away from the labour market is low during an income shock and the released time can be invested in other time-consuming activities, such as child healthcare (Miller and Urdinola, 2010). On the other hand, the poorer households, devoid of buffer stocks, are forced to spend more hours in the labour market working on other income-generating jobs. Previous literature already showcases that households offset transitory income shocks by using asset holdings (either as a buffer or collateral against credit) (Deaton, 1992; Beegle et al., 2006); while the relatively wealthy can use savings or borrow credit

[46]Livelihood/income diversification in on- and off-farm sources is a common phenomenon in the rural agricultural setting in African countries, primarily due to weather and volatility of markets (Heumesser and Kray, 2019). In times of negative shocks that affect agriculture (e.g. rainfall or droughts), families can rely on off-farm income to maintain their livelihoods (Rapsomanikis, 2015). Further evidence from African rural settings shows that while poorer households tend to do so as a survival strategy, wealthier smallholder farmers successfully diversify as an asset accumulation strategy (Dimova et al., 2021). Uganda's diversification picture is typical of this setting. Evidence from the first three waves of the same UNPS survey shows that Ugandan households engage in 2-5 income-generating sources, with an upward trend over time in - (1) the number of non-farm workers in the household, (2) the share of households with both agricultural wage and non-agricultural self-employment and (3) the average number of labour activities an individual in a household engages in (Khan and Morrissey, 2019). See Khan and Morrissey (2023) for a summary of Uganda's diversification in the 1990s and 2000s.

to cope with shocks, the poor resort to multiple employments or migration besides reducing consumption (Van Campenhout et al., 2016). Moreover, Figure A.1 gives an overview of the most-used coping strategies during the income shock by households in different wealth percentiles. It appears that the poorest quartile primarily responds to an income shock by finding more employment, while the households above the third quartile draw down savings or borrow credit as their most-used strategy.

This likely underlies the observed results. The average effect on VAS take-up in Table A5 appears to primarily result from a dominating substitution effect of the income shock among the relatively wealthy. While the sample is limited in exploring this plausible mechanism any further by exploiting other parameters, some descriptive suggestion arises from a pattern showing that the VAS take-up and the average time spent in labour supply by households across different wealth percentiles are somewhat correlated (Figure A.2).[47] Nevertheless, note that the average labour time is the closest measure of time allocation available in this survey; it is hard to get a perfect mapping of the released time from the labour market during shock and VAS take-up.

All in all, although it is evident that the relatively wealthy household faces a dominating substitution effect of the income shock, and that plausibly drives the average positive effects on VAS take-up, the study lacks a better mapping of this pathway through more convincing analyses.

6.4.1. (In)separability of health and income shock

With multiple robustness checks, I further stress that the channel of health shock is not entangled with income shock and that the health shock estimate in Table 3 is reliable. First, I analyse separate regressions for each shock to account for potential spillovers. For instance, rainfall or drought might affect household health. Comparing direct shock effects in separate regressions (Panels A and B, Table A8) reveals minimal coefficient changes from that in Table A5.[48] This confirms that the two shock types are uncorrelated.

In another exercise, I adjust the health shock definition to minimise potential links between the shock types. The current definition considers any household member's illness or death in the last six months, including the primary earner. However, this primary earner's health shock could culminate in an income shock. To address this, I revise the *HealthShock* variable such that it accounts for the illness or death of any household member except the primary earner. This, however, lowers the proportion of households affected (from 7% to around 4%). Table A9 Panel A summarises the outcomes. Across all specifications, the key result regarding VAS intake remains consistent. The positive impact of a health shock maintains similar strength, but in Column (3), the coefficient loses precision.

Regarding the health shock measure, it is worth noting that not all deaths qualify as health shocks, such

[47] This is, however, only a simple correlation of VAS and labour supply across the different wealth percentiles during income shock. It neither considers whether the households beyond the third quartile work more hours compared to the lower quartiles, to begin with, nor depicts the intra-household time allocation in and out of income shock.

[48] Too different shock coefficients in the separate regression models compared to the original one (Table A5) would imply that the two shocks are correlated, and the omission of one shock in the separate regressions introduces estimate bias.

as those from old age or accidents. To address this, I analyse only the illness of household members (excluding the primary earner) as a health shock indicator. It reduces the proportion of households affected even further (as death constitutes 12% of original health shocks). Outcomes are summarised in Table A9 Panel B. The magnitude of the positive health shock effect slightly decreases compared to Panel A, and estimates are imprecise. While excluding deaths further decreases the health shock proportion, potentially affecting the estimate precision, it is important to acknowledge this as a plausible lower bound. Some deaths could follow illnesses (and consequent health centre visits) thus keeping the discussion on VAS take-up channel valid.

Despite the mentioned robustness checks, a caveat remains: health shocks to other household members could affect the household's income too through their potential contribution to the labour force and income pool. An easy solution to this problem could be examining if the experience of health shock in the household in the last six months correlates with the household's asset holdings. This examination, using the original health shock measure, reveals no statistically significant association. In contrast, an income shock in the last six months is negatively and significantly linked to the household's overall asset holdings. It implies that the health shock measure used here does not confound as an income shock. Results are reported in Table A10.

While these above robustness tests still do not foreclose the possibility of an income shock causing a health shock, one can (optimistically) deduce from the positive association of an income shock and average labour hours of the household (Table A6) that this is unlikely, at least within this sample.

6.5. Other robustness and sample issues

In this section, I briefly outline some further exercises conducted to understand the reliability of the results. They are reported and discussed in greater detail in the Online Appendices (OA). Through these examinations, I confirm that the results of the main effects of the household shock on VAS hold when the following are considered: (1) when child FE are controlled for instead of household FE, to account for the situation when the children eligible for VAS themselves suffer from health shock (OA C) (only suggestive evidence obtained), (2) when the shock intensity (in terms of months suffered due to shock) is taken into account (OA D). I also confirm that neither the sample suffers from attrition bias (OA E) nor any selection issue, such as relatively poor households tending to under-report subjective health status (OA F).

Moreover, since this study is also interested in distinguishing the impact of the income shock from that of health shock, I also use an alternative income shock measure by replacing the self-reported income shock with weather shocks based on historical monthly precipitation data (OA G). Lastly, in light of the nascent literature on biases arising from two-way-fixed-effects identification strategy in the case of heterogeneous treatment effect (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021), I confirm that in this study, heterogeneity in shock is not severe enough to alarmingly bias my results on VAS take-up (OA H).

7. Discussion and Conclusion

This paper aims to empirically examine how low-income households in developing countries trade off time investment in their children's preventive healthcare during health shocks. The Ugandan context is such that even though preventive healthcare for small children, such as vaccinations and health-promoting supplements, are publicly provided free of cost at public healthcare facilities, households have to travel long distances and face long waiting hours (which translate to a high opportunity cost of time due to lost wages) to access them (or, any healthcare services in general). As this fixed cost is quite high, adults in households may prefer to postpone these preventive healthcare activities for their children and avail them only while visiting healthcare facilities to obtain remedial care from a health shock.

Using the illness of any household member as an indicator of negative health shock, I examine how the receipt of VAS doses by children of 12-24 months, as a part of their immunisation and health promotion programme, is affected, and I find the average effect to be positive. In order to explore the pathway, the effect of the shock on labour market participation is also examined. I find that the average time spent in labour supply by the members of a household hit by health shock is less compared to facing no health shock. Some descriptive evidence on the health supply-side scenario in Uganda argues for economies of scale mechanism by which the household adults arguably minimise the fixed cost of travelling and waiting time by obtaining both remedial care for health shock and VAS for their children in one visit to the health centre (i.e. the study finds a significant positive association between VAS take-up and availability of general outpatient services in the most accessed health centre by the household, with a suggestive evidence of increase in take-up during health shock). Furthermore, given that lower-tier (parish-level) Health Centres II may not always be well-equipped to provide multiple services, the households perhaps even prefer to access the upper-tier (and often, more distant) Health Centres III (at sub-county-level), which are likely to have more facilities. It means higher fixed cost but maximisation of services in one go. The theoretical underpinnings of this economies of scale argument are rooted in the model for healthcare demand à la Goldman and Grossman (1978), where the authors formally prove that the number of visits falls and the quality of healthcare sought per visit rises as the fixed cost per visit rises. (In this study's context, the quality of care sought per visit is analogous to the number of services demanded.)

Existing literature has offered some insight into how the dynamics within the household members may play out during the shock. 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. Women's role in Uganda's rural agriculture is vital as they contribute to 50% of the workforce, yet their productivity in agriculture is lowered by their time demand in childcare, unpaid care and domestic work (Ali et al., 2016; Guloba et al., 2018). The Demographic and Health Surveys of 2000-01 report that 4 in 10 children (5-17 years) worked for their family, the older the age the higher the figure; taking care of younger siblings is a common task for elder children (13-17 years), especially girls (Guloba et al., 2018). To reconcile our findings of the health shock in the sample households, it is plausible that one of the adults, usually the mother, diverts time away from agricultural tasks to care for the ailing and/or take them to healthcare facilities for remedial purposes. The typical household structure with two adults and two children under five years in this sample lets us speculate that when one of the adults (perhaps the parents) is sick, s/he visits the healthcare facility for remedial care and takes the children along, while the other adult works; alternatively, if one of the children is sick, the mother usually stays back from work to take the children to health centres. In any case, the VAS doses of the children are updated during the visits. This argument holds even if one of the adults in the household is an elderly dependent - then the other adult stays back and cares for the former; should a health centre visit be necessary, the children are not left behind at home. This is, of course, a plausible narrative of how a household in my sample may allocate their time; nevertheless, future research should delve deeper into the dynamics within households with adolescents and even multiple nuclear families living together under one roof.

This study also delves into a second line of research inquiry, aiming to differentiate the impact of health shocks from income shocks, the latter defined as instances of flood or drought. However, it is essential to interpret the mechanism of income shock with caution due to the absence of rigorous analysis. In the case of income shocks, despite the average positive effect on labour market engagement, interaction with household wealth levels reveals that the relatively wealthy dedicate less time to the labour market during income shocks. This observation suggests that for wealthier households, income shocks through floods or droughts may reduce the opportunity cost of time away from work, possibly facilitated by buffer stocks or borrowing. This dynamic may contribute to the observed average increase in VAS take-up during income shocks, with wealthier households potentially reallocating labour hours to health-promoting activities. Although I lack rigorous analysis to conclusively validate the argued link between labour-free time and VAS take-up, it emerges as a plausible explanation.[49] Nevertheless, a crucial lesson from the average positive effect of the income shock on VAS take-up is: when shaping policies, we need to look beyond the average effect and consider the tails of the distribution more often. In other words, the observed positive average effect on VAS take-up does not diminish the fact that a negative income shock would, in fact, worsen the VAS take-up rate of the poorer households in the bottom income percentiles, who face a dominating income effect.

Furthermore, it is worth noting that this study focuses solely on the take-up of VAS as a type of preventive healthcare for children. While VAS closely aligns with other immunisation categories in terms of emphasis on implementation (in the national immunisation programme), this study is unable to replicate a similar effect for vaccines on measles and DPT-3 due to data limitations. Additionally, I recognise that the relationship between household shocks and other preventive healthcare measures meant for daily life, which might operate through different channels, is outside the scope of this study. On a somewhat related note, the use of the phrase VAS "take-up" may be a misnomer here because the mechanism in this study implies that it is not

[49] The findings on this mechanism are only indicative and do not negate the role of other factors in parallel. For example, it is crucial to distinguish if the increase in VAS take-up during income shock is caused only by the substitution effect or does experiencing adverse weather conditions makes adults more health-conscious in general.

an *active take-up* per se by the households. It is rather obtained as a "secondary" service; sometimes, it is perhaps even obtained passively if the healthcare provider initiates the process when the family visits the health centre primarily for remedial purposes and the child simply tags along.[50] Nevertheless, it still highlights a pathway of how children in these settings usually get their VAS doses.

It is worth mentioning here that Uganda, like other African countries, started organising *Child Health Days* (or, *Child Days Plus*), twice annually since the mid-2000s, as a temporary strategy to supplement routine immunisations and improve child health status. These month-long outreach initiatives target children aged 0.5-14 years, providing them with vaccinations, health supplements, and various health promotion measures in one session. These services are not only available at public health centres but also in schools and communities, aiming to offer adults a convenient "one-stop-shopping" experience for their children's healthcare needs. However, as Fiedler and Semakula (2014) highlight in their study conducted in 2010, the programme was underfinanced in the first place and thus might have suffered disruption in outreach, and in turn, created uncertainties in the minds of implementers and the public alike about the quality and coverage. The authors' study revealed that in 2010, only a small fraction of health facilities managed to implement the core activities of this programme. Given this controversial coverage, I argue that the potential impact of that programme in the study should remain minimal.

Finally, this study underscores the importance of time in child healthcare and development, as has been previously discussed by Grossman (1972); Gronau (1977); Vistnes and Hamilton (1995) for developed countries, and Miller and Urdinola (2010) for developing countries. The result that VAS take-up rises even in unexpectedly released times during shocks highlights the need for social policies to consider time constraints. In developed countries like the United States, more working hours of adults, especially mothers, are negatively associated with illness-related health centre visits for children (Vistnes and Hamilton, 1995), preventive healthcare visits such as receipt of influenza vaccines and dental care (Hamman, 2011; Shepherd-Banigan et al., 2017). In those societies where health service delivery is not necessarily mediocre, skilled working adults are primarily limited in time flexibility in obtaining healthcare. Furthermore, adults working in low-skilled hourly wage jobs also face monetary constraints, and their children are at the highest risk of not receiving recommended paediatric care. Existing literature stresses the need for well-designed organisational policies, such as universal and flexible paid leave benefits, allowing employees to allocate resources for family medical issues, which, in turn, could address the disparities in the receipt of children's preventive care. At the same time, they highlight the need for more accommodating policies in healthcare and educational sectors, such as extended clinic hours and improved school-based preventive healthcare service programmes (see Shepherd-Banigan et al. (2017) for an overview). On the other hand, in the context of developing countries, where the challenges are both in the demand and supply sides, in terms of time and monetary constraints of adults (demand-side) and in terms of quality and coverage mediocrity of healthcare (supply-side), policies

[50]In that case, lack of information on the importance of preventive healthcare is also a concern (Dupas, 2011). This study abstracts away from exploring that.

need to be more nuanced and extend beyond free provision. Particularly in settings like Uganda and most of sub-Saharan Africa and South Asia, where the informal labour market is predominant, a paid day off work is not appropriate and all-encompassing. While in these settings, mass campaigns using healthcare volunteers have shown some positive effect on outreach and take-up, bundling them together with food ration incentives have been more effective (Loevinsohn and Loevinsohn, 1987; Banerjee et al., 2010), where the food incentives essentially offset the opportunity cost of a health centre visit.[51] At the same time, conditional cash transfers have proven beneficial in improving the take-up of preventive healthcare services, such as vaccinations (Barham and Maluccio, 2009; Robertson et al., 2013) and the utilisation of public health services in general (see Baulia (2023) for an overview). In Uganda, reviving the *Child Health Days*-like mass programmes could supplement routine immunisations; it requires dedicated government investment in bringing the services closer to the public through social mobilisation and outreach activities within the communities, alongside improvement in actual service delivery through motivated healthcare workers. Putting the thrust back onto this "one-stop-shop" approach could help alleviate the direct and indirect costs faced by time-constrained adults, and also increase their awareness. At the same time, to reach out to very remote villages and neighbourhoods, mass campaigns with mobile clinics along with food incentives could be implemented to improve attendance.

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[51]Loevinsohn and Loevinsohn (1987) note that these food incentives are too small and well-spaced in time and thus neither create any dependency of the households nor affect local food prices.

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Main tables and figures

Table 1: Summary statistics of households with and without health shock

Variable	HH without health shock Mean (1)	Std Dev (2)	HH with health shock Mean (3)	Std Dev (4)	Mann-Whitney U test z-stat (5)
Child related variables:					
Children (12-24 mo.) received VAS in the last 6 mo.	0.73	0.44	0.76	0.43	-0.72
Children (12-24 mo.) received DPT3 vaccine	0.86	0.34	0.87	0.34	-0.20
Children (12-24 mo.) received measles vaccine	0.84	0.36	0.84	0.37	0.12
Avg. age of children (12-24 mo.) in HH	18.05	3.89	18.72	3.88	-1.97**
HH related variables:					
Age of HH-head (yrs.)	39.75	12.82	44.75	16.18	-3.70***
HH-head ever attended school	0.87	0.33	0.85	0.35	0.60
HH-head married	0.88	0.32	0.76	0.43	4.16***
Members living in HH all year	4.27	2.55	4.21	2.35	-0.04
Wealth percentile (land & housing value)	2.44	1.12	2.60	1.11	-1.60
Avg. no. of weeks of labour supply by a HH member	12.34	14.01	11.89	11.62	-0.35
No. of children under five in HH	2.10	0.97	2.20	1.05	-0.83
HH faced income shock in the last 6 mo.	0.21	0.41	0.32	0.47	-2.82***
Number of observations	1967		142		

Notes: This table reports the summary statistics of HHs without health shock and with health shock. The HHs considered are those which had at least one child (12-24 mo.) in at least one of the four survey waves of UNPS (See details of the sample structure in Section 3.2). The unit of observation is a child (12-24 mo.). The variable on wealth percentile is categorical where 1= 0-25th percentile, 2= 26-50th percentile, 3= 51-75th percentile, 4= above 75th percentile. The total number of observations is 2109. The summary statistics of the variable *avg. weeks of labour supply by a HH member* is obtained from 1518 observations from the last three survey waves only, due to lack of data in the first wave. The non-parametric Mann-Whitney U test compares the equality of means across the two groups; the z-statistic and p-values are reported. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table 2: Overall summary statistics

Variable	Mean	Std Dev
Child related variables:		
Children (12-24 mo.) who received VAS in the last 6 mo. from the interview date	0.73	0.44
Children (12-24 mo.) who has received DPT3 vaccine	0.86	0.34
Children (12-24 mo.) who have received measles vaccine	0.84	0.36
Children (12-24 mo.) who were breastfed	0.97	0.17
Children (12-24 mo.) who slept under a bednet the prior night	0.60	0.49
Children (12-24 mo.) whose mother lives in the same HH	0.92	0.26
Children (12-24 mo.) whose father lives in the same HH	0.74	0.44
Children (12-24 mo.) whose mother has no education	0.002	0.05
Children (12-24 mo.) whose father has no education	0.02	0.13
HH related variables:		
Wealth percentile (land & housing value)	2.45	1.12
HH with main income source as agriculture	0.53	0.50
HH with main income source as subsistence farming	0.51	0.50
HH members present in the HH all year round	4.27	2.54
Number of children up to five years present in HH	2.11	0.98
Avg. no. of weeks of labour supply by a HH member	12.32	13.87
Shock related variables:		
HHs suffering from health shock in the last six mo.	0.07	0.25
Number of months suffered due to health shock	2.75	2.98
HHs suffering from income shock in the last six mo.	0.22	0.42
Number of months suffered due to income shock	3.52	2.04

Notes: This table reports the mean over all four waves of UNPS. The HHs considered are those which had at least one child (12-24 mo.) in at least one of the four survey waves of UNPS (See details of the sample structure in Section 3.2). The unit of observation is a child (12-24 mo.). The variable on wealth percentile is categorical where 1= 0-25th percentile, 2= 26-50th percentile, 3= 51-75th percentile, 4= above 75th percentile. The total number of observations is 2109. The summary statistics of the variable *avg. weeks of labour supply by a HH member* is obtained from 1518 observations from the last three survey waves only, due to lack of data in the first wave.

Table 3: Effect of health shock on VAS intake by the child in the household

Dependent variable:	If the child received a VAS dose in the last 6 months				
	(1)	(2)	(3)	(4)	(5)
Health Shock	0.025	0.053	0.146*	0.147*	0.160*
	(0.038)	(0.038)	(0.080)	(0.079)	(0.083)
Controls[a]	No	Yes	Yes	Yes	Yes
Health supply covariates	No	Yes	No	Yes	Yes
Distance covariates	No	Yes	No	No	Yes
HH FE	No	No	Yes	Yes	Yes
Survey-wave FE	No	Yes	Yes	Yes	Yes
F-test that HH intercepts are jointly zero					
F-statistic			1.14	1.14	1.14
p-value			0.03	0.04	0.04
No. of obs.	2109	2109	937	937	937
No.of HHs	1592	1592	420	420	420
R-sq.	0.001	0.091	0.072	0.081	0.120

Notes: **(1)** The pooled OLS models in Columns (1)-(2) analyse HHs with at least one child between 12-24 mo. in at least one survey wave. The HH FE models in Columns (3)-(5) analyse HHs that appear more than once across all four survey waves (it could be either with >1 child (12-24 mo.) in one single wave or ≥1 child (12-24 mo.) in each of multiple survey waves). The unit of observation is a child (12-24 mo.). Dep. var. is binary and equals 1 if the child (12-24 mo.) in the HH received a VAS dose in the last 6 months. Indep. var. *Health Shock* is binary and equals 1 if any HH member was ill or died in the last 6 months. **(2)** [a] includes HH level controls - if faced an income shock through flood or drought in the last 6 months, wealth measure proxied by percentiles in the valuation of land and housing owned, number of children under five, number of permanent members, if the family had moved in the recent past, if interviewed in a rainy season, if lived in a flood-prone region; and individual level controls - neonatal care received (breastfed at birth), presence of the mother, presence of the father, education of mother and father. **(3)** Health supply covariates include - if the healthcare facility accessed by the HH offered general outpatient care, if it offered immunisation service, if a major limitation was its distance, and if a major limitation was lack of skilled staff. **(4)** Distance covariates include - categorical distances to the nearest public health centre, the market selling agricultural inputs, agricultural and non-agricultural outputs, and the trunk and feeder roads. **(5)** The restricted F-test tests the null hypothesis that all observed and unobserved FE at the HH level are equal to zero. A rejection of the null hypothesis for Columns (3)-(5) specifications indicates that the HH FE model is preferred over pooled OLS. When conducting the F-test, the original sample including the singleton HHs is utilised, i.e. the sample considers HHs with at least one child between 12-24 mo. in at least one survey wave. **(6)** Standard errors in parentheses, clustered at the HH level. **(7)** The overall mean of VAS intake is 0.73. **(8)** The R-squared for the HH fixed effects models in Columns (3)-(5) is the within-R-squared. **(9)** $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 4: Effect of health shock on the household's labour force participation

Dependent variable:	Avg. weeks spent in the labour force by a HH member				
	(1)	(2)	(3)	(4)	(5)
Health Shock	-0.113	-1.953**	-6.412***	-6.114***	-4.549**
	(1.229)	(0.973)	(2.321)	(2.390)	(2.058)
Controls[a]	No	Yes	Yes	Yes	Yes
Health supply covariates	No	Yes	No	Yes	Yes
Distance covariates	No	Yes	No	No	Yes
HH FE	No	No	Yes	Yes	Yes
Survey-wave FE	No	Yes	Yes	Yes	Yes
F-test that HH intercepts are jointly zero					
F-statistic			1.11	1.10	1.19
p-value			0.144	0.184	0.052
No. of obs.	1518	1518	494	494	494
No.of HHs	1255	1255	231	231	231
R-sq.	0.011	0.539	0.650	0.652	0.707

Notes: **(1)** The pooled OLS models in Columns (1)-(2) analyse HHs with at least one child between 12-24 mo. in at least one survey wave. The HH FE models in Columns (3)-(5) analyse HHs that appear more than once across all four survey waves (it could be either with >1 child (12-24 mo.) in one single wave or ≥1 child (12-24 mo.) in each of multiple survey waves). The unit of observation is a child (12-24 mo.). Dep. var. is the average number of weeks a typical permanent HH member spends in the labour market. Indep. var. *Health Shock* is binary and equals 1 if any HH member was ill or died in the last 6 months. **(2)** This analysis involves only the survey waves of 2010-11, 2011-12 and 2013-14 since the labour force participation hours or weeks cannot be calculated for wave 2009-10, due to lack of data. **(3)** [a] includes HH level controls - if faced an income shock through flood or drought in the last 6 months, wealth measure proxied by percentiles in the valuation of land and housing owned, 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. **(4)** Health supply covariates include - if the healthcare facility accessed by the HH offered general outpatient care, if it offered immunisation service, if a major limitation was its distance, and if a major limitation was lack of skilled staff. **(5)** Distance covariates include - categorical distances to the nearest public health centre, the market selling agricultural inputs, agricultural and non-agricultural outputs, and the trunk and feeder roads. **(6)** The restricted *F*-test tests the null hypothesis that all observed and unobserved FE at the HH level are equal to zero. A rejection of the null hypothesis for Column (5) specification indicates that the HH FE model is preferred over pooled OLS; however, the null is not rejected in Columns (3) and (4). When conducting the *F*-test, the original sample including the singleton HHs is utilised, i.e. the sample considers HHs with at least one child between 12-24 mo. in at least one survey wave. **(7)** Standard errors in parentheses, clustered at the HH level. **(8)** The overall mean of HH labour weeks is 12.32. **(9)** The R-squared for the HH FE models in Columns (3)-(5) is the within-R-squared. **(10)** $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 5: Summary statistics of healthcare facilities

Healthcare facility level	GOP offered (1)	Immunis. offered (2)	Vaccine fridge (3)	Limited skilled staff (4)	Located far (5)
Health Centre II (N=481)	0.99	0.89	0.59	0.30	0.32
	(0.09)	(0.31)	(0.49)	(0.46)	(0.47)
Health Centre III (N=814)	0.99	0.99	0.92	0.34	0.36
	(0.03)	(0.06)	(0.27)	(0.47)	(0.48)
Health Centre IV (N=167)	1	1	0.98	0.28	0.30
	(0.00)	(0.00)	(0.15)	(0.45)	(0.46)
Other (N=24)	1	0.75	0.67	0.17	0.08
	(0.00)	(0.44)	(0.48)	(0.38)	(0.28)

Notes: This table reports the summary statistics of the following features among the different types of healthcare facilities to which the HHs in the sample have the most access. The features considered are: if general outpatient services (GOP) are offered, if immunisation services are offered, if vaccines are stored in a fridge, if a major limitation of the facility is a lack of skilled staff, and if a major limitation of the facility is its distance. Primary healthcare in Uganda is delivered through the tiered system of healthcare facilities: Health Centres II, III and IV. "Other" comprises small, dispersed health units within a community. Only those HHs with at least one child of 12-24 mo. in at least one survey wave are considered for this analysis (however, not all HHs used in the main sample have detailed information on the healthcare facility used). The unit of observation is at the HH-surveywave level. N denotes the number of observations per healthcare facility type.

Table 6: Services offered by the most-accessed health centre and VAS intake by the child in the household

Dependent variable:	If the child received a VAS dose in the last 6 months	
Health Shock	-0.014	0.044
	(0.145)	(0.143)
If health centre offers GOP	0.529**	
	(0.231)	
If health centre offers GOP X Health Shock	0.176	
	(0.174)	
If health centre offers immu.		-0.414**
		(0.206)
If health centre offers immu. X Health Shock		0.101
		(0.172)
Controls[a]	Yes	Yes
HH FE	Yes	Yes
Survey-wave FE	Yes	Yes
F-test that HH intercepts are jointly zero		
F-statistic	1.17	1.17
p-value	0.02	0.01
No. of obs.	937	937
No.of HHs	420	420
R-sq.	0.062	0.061

Notes: **(1)** The sample consists of HHs that appear more than once across all four survey waves (it could be either with >1 child (12-24 mo.) in one single wave or ≥1 child (12-24 mo.) in each of multiple survey waves). Dep. var. is binary and takes the value 1 if the child (12-24 mo.) in the HH received a VAS dose in the last 6 months. Indep. var. *Health Shock* is binary and takes the value 1 if any HH member was ill or died in the last 6 months. In Column (1) specification, another indep. var. is *If health centre offers GOP* - binary variable taking the value 1 if the health centre the HH has access to offers general outpatient services (GOP), and this variable has an interaction with the *Health Shock*. In Column (2) specification, another indep. var. is *If health centre offers immunisation* - binary variable taking the value 1 if the health centre the HH has access to offers immunisation services, and this variable has an interaction with the *Health Shock*. **(2)** [a] includes if the HH had an income shock in the past 6 months; if a major limitation of the healthcare facility was its distance, and if a major limitation of the healthcare facility was lack of skilled staff; and categorical distances to the trunk and feeder roads. Further, Column (1) specification controls that immunisation services are provided in the same health centre and Column (2) specification controls the provision of GOP services in the same health centre. **(3)** The restricted F-test tests the null hypothesis that all observed and unobserved FE at the HH level are equal to zero. A rejection of the null hypothesis indicates that the HH FE model is preferred over pooled OLS. When conducting the F-test, the original sample including the singleton HHs is utilised, i.e. the sample consists of HHs with at least one child between 12-24 mo. in at least one survey wave. **(4)** Standard errors in parentheses, clustered at the HH level. **(5)** The overall mean of VAS intake is 0.73. **(6)** The R-squared is the within-R-squared. **(7)** $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Appendix A.

Table A1: Robustness to omitted variable bias, based on Oster (2019)

Specification	No controls $\dot{\beta}$	$\dot{R}^2$	All controls $\tilde{\beta}$	$\tilde{R}^2$	Bounding values $\beta^*_{\pi=1.3}$	$\beta^*_{\pi=2}$	Delta $\delta^*_{\pi=1.3}$	$\delta^*_{\pi=2}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pooled OLS:								
Health shock	0.046	0.031	0.053	0.091	0.061	0.080	-6.874	-2.110
	(0.037)		(0.038)					
HH FE:								
Health shock	0.126*	0.043	0.160*	0.120	0.181	0.235	-10.516	-3.239
	(0.078)		(0.082)					

Notes: **(1)** Two specifications are considered - one with Pooled OLS (equivalent to Column (2) of Table 3 and the other with HH FE (equivalent to Column (5) of Table 3. **(2)** Baseline effect in Column (1) controls only for survey wave dummies, and also for HH dummies in the latter specification. Controlled effects in Column (3) include all controls used in the main analysis. **(3)** In Columns (5)-(6), bias-adjusted coefficients are reported for the rule-of-thumb values of R^2_{max} when δ is assumed to be 1. **(4)** In Columns (7)-(8), the values of δ are reported, which would produce $\beta = 0$ for the given values of R^2_{max}. **(5)** Standard errors in parentheses, clustered at the HH level. **(6)** $^*p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

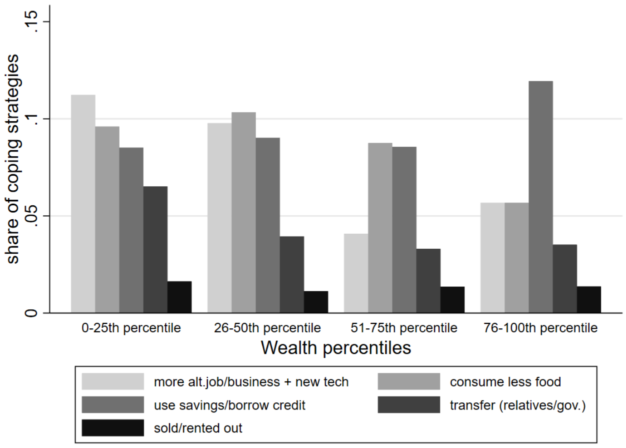

Figure A.1: Income shock coping strategies across households in different wealth percentiles

Notes: The figure shows the share of most-used coping strategies during an income shock across the wealth percentiles. The wealth percentiles are obtained from the distribution of valuation of land and housing of households in each survey wave. The HHs used in the main study sample are used to generate this figure. The coping strategies considered are: (1) more hours spent by (more) HH members in alternative employment or self-employment, or in adopting a new cropping pattern/technology, (2) reduced food consumption, (3) use of savings or borrowing credit, (4) receipt of transfers from the government or relatives, and (5) selling or renting out land, property, cattle, etc. The bar signifying alternative jobs or businesses includes - (a) more on-farm wage employment and off-farm self- or wage-employment by (more) household members and (b) the take-up of new cropping patterns or technology. [Taking on more wage- or self-employment would imply spending more hours in labour supply, and adopting other cropping technology would also require some labour hours. The slight uptick in the alternative jobs/businesses category in the topmost income group (compared to the 51-75th percentile) could be due to shifting to new technologies and self-employment, which according to the literature (Dimova et al., 2021), is usually more in relatively high-income households.]

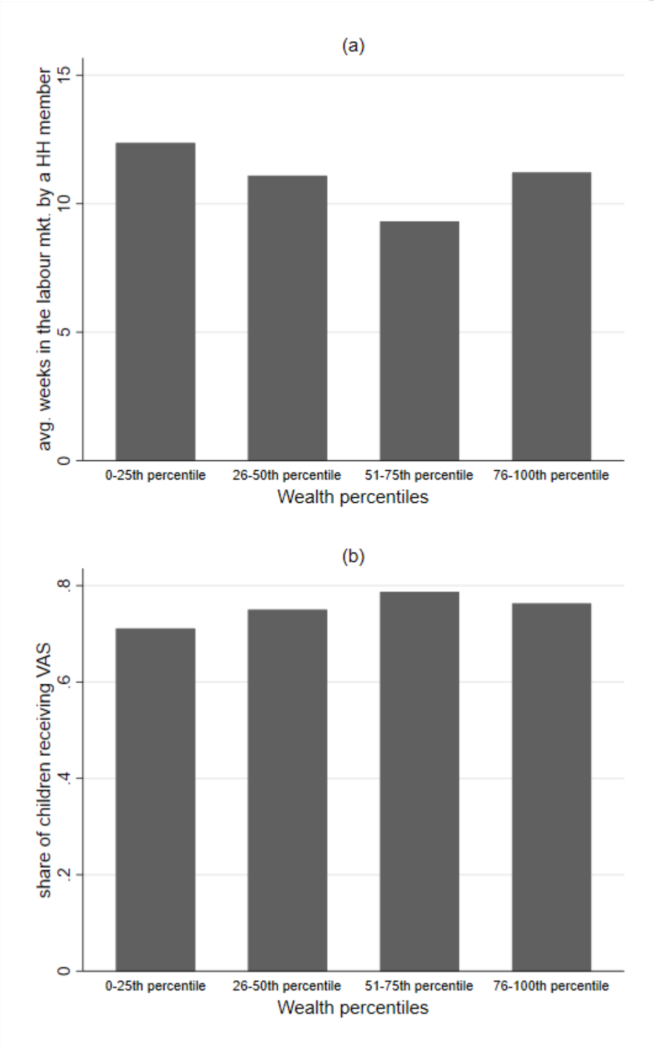

Figure A.2: Labour supply and VAS intake during income shock across households in different wealth percentiles

Notes: The figure shows the average number of weeks spent in the labour market by a typical HH member during an income shock (in Panel (a)) and the share of children (12-24 mo.) receiving VAS during an income shock (in Panel (b)) across the wealth percentiles. The wealth percentiles are obtained from the distribution of valuation of land and housing of households in each survey wave. The HHs used in the main study sample are used to generate this figure.

Table A2: Health shock and measles and DPT-3 immunisation of the child in the household

Panel A:			
Dependent variable:	If the child received measles vaccine		
	(1)	(2)	(3)
Health Shock	0.002	0.023	0.078
	(0.127)	(0.133)	(0.142)
Controls[a]	Yes	Yes	Yes
Health supply covariates	No	Yes	Yes
Distance covariates	No	No	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
F-test that HH intercepts are jointly zero			
F-statistic	1.22	1.20	1.27
p-value	0.06	0.08	0.05
No. of obs.	325	325	325
No.of HHs	155	155	155
R-sq.	0.134	0.158	0.311

Panel B:			
Dependent variable:	If the child received DPT-3 vaccine		
	(1)	(2)	(3)
Health Shock	0.009	0.001	0.013
	(0.085)	(0.081)	(0.086)
Controls[a]	Yes	Yes	Yes
Health supply covariates	No	Yes	Yes
Distance covariates	No	No	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
F-test that HH intercepts are jointly zero			
F-statistic	1.20	1.24	1.24
p-value	0.02	0.01	0.01
No. of obs.	648	648	648
No.of HHs	296	296	296
R-sq.	0.134	0.172	0.221

Notes: (1) In Panel A, the HH FE models consider HHs that appear more than once across all four survey waves (it could be either with >1 child (9-15 mo.) in one single wave or ≥1 child (9-15 mo.) in multiple survey waves). The unit of observation is a child (9-15 mo.). In Panel A, dep. var. is binary and equals 1 if the child (9-15 mo.) in the HH received the measles vaccine. Indep. var. *Health Shock* is binary and equals 1 if any HH member was ill or died in the last 6 months. **(2)** In Panel B, The HH FE models consider HHs that appear more than once across all four survey waves (it could be either with >1 child (0-12 mo.) in one single wave or ≥1 child (0-12 mo.) in multiple survey waves). The unit of observation is a child (0-12 mo.). In Panel B, dep. var. is binary and equals 1 if the child (0-12 mo.) in the HH received the DPT-3 vaccine. Indep. var. *Health Shock* is binary and equals 1 if any HH member was ill or died in the last 12 months. **(3)** [a] includes HH level controls - if faced an income shock through flood or drought in the past, wealth measure proxied by percentiles in the valuation of land and housing owned, number of children under five, number of permanent members, if the family had moved in the recent past, if interviewed in a rainy season, if lived in a flood-prone region; and individual level controls - neonatal care received (breastfed at birth), presence of the mother, presence of the father, education of mother and father. **(4)** Health supply covariates include - if the healthcare facility accessed by the HH offered general outpatient care, if it offered immunisation service, if a major limitation was its distance, and if a major limitation was lack of skilled staff. **(5)** Distance covariates include - categorical distances to the nearest public health centre, the market selling agricultural inputs, agricultural and non-agricultural outputs, and the trunk and feeder roads. **(6)** In both panels, the restricted F-test tests the null hypothesis that all observed and unobserved FE at the HH level are equal to zero. A rejection of the null hypothesis for Columns (1)-(3) specifications indicates that the HH FE model is preferred over pooled OLS. When conducting the F-test, the original sample including the singleton HHs is utilised, i.e. the sample considers HHs with at least one child (in the age range of interest) in at least one survey wave. **(7)** Standard errors in parentheses, clustered at the HH level. **(8)** The overall means of measles and DPT-3 immunisations are 0.76 and 0.55 in the respective samples used. **(9)** The R-squared for the HH fixed effects models in Columns (1)-(3) is the within-R-squared. **(10)** $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table A3: First-stage regression results - 2SLS IV approach for health shock

Dependent variable:	If the HH faced a health shock in the last 6 months		
	(1)	(2)	(3)
Parish-level health shock weighted by age-group of HH head	0.267***		0.268***
	(0.047)		(0.047)
Bednet use in HH in recent past		-0.042*	-0.040*
		(0.024)	(0.022)
Controls[a]	Yes	Yes	Yes
Health supply covariates	Yes	Yes	Yes
Distance covariates	Yes	Yes	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
Under-identification test:			
Kleibergen-Paap rk LM statistic	16.39	1.94	17.55
p-value	0.000	0.164	0.000
Weak identification test:			
Kleibergen-Paap rk Wald F statistic	33.70	1.87	18.72
Stock-Yogo critical values: 10% maximal IV size	16.38	16.38	19.93
Over-identification test:			
Hansen J statistic	n/a	n/a	0.244
p-value	n/a	n/a	0.621
No. of obs.	911	951	911
No.of HHs	407	426	407
R-sq.	0.197	0.073	0.202

Notes: (1) The HH FE models consider HHs that appear more than once across all four survey waves (it could be either with >1 child (12-24 mo.) in one single wave or ≥1 child (12-24 mo.) in each of multiple survey waves). The unit of observation is a child (12-24 mo.). Dep. var. is binary and equals 1 if any HH member was ill or died in the last 6 months. **(2)** Two IVs are considered: (a) Parish-level health shock weighted by the age group of HH head and (b) Bednet use in HH in the recent past. Columns (1) and (2) consider the two instrumental variables separately, and Column (3) considers both. **(3)** [a] includes HH level controls - wealth measure proxied by percentiles in the valuation of land and housing owned, number of children under five, number of permanent members, if the family had moved in the recent past, if interviewed in a rainy season, and if lived in a flood-prone region. **(4)** Health supply covariates include - if the healthcare facility accessed by the HH offered general outpatient care, if it offered immunisation service, if a major limitation was its distance, and if a major limitation was lack of skilled staff. **(5)** Distance covariates include - categorical distances to the nearest public health centre and the trunk and feeder roads. **(6)** Standard errors in parentheses, clustered at the HH level. **(7)** Within-R-squared is reported. **(8)** $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table A4: Second-stage regression results - 2SLS IV approach for health shock

Dependent variable:	If the child received VAS in the last 6 months	
	(1)	(2)
Health Shock	0.426*	0.406*
	(0.242)	(0.237)
Controls[a]	Yes	Yes
Health supply covariates	Yes	Yes
Distance covariates	Yes	Yes
HH FE	Yes	Yes
Survey-wave FE	Yes	Yes
Under-identification test:		
Kleibergen-Paap rk LM statistic	16.39	17.55
p-value	0.000	0.000
Weak identification test:		
Kleibergen-Paap rk Wald F statistic	33.70	18.72
Stock-Yogo critical values: 10% maximal IV size	16.38	19.93
Over-identification test:		
Hansen J statistic	n/a	0.244
p-value	n/a	0.621
No. of obs.	911	911
No.of HHs	407	407

Notes: (1) Column (1) considers Health Shock instrumented by Parish-level health shock weighted by the age-group of HH head, and Column (2) considers Health Shock instrumented by both instruments - Parish-level health shock weighted by the age-group of HH head and Bednet use in HH in recent past. **(2)** The HH FE models consider HHs that appear more than once across all four survey waves (it could be either with >1 child (12-24 mo.) in one single wave or ≥1 child (12-24 mo.) in each of multiple survey waves). The unit of observation is a child (12-24 mo.). Dep. var. is binary and equals 1 if the child under two years in the HH received a VAS dose in the last 6 months. Indep. var. *Health Shock* is binary and equals 1 if any HH member was ill or died in the last 6 months. Indep. var. **(3)** [a] includes HH level controls - if faced an income shock through flood or drought in the past, wealth measure proxied by percentiles in the valuation of land and housing owned, number of children under five, number of permanent members, if the family had moved in the recent past, if interviewed in a rainy season, if lived in a flood-prone region; and individual level controls - neonatal care received (breastfed at birth), presence of the mother, presence of the father, education of mother and father. **(4)** Health supply covariates include - if the healthcare facility accessed by the HH offered general outpatient care, if it offered immunisation service, if a major limitation was its distance, and if a major limitation was lack of skilled staff. **(5)** Distance covariates include - categorical distances to the nearest public health centre, the market selling agricultural inputs, agricultural and non-agricultural outputs, and the trunk and feeder roads. **(6)** Standard errors in parentheses, clustered at the HH level. **(7)** $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table A5: Effect of income shock on VAS intake by the child in the household

Dependent variable:	If the child received a VAS dose in the last 6 months		
	(1)	(2)	(3)
Health Shock	0.146*	0.147*	0.160*
	(0.080)	(0.079)	(0.083)
Income Shock	0.092*	0.093*	0.084
	(0.056)	(0.056)	(0.058)
Controls[a]	Yes	Yes	Yes
Health supply covariates	No	Yes	Yes
Distance covariates	No	No	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
F-test that HH intercepts are jointly zero			
F-statistic	1.14	1.14	1.14
p-value	0.03	0.04	0.04
No. of obs.	937	937	937
No.of HHs	420	420	420
R-sq.	0.072	0.081	0.120

Notes: **(1)** The HH FE models in Columns (1)-(3) analyse HHs that appear more than once across all four survey waves (it could be either with >1 child (12-24 mo.) in one single wave or ≥1 child (12-24 mo.) in each of multiple survey waves). The unit of observation is a child (12-24 mo.). Dep. var. is binary and equals 1 if the child (12-24 mo.) in the HH received a VAS dose in the last 6 months. Indep. var. *Health Shock* is binary and equals 1 if any HH member was ill or died in the last 6 months. Indep. var. *Income Shock* is binary and equals 1 if the HH faced flood or drought/irregular rains in the last 6 months. **(2)** [a] includes HH level controls - wealth measure proxied by percentiles in the valuation of land and housing owned, number of children under five, number of permanent members, if the family had moved in the recent past, if interviewed in a rainy season, if lived in a flood-prone region; and individual level controls - neonatal care received (breastfed at birth), presence of the mother, presence of the father, education of mother and father. **(3)** Health supply covariates include - if the healthcare facility accessed by the HH offered general outpatient care, if it offered immunisation service, if a major limitation was its distance, and if a major limitation was lack of skilled staff. **(4)** Distance covariates include - categorical distances to the nearest public health centre, the market selling agricultural inputs, agricultural and non-agricultural outputs, and the trunk and feeder roads. **(5)** The restricted F-test tests the null hypothesis that all observed and unobserved FE at the HH level are equal to zero. A rejection of the null hypothesis for Columns (1)-(3) specifications indicates that the HH FE model is preferred over pooled OLS. When conducting the F-test, the original sample including the singleton HHs is utilised, i.e. the sample considers HHs with at least one child between 12-24 mo. in at least one survey wave. **(6)** Standard errors in parentheses, clustered at the HH level. **(7)** The overall mean of VAS intake is 0.73. **(8)** Within R-squared is reported. **(9)** $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table A6: Effect of income shock on the household's labour force participation

Dependent variable:	Avg. weeks spent in the labour force by a HH member		
	(1)	(2)	(3)
Health Shock	-6.412***	-6.114***	-4.549**
	(2.321)	(2.390)	(2.058)
Income Shock	4.076**	4.070**	3.737**
	(1.785)	(1.750)	(1.649)
Controls[a]	Yes	Yes	Yes
Health supply covariates	No	Yes	Yes
Distance covariates	No	No	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
F-test that HH intercepts are jointly zero			
F-statistic	1.11	1.10	1.19
p-value	0.144	0.184	0.052
No. of obs.	494	494	494
No.of HHs	231	231	231
R-sq.	0.650	0.652	0.707

Notes: **(1)** The HH FE models in Columns (1)-(3) analyse HHs that appear more than once across all four survey waves (it could be either with >1 child (12-24 mo.) in one single wave or ≥1 child (12-24 mo.) in each of multiple survey waves). The unit of observation is a child (12-24 mo.). Dep. var. is the average number of weeks a typical permanent HH member spends in the labour market. Indep. var. *Health Shock* is binary and equals 1 if any HH member was ill or died in the last 6 months. Indep. var. *Income Shock* is binary and equals 1 if the HH faced flood or drought/irregular rains in the last 6 months. **(2)** This analysis involves only the survey waves of 2010-11, 2011-12 and 2013-14 since the labour force participation hours or weeks cannot be calculated for wave 2009-10, due to lack of data. **(3)** [a] includes HH level controls - wealth measure proxied by percentiles in the valuation of land and housing owned, 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. **(4)** Health supply covariates include - if the healthcare facility accessed by the HH offered general outpatient care, if it offered immunisation service, if a major limitation was its distance, and if a major limitation was lack of skilled staff. **(5)** Distance covariates include - categorical distances to the nearest public health centre, the market selling agricultural inputs, agricultural and non-agricultural outputs, and the trunk and feeder roads. **(6)** The restricted F-test tests the null hypothesis that all observed and unobserved FE at the HH level are equal to zero. A rejection of the null hypothesis for Column (5) specifications indicates that the HH FE model is preferred over pooled OLS; however, the null is not rejected in Columns (1) and (2). When conducting the F-test, the original sample including the singleton HHs is utilised, i.e. the sample considers HHs with at least one child between 12-24 mo. in at least one survey wave. **(7)** Standard errors in parentheses, clustered at the HH level. **(8)** The overall mean of HH labour weeks is 12.32. **(9)** Within R-squared is reported. **(10)** $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table A7: Effect of income shock on labour force participation in households with different wealth levels

Dependent variable:	Avg. weeks spent in the labour force by a HH member		
	(1)	(2)	(3)
Panel A:			
Health shock	-5.437**	-4.846*	-2.886
	(2.604)	(2.698)	(2.260)
Income shock (base = 0-25th wealth percentile)	7.613*	7.760*	8.488*
	(4.514)	(4.445)	(4.474)
Income shock X 26-50th wealth percentile	-3.857	-4.035	-6.148
	(5.681)	(5.589)	(5.695)
Income shock X 51-75th wealth percentile	-5.384	-5.478	-7.807
	(5.679)	(5.773)	(6.015)
Income shock X above 75th wealth percentile	-7.578	-8.198	-7.711
	(5.737)	(5.713)	(5.702)
Controls[a]	Yes	Yes	Yes
Health supply covariates	No	Yes	Yes
Distance covariates	No	No	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
F-test that HH intercepts are jointly zero			
F-statistic	1.15	1.15	1.24
p-value	0.08	0.09	0.02
No. of obs.	494	494	494
No.of HHs	231	231	231
R-sq.	0.666	0.671	0.726
Panel B:			
Health shock	-2.180**	-2.197**	-2.129**
	(0.994)	(0.997)	(0.971)
Income shock (base = 0-25th wealth percentile)	3.930***	3.958***	4.101***
	(1.385)	(1.381)	(1.404)
Income shock X 26-50th wealth percentile	-3.358*	-3.370*	-4.097**
	(1.813)	(1.822)	(1.833)
Income shock X 51-75th wealth percentile	-2.697	-2.753	-3.050*
	(1.799)	(1.792)	(1.805)
Income shock X above 75th wealth percentile	-3.316*	-3.391*	-3.683**
	(1.804)	(1.822)	(1.802)
Controls[a]	Yes	Yes	Yes
Health supply covariates	No	Yes	Yes
Distance covariates	No	No	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
F-test that HH intercepts are jointly zero			
F-statistic	2.56	2.56	2.59
p-value	0.00	0.00	0.00
No. of obs.	6423	6423	6423
No.of HHs	1882	1882	1882
R-sq.	0.654	0.655	0.662

Notes: **(1)** In Panel A, the HH FE models in Columns (1)-(3) analyse HHs that appear more than once across all four survey waves (it could be either with >1 child (12-24 mo.) in one single wave or ≥1 child (12-24 mo.) in each of multiple survey waves). The unit of observation is a child (12-24 mo.).In Panel B, the HH FE models in Columns (1)-(3) analyse HHs that appear more than once across all four survey waves (it could be either with >1 child (≤ 5 years) in one single wave or ≥1 child (≤ 5 years) in each of multiple survey waves). The unit of observation is a child (≤ 5 years). **(2)** Dep. var. is the average number of weeks a typical permanent HH member spends in the labour market. Indep. var. *Health Shock* is binary and equals 1 if any HH member was ill or died in the last 6 months. Indep. var. *Income Shock* (of base wealth level 0-25th percentile) is binary and equals 1 if the HH faced flood or drought/irregular rains in the last 6 months. The interaction terms give the differences in the slopes of the wealth index when under income shock. The wealth measure is proxied by percentiles in the valuation of land and housing owned by the HH. **(3)** This analysis involves only the survey waves of 2010-11, 2011-12 and 2013-14 since the labour force participation hours or weeks cannot be calculated for wave 2009-10, due to lack of data. **(4)** [a] includes HH level controls - 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. **(5)** Health supply covariates include - if the healthcare facility accessed by the HH offered general outpatient care, if it offered immunisation service, if a major limitation was its distance, and if a major limitation was lack of skilled staff. **(6)** Distance covariates include - categorical distances to the nearest public health centre, the market selling agricultural inputs, agricultural and non-agricultural outputs, and the trunk and feeder roads. **(7)** The restricted *F*-test tests the null hypothesis that all observed and unobserved FE at the HH level are equal to zero. A rejection of the null hypothesis for Columns (1)-(3) specifications in both Panels A and B indicates that the HH FE model is preferred over pooled OLS. When conducting the *F*-test, the original sample including the singleton HHs is utilised, i.e. the sample considers HHs with at least one child between 12-24 mo. in at least one survey wave in Panel A and the sample considers HHs with at least one child (≤ 5 years) in at least one survey wave in Panel B . **(8)** Standard errors in parentheses, clustered at the HH level. **(9)** The overall mean of HH labour weeks is 12.32. **(10)** Within R-squared is reported. **(11)** $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A8: Effects of the two shocks in separate regressions on VAS intake of a child in the household

Dependent variable:	If the child received a VAS dose in the last 6 months		
	(1)	(2)	(3)
Panel A:			
Health Shock	0.151*	0.154**	0.164**
	(0.080)	(0.080)	(0.084)
Controls[a]	Yes	Yes	Yes
Health supply covariates	No	Yes	Yes
Distance covariates	No	No	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
F-test that HH intercepts are jointly zero			
F-statistic	1.14	1.14	1.13
p-value	0.04	0.04	0.05
No. of obs.	937	937	937
No.of HHs	420	420	420
R-sq.	0.066	0.075	0.115
Panel B:			
Income Shock	0.096*	0.097*	0.087
	(0.056)	(0.057)	(0.058)
Controls[a]	Yes	Yes	Yes
Health supply covariates	No	Yes	Yes
Distance covariates	No	No	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
F-test that HH intercepts are jointly zero			
F-statistic	1.14	1.14	1.13
p-value	0.04	0.04	0.05
No. of obs.	937	937	937
No.of HHs	420	420	420
R-sq.	0.066	0.075	0.114

Notes: (1) Panel A shows the estimates of the regression with only *Health Shock* as the predictor and Panel B shows the estimates of the regression with only *Income Shock* as the predictor. **(2)** The HH FE models consider HHs that appear more than once across all four survey waves (it could be either with >1 child (12-24 mo.) in one single wave or ≥1 child (12-24 mo.) in each of multiple survey waves). The unit of observation is a child (12-24 mo.). Dep. var. is binary and equals 1 if the child (12-24 mo.) in the HH received a VAS dose in the last 6 months. In Panel A, the indep. var. *Health Shock* is binary and equals 1 if any HH member was ill or died in the last 6 months. In Panel B, the indep. var. *Income Shock* is binary and equals 1 if the HH faced flood or drought/irregular rains in the last 6 months. **(3)** [a] includes household level controls - wealth measure proxied by percentiles in the valuation of land and housing owned, number of children under five, number of permanent members, if the family had moved in the recent past, if interviewed in a rainy season, if lived in a flood-prone region; and individual level controls - neonatal care received (breastfed at birth), presence of the mother, presence of the father, education of mother and father. **(4)** Health supply covariates include - if the healthcare facility accessed by the HH offered general outpatient care, if it offered immunisation service, if a major limitation was its distance, and if a major limitation was lack of skilled staff. **(5)** Distance covariates include - categorical distances to the nearest public health centre, the market selling agricultural inputs, agricultural and non-agricultural outputs, and the trunk and feeder roads. **(6)** In both panels, the restricted F-test tests the null hypothesis that all observed and unobserved FE at the HH level are equal to zero. A rejection of the null hypothesis for Columns (1)-(3) specifications indicates that the HH FE model is preferred over pooled OLS. When conducting the F-test, the original sample including the singleton HHs is utilised, i.e. the sample considers HHs with at least one child between 12-24 mo. in at least one survey wave. **(7)** Standard errors in parentheses, clustered at the HH level. **(8)** The overall mean of VAS intake is 0.73. **(9)** Within-R-squared is reported. **(10)** $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table A9: Effect of health shock of any household member except the main income earner on VAS intake of a child in the household

Dependent variable:	If the child received a VAS dose in the last 6 months		
	(1)	(2)	(3)
Panel A:			
Health Shock	0.165*	0.152*	0.145
	(0.090)	(0.087)	(0.093)
Controls[a]	Yes	Yes	Yes
Health supply covariates	No	Yes	Yes
Distance covariates	No	No	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
F-test that HH intercepts are jointly zero			
F-statistic	1.14	1.14	1.13
p-value	0.04	0.04	0.05
No. of obs.	937	937	937
No.of HHs	420	420	420
R-sq.	0.071	0.078	0.119
Panel B:			
Health Shock	0.107	0.089	0.088
	(0.086)	(0.082)	(0.090)
Controls[a]	Yes	Yes	Yes
Health supply covariates	No	Yes	Yes
Distance covariates	No	No	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
F-test that HH intercepts are jointly zero			
F-statistic	1.14	1.14	1.13
p-value	0.04	0.04	0.05
No. of obs.	937	937	937
No.of HHs	420	420	420
R-sq.	0.068	0.077	0.118

Notes: (1) The HH FE models consider HHs that appear more than once across all four survey waves (it could be either with >1 child (12-24 mo.) in one single wave or ≥1 child (12-24 mo.) in each of multiple survey waves). The unit of observation is a child (12-24 mo.). Panel A reports the estimates of the regression where indep. var. *Health Shock* is binary and equals 1 if any HH member except the main earner was **ill or died** in the last 6 months. Panel B reports the estimates of the regression where *Health Shock* is binary and equals 1 if any HH member except the main earner was **only ill** in the last 6 months. **(2)** Dep.var. is binary and equals 1 if the child between 12-24 months in the HH received a VAS dose in the last 6 months. **(3)** [a] includes HH level controls - if faced an income shock through flood or drought in the past, wealth measure proxied by percentiles in the valuation of land and housing owned, number of children under five, number of permanent members, if the family had moved in the recent past, if interviewed in a rainy season, if lived in a flood-prone region; and individual level controls - neonatal care received (breastfed at birth), presence of the mother, presence of the father, education of mother and father. **(4)** Health supply covariates include - if the healthcare facility accessed by the HH offered general outpatient care, if it offered immunisation service, if a major limitation was its distance, and if a major limitation was lack of skilled staff. **(5)** Distance covariates include - categorical distances to the nearest public health centre, the market selling agricultural inputs, agricultural and non-agricultural outputs, and the trunk and feeder roads. **(6)** In both panels, the restricted *F*-test tests the null hypothesis that all observed and unobserved FE at the HH level are equal to zero. A rejection of the null hypothesis for Columns (1)-(3) specifications indicates that the HH FE model is preferred over pooled OLS. When conducting the *F*-test, the original sample including the singleton HHs is utilised, i.e. the sample considers HHs with at least one child between 12-24 mo. in at least one survey wave. **(7)** Standard errors in parentheses, clustered at the HH level. **(8)** The overall mean of VAS intake is 0.73. **(9)** Within-R-squared is reported. **(10)** $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table A10: Shocks in the last six months and household assets

Dependent variable:	Logarithm of all assets in the HH		
	(1)	(2)	(3)
Health shock	0.060	0.060	0.057
	(0.080)	(0.080)	(0.080)
Income shock	-0.142***	-0.142***	-0.136***
	(0.046)	(0.046)	(0.046)
Controls[a]	Yes	Yes	Yes
Health supply covariates	No	Yes	Yes
Distance covariates	No	No	Yes
HH FE	Yes	Yes	Yes
Survey-wave FE	Yes	Yes	Yes
F-test that HH intercepts are jointly zero			
F-statistic	6.85	6.83	6.71
p-value	0.00	0.00	0.00
No. of obs.	8984	8984	8984
No.of HHs	2177	2177	2177
R-sq.	0.101	0.105	0.112

Notes: **(1)** The HH FE models consider HHs that appear more than once across all four survey waves (it could be either with >1 child ($\leq$ 5 years) in one single wave or $\geq$1 child ($\leq$ 5 years) in each of multiple survey waves). The unit of observation is a child ($\leq$ 5 years). **(2)** Dep.var. is the logarithm of the total assets (incl. durables) valuation of the HH. Indep. var. *Health Shock* is binary and equals 1 if any HH member was ill or died in the last 6 months. Indep. var. *Income Shock* is binary and equals 1 if the HH faced flood or drought/irregular rains in the last 6 months. **(3)** [a] includes HH level controls - number of permanent members, number of members in prime years of their age, if the family had moved in the recent past, if interviewed in a rainy season, if lived in a flood-prone region. **(4)** Health supply covariates include - if the healthcare facility accessed by the HH offered general outpatient care, if it offered immunisation service, if a major limitation was its distance, and if a major limitation was lack of skilled staff. **(5)** Distance covariates include - categorical distances to the nearest public health centre, the market selling agricultural inputs, agricultural and non-agricultural outputs, and the trunk and feeder roads. **(6)** The restricted *F*-test tests the null hypothesis that all observed and unobserved FE at the HH level are equal to zero. A rejection of the null hypothesis for Columns (1)-(3) specifications indicates that the HH FE model is preferred over pooled OLS. When conducting the *F*-test, the original sample including the singleton HHs is utilised, i.e. the sample considers HHs with at least one child between 12-24 mo. in at least one survey wave. **(7)** Standard errors in parentheses, clustered at the HH level. **(9)** The overall mean value of the logarithm of the HH's assets is about 15. **(10)** Within-R-squared is reported. **(11)** $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

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

Author: Susmita Baulia

Highlights:

- Adverse household shocks increase Vitamin A take-up for Ugandan children
- Cure for health shock and Vitamin A take-up sought in one visit to health centre
- Findings show how poor households in developing countries deal with time constraint
- Time released, even through negative household shocks, may improve child healthcare

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CRediT authorship contribution statement

Susmita Baulia: Conceptualization; Formal analysis; Writing - original draft; Writing - review & editing.