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Do subsidies on seed and fertilizer lead to child labour? Evidence from Malawi

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Summary

Motivation: Sub-Saharan African governments have subsidized farm inputs—fertilizer and seed especially—to increase food production by small-scale farmers to improve food security. A potential drawback of such schemes is that they may encourage farmers to put their children to work in the fields, harming their education.

Purpose: Did the Malawi Farm Input Subsidy Programme that began in 2005/2006 increase child labour on the holdings of beneficiary smallholders?

Methods and approach: The article analyses data from the Malawi Integrated Household Panel Survey to examine the effect of seed and fertilizer subsidies on child labour. The study employs a correlated-random-effects-control function regression, using district coupon allocation as an instrumental variable for coupons received by households.

Findings: There was statistically significant evidence that the Farm Input Subsidy Programme (FISP) increased child labour. The effect, however, was relatively small. At the sample mean, it was estimated that the programme led to a 12 percentage point increase in the likelihood that children would work on the farm and that the children would work an additional 72 minutes a week on the fields. The FISP, however, did not affect the enrolment of children in school.

Effects varied socially: children in male-headed, uneducated, and smallholder households were the most affected.

Policy implications: Although the observed effects are not large, they are unwelcome. Two policy corrections could eliminate them. One, the award of subsidy coupons could be made conditional on children's school performance. Two, given that the effects barely applied in households where parents had been to school, agricultural training should stress the importance of children attending school and not working in the fields.

KEYWORDS

Africa, agricultural input subsidy, child labour, fertilizer, maize, Malawi

1 | INTRODUCTION

Following Malawi's Farm Input Subsidy Programme (FISP), several African countries have returned to various forms of agriculture subsidy to promote agricultural production (Denning et al., 2009; Javdani, 2012). Significant national budgets are spent on these programmes to provide fertilizer and improved crop varieties to increase food production and reduce poverty among small-scale farmers.[1] Income, food security, improved nutrition, and job creation are often the immediate and direct aims of these agricultural interventions. However, agriculture employs the highest percentage of the world's working children (Zdunnek et al., 2008), about 71%, according to ILO (2017). Hence, these interventions may have direct and indirect effects on child labour.

On the one hand, a successful agricultural intervention could increase income, allowing households to free children from work and ensure that they receive quality education and leisure. On the other hand, some interventions may lead to more child labour by increasing the productivity of the child's time on the farm and its opportunity costs. There is, therefore, the need to study the potential impact on child labour of these programmes. Understanding how agricultural interventions affect child labour will improve their design, targeting, and implementation. A clearer understanding of the link between agriculture subsidies and child labour will enhance household welfare and reduce its potential adverse effects on human capital development. This will, eventually, maximize the gains of these policy interventions.

Child labour is primarily considered a poverty phenomenon (Basu, 2003; Dwibedi & Chaudhuri, 2014; Ersado, 2005; Frempong & Stadelmann, 2019). According to Basu and Van's (1998) luxury axiom, increasing income/wealth may reduce child labour incidence. Indeed, certain farming practices could eliminate child labour (Rosenzweig & Wolpin, 1982; Zdunnek et al., 2008). For example, the mechanization of agriculture leads to a shift in labour demand from the unskilled workforce to skilled labour, which reduces the need for child labour. Besides, as productivity and income increase, the household can afford better education and more leisure for its children. Therefore, agricultural interventions may reduce the incentive to engage in child labour from both the demand and supply sides. However, this is an idealized and simplistic view of the complex relationship between agricultural interventions and child labour. The nature of agriculture and farming interventions in sub-Saharan Africa (SSA) could induce child labour. For instance, the need for adults to attend training programmes or farmer field schools could mean that children might have to take on tasks that were supposed to be performed by their parents. Second, labour-augmenting interventions that increase labour productivity could increase the demand for child labour without a well-functioning agricultural labour market.

This study evaluates the impact of FISP on child labour. Aside from the relative success and magnitude of FISP, the study focuses on Malawi because it is one of the world's poorest countries, with a high incidence of child labour. The 2015 Malawi National Child Labour Survey estimated that about 48% of children in the country were economically active, while 29.9% worked under hazardous conditions. The United States Department of Labor (USDOL) also estimates that about 43% of 5–14-year-olds are child labourers in Malawi (USDOL, 2019). The report cites working on tobacco plantations, fishing, and sexual exploitation as predominant activities for child labourers. These activities expose children to risks, including nicotine absorption and sexually transmitted diseases. Orphaned children and those whose parents have chronic health conditions are the most vulnerable since they sometimes assume the roles of adults and household heads at a relatively tender age (USDOL, 2016). Child labour in Malawi is also often driven by poverty and the lack of credit access (Hazarika & Sarangi, 2008).

In Malawi, farming is largely unmechanized (Sheahan & Barrett, 2017). Therefore, farmers rely heavily on hoes, cutlasses, and manual labour for routine farm work. Agricultural labour demand is very high, and much of it is supplied by household members (Fisher & Kandiwa, 2014). The authors further note that modern maize varieties and fertilizers increase the demand for labour during the peak farming season. It is, therefore, expected that FISP would increase labour demand. Because household adult labour supply does not always meet the high demand for farm labour, children may be required to supplement adult labour when productivity increases due to the programme. For instance, Xia and Deininger (2019) found that children spend time as casual workers in tobacco-growing communities.

[1]Jayne and Rashid (2013) report that in 2011 about USD 1.05 billion (28.6% of public expenditure) was spent by 10 African countries on input subsidies.

The study contributes directly to discussions on how access to productive assets and resources by poor households in developing countries may affect child labour and human development (Chowa et al., 2010; Edmonds & Schady, 2012; Islam & Choe, 2013; de Janvry & Sadoulet, 1996; Rogers & Swinnerton, 2004). In this literature, there are two strands of argument. The first line of thought argues that lack of assets is the primary determinant of poverty and child labour. Therefore, providing households with assets can reduce poverty while keeping children in school and out of work (de Janvry & Sadoulet, 1996). This assumes education to be a normal good. However, increased parental income could lead to higher child labour if parents believe their wealth could reduce their chance of receiving transfers from their adult children (Rogers & Swinnerton, 2004). The second strand of the argument maintains that access to productive assets could raise child labour returns and encourage child labour among poor households (Cockburn & Dostie, 2007). Cain (1977) found empirical evidence for this in Bangladesh.

In reviewing studies on how public policy affects child labour in developing countries, Dammert et al. (2018) draw different conclusions depending on a programme's design and nature. They concluded that some public work programmes could increase child labour because children might perform the domestic chores of participating adult household members. The authors further find that labour-supply interventions to provide skill training or capital to individuals have a limited effect on child labour. Despite the extensive nature of the child labour literature, empirical evidence on the direct impact on child labour of an input subsidy programme such as those implemented in some SSA countries is missing. Therefore, this study contributes to this literature by providing empirical evidence of the effect of farm input subsidy on child labour.

The remainder of the article is structured as follows: Section 2 reviews FISP in Malawi. Data, methods, variables, and identification strategies are outlined in Section 3. The empirical results and discussion are presented in Section 4. Section 5 concludes the study.

2 | THE MALAWI FARM INPUT SUBSIDY PROGRAMME (FISP)

The foremost aims of FISP in Malawi are to increase smallholder farmers' food production and income, reduce poverty, and improve national food security (Chirwa & Dorward, 2013; Denning et al., 2009). As a result, empirical studies that have sought to evaluate the programme have mainly done so using indicators of these broad objectives. This section presents some of the main findings from these studies and how they relate to this study.

FISP was introduced in the 2005/2006 financial year to improve smallholder farmers' access to improved agricultural inputs to achieve national food self-sufficiency and raise farmers' income (Chirwa & Dorward, 2013). The programme was the government's response to the recurring food shortages and the abysmal maize harvest of 2005 (Messina et al., 2017). At its inception, the programme targeted at least 50% of all smallholder farmers to benefit from subsidized fertilizer and improved maize seedlings. Qualified farmers were given coupons for hybrid or open-pollinated maize variety seeds and four types of fertilizer. Coupon beneficiaries were eligible to redeem their vouchers at no cost for 2–5 kg of hybrid maize seed. They were also allocated two 50 kg bags of fertilizer, subsidized at one-third to two-thirds of the market price (Chibwana et al., 2012).

The programme comes at a high cost to the national budget. For example, the cost of financing the programme steadily increased from 5.6% (USD 51.4 million) in 2005/2006 to about 16.2% (USD 265.4 million) of the national budget in 2008/2009 (Dorward & Chirwa, 2011). Out of the total cost in 2008/2009, about 14% came from donor support and the remaining from the government's budgetary allocations to MoAFS.

Despite some criticisms, FISP has been praised as a success (Dugger, 2007). Though the magnitude of maize production is in contention,[2] the consensus is that maize production was increased considerably because of the programme (Arndt et al., 2016; Dorward & Chirwa, 2011; Messina et al., 2017). Higher maize production, lower

[2]Messina et al. (2017) report irreconcilable differences between maize production estimates distributed by the Food and Agriculture Organization of the United Nations (FAO), the Malawi Ministry of Agriculture and Food Security (MoAFS), and the National Statistical Office (NSO) of Malawi.

food prices, higher wages, and lower poverty rates, particularly in rural areas, are some of the documented direct and indirect impacts of the programme (Arndt et al., 2016).

The available empirical evidence shows that maize production increased in Malawi in the programme years (Arndt et al., 2016; Dorward & Chirwa, 2011; Lunduka et al., 2013). Theoretically, increased production could increase agricultural labour demand. The literature suggests that changes in input prices may ultimately affect household labour decisions directly or indirectly (Skoufias, 1994). The direct effect occurs through its impact on the household shadow profit. The indirect impact occurs through changes in the shadow wages of household labour. Ricker-Gilbert (2014) found a marginal increase in labour demand due to the project, suggesting that households rely on their members, including children, for farm labour. This study contributes to the literature by providing evidence on the child labour impact of the programme.

There have been several empirical studies of the effect of the programme on household income. For example, Ricker-Gilbert and Jayne (2012) found that fertilizer subsidy increased annual yield by about USD 0.69 per household and about USD 1.23 for beneficiaries in the 90th percentile of total yearly crop output. A further question is how the additional income impacts real household welfare—school enrolment, child labour, food consumption, and health outcome. Chirwa and Dorward (2011) have shown that school enrolment increased among programme beneficiaries. This result is positive in terms of the child's human capital development. However, the result may not directly translate to a reduction in child labour since children in developing countries usually combine schooling with work. Indeed, school enrolment differs from attainment and academic performance, two crucial factors that could be affected by child labour.

3 | METHODOLOGY

3.1 | Measurement of child labour and FISP variables

3.1.1 | Child labour

Child labour is defined for the purposes of this study as being when a person between five and 17 years of age is engaged in any form of work in the seven days preceding the survey. The article further examines the child labour effect of policy on ages 5–14 and 15–17. The age 5–14 is critical because international conventions and Malawian laws prohibit children under 15 years from work that conflicts with their schooling. I use two indicators of child labour. A dummy variable to estimate the probability of child labour and the hours of work used to assess child labour intensity. The study also considers the differences between agricultural, commercial, and domestic work by estimating separate models for these kinds of work.

3.1.2 | Farm input subsidy

The FISP treatment is measured by the number of coupons received by the household during the last farming season.

3.1.3 | Control variables

Several variables are included in the analysis as controls for the heterogeneities in child and household characteristics. The empirical model includes the age and sex of the child. Sex is a dummy variable that takes one if the child is male. There is a dummy variable for whether the child is currently enrolled in school and another for orphan children.

At the household level, the models include two dummies for the sex of the household head and whether he or she has ever been to school. To control for household endowments and wealth, I include the size of farmland tilled by the household in the last farming season, an index of the household asset holdings and a dummy for access to credit. The asset-holding index is computed with a principal component analysis (PCA) of all durable assets owned by the household (Appendix B explains the PCA procedure; Table B1). Household size captures labour supply. Finally, I include a dummy to control the potential effect of adverse economic shock on child labour.

3.2 | Empirical model and identification

The article studies the effect of FISP on child labour with the child labour participation model in equation (1)

$$Childlabour_{it} = \psi_i + \beta_1 FISP_{it} + HH_{it}\beta_2 + CH_{it}\beta_3 + t + \epsilon_{it} \tag{1}$$

The β's are coefficients to be estimated, HH and CH are vectors of household and child variables. FISP is the number of coupons received by the child's household, i, in time t. The variables t and ψ are time and individual fixed effects. And ϵ is the error term of the model. Child-level control variables are age, sex, schooling status, and whether the child is an orphan. Household control variables are age and sex of household head, education status, household size, access to credit, household asset holding, experience with income shock, and farmland size. I rewrite equation (1) compactly in equation (2) to make the subsequent discussions easier.

$$childlbour_{it} = \psi_i + X_{it}\Omega + \epsilon_{it} \tag{2}$$

Where X_{it} is a composite vector of FISP, CH, HH, and t.

3.3 | Estimation

A concern in estimating equation (2) is the potential endogeneity of FISP in the child labour equation. Because child labour and FISP are decision variables, unobserved heterogeneities may make FISP endogenous. The first potential endogeneity emanates from the correlation between FISP and time-constant unobservables, ψ. This endogeneity can be dealt with based on the assumption we put on the correlation between ψ and the observable variables. If we assume ψ is uncorrelated with the observed covariates, then ψ and ϵ_{it} can be taken as a composite error term and estimate a random effect model. However, this assumption is very restrictive and is rarely satisfied. An alternative is a fixed-effect model, which allows for correlation between ψ and the control variables. While fixed effects are often employed in linear models, they cannot be easily applied to nonlinear models because of the incidental parameter problem (Bezu et al., 2014). Therefore, the study adopts Mundlak's (1978) device and models the unobserved heterogeneities as a function of the mean of the time-varying characteristics.

$$\psi = \pi + \overline{X_i}\phi + u_i \tag{3}$$

where, $\overline{X_i}$ is the row vector of the averages of time-varying exogenous variables in equation (1). Plugging (3) into (2) gives the correlated random effect (CRE) model of the child labour participation equation

$$Childlabour_{it} = \alpha + X_{it}\Omega + \overline{X_i}\phi + \xi_{it} \tag{4}$$

The second source of endogeneity is the correlation between FISP and the idiosyncratic error, or the correlation between FISP and the time-varying unobservables (Lin & Wooldridge, 2019). This endogeneity could result from misreporting and recall bias usually associated with historical data. Moreover, various targeting inefficiencies and inaccuracies that affect participating programmes' participation rates have been reported (Holden & Lunduka, 2013). In the light of these problems controlling for the targeting criteria and the time-constant heterogeneities will not be enough to identify the effect of FISP on child labour. Hence, the study adopts the control function (CF) approach to correct the possible endogeneity of FISP. CF is a two-stage procedure that requires estimating a reduced form model of access to input subsidy. This requires an instrumental variable that can be excluded from the child labour participation equation. I use the number of coupons allocated to each district by the central government as an instrument for FISP. The government maintains a district-level beneficiary database for the respective farming season. Coupon allocations are then done in two stages. First, the central government allocates coupons based on each district's eligible farmers. In the second stage, inputs are distributed to qualified farmers. Since the total coupon allocation to the district is usually less than the total number of eligible farmers, some farmers who qualify may not get the coupons. Regardless of this, district coupon allocation could predict the number of vouchers received at the household level.

Equation (5) writes *FISP* as a function of the control variables in equation (3) and the number of coupons allocated to the district, the instrumental variable.

$$FISP_{it} = X_{it}\eta_1 + \overline{X}_i\eta_2 + \gamma distCoupon_{it} + \overline{distCoupon_i} + Pop_{it} + \overline{Pop_i}v_{it} \tag{5}$$

Equation (5) is estimated as a CRE model allowing different time intercepts (Lin & Wooldridge, 2019). Results of the equations are reported in Table A1 in Appendix A. Subsequently, the residual $\hat{v_{it}}$ is predicted and used as an additional control variable in the child labour participation equations in the second stage. The second stage equation is expressed as

$$Childlabour_{it} = \alpha + X_{it}\Omega + \overline{X_i}\Omega + \omega\hat{v_{it}} + \xi_{it} \tag{6}$$

Equation (6) is a correlated random effect-control function (CRE-CF) of child labour participation. The variable, $\hat{v_{it}}$, controls and checks for the endogeneity of FISP in equation (6). A statistically significant ω indicates the presence of endogeneity.

The study uses two proxies for child labour, a dummy variable for the probability of work and the number of hours for work intensity. Equation (6) is estimated with the Probit model for the dummy variable, and the marginal effects are reported and discussed. Following Wooldridge (2002), I consider child labour hours a corner solution response and estimate the corresponding model with the Tobit estimator. In the results section, I present the marginal effects of the probability of positive work hours (the marginal effect of zero and positive hours of work are presented in Tables A2, A3, and A4 in Appendix A). To take care of the two-stage stage nature of the models, I compute bootstrap standard errors with 1000 replications. Additionally, the standard errors are clustered at the individual level to account for possible serial correlation among the individual error terms over time (Lin & Wooldridge, 2019).

Attrition bias poses another challenge to identifying the effect of FISP on child labour. Attrition in the data arises from two sources. First, children drop out of the sample when they become older than 17 years. At the same time, younger children join when they reach the age of five.

Second, some children could not be interviewed in subsequent periods for different reasons. Attrition bias may arise in this context if FISP affects attrition. While there is no reason to suggest that FISP will influence ageing into or out of the sample, FISP could potentially influence people to migrate out of their locality. The National Statistics Office (NSO) tries to follow all individuals in the sample in the subsequent surveys. However, only a proportion of the sample is track eligible if they move out of their location. To test the potential effect of FISP on attrition, I generate a variable that determines whether the child leaves or stays in the sample in the subsequent year. Then I regress attrition on FISP and the covariates in the child labour model. The results in Table A6 in Appendix A show that FISP does not statistically influence the attrition rate. Hence, attrition bias may not be a concern in Table 3.

3.4 | Data

The study uses four rounds of the Malawi Integrated Household Panel Surveys (IHPS), which the Malawi NSO collected in 2010/2011, 2013/2014, 2016/2017, and 2019/2020. These surveys provide a multi-topic socioeconomic data set with additional agriculture modules. In addition to the household's demographic, economic, and social variables, they are also nationally representative in terms of size and topics covered. They contain detailed information on individual household's agricultural activities and whether they benefited from FISP in the last wet and dry farming seasons. Besides, the data sets provide information on the time-use of household members who are at least five years old. This provides adequate information to identify how a child's time was allocated. Information on individual and household characteristics makes it possible to control for relevant covariates and other observable factors that could confound the relationship between FISP and child labour.

3.5 | Summary description of the main variables

Approximately 49% of the children in the sample worked in the seven days immediately preceding the survey. The participation rates for the different survey years are 46, 51, 47, and 50%. Child labour in agriculture-related activities increased from 18% in 2010/2011 to 24% in 2019/2020, while about 37% of children in the sample performed household chores (fetched firewood or water). The number of children in commercial work (non-family farm, non-domestic work) was lower than in agriculture and domestic work. While only 3% of Malawian children worked outside the household in 2010/2011, the figure increased to 11% in 2019/2020. On average, children in the sample worked between 2.5 to 3.5 hours per week. Most of the hours were spent on agriculture, followed by commercial work. Thus, even though the participation in commercial work was low, it was more intense.

The average age of the children was about 11 years, and there were nearly as many girls as there were boys. About 82% of the children were in school, and 22% of the sample were orphans. At the household level, 74% of the sampled children are found in male-headed households, and the average age of the household head was 45 years. The average household size was about six people. Table 1 shows that 26% of Malawian children lived in households with access to credit. However, the average value of the asset index, −26, indicates that most households in the analysis were relatively poor. Households cultivated an average of 2.08 acres of land within the four years. Nearly 83% of the sample lived in households where the head had been to school. Only 3% of them were affected by an adverse economic shock over the four years.

Table 2 tests whether the differences in child labour beneficiaries and non-beneficiary households were statistically different. Children in beneficiary households were more likely to work across all years. These differences were statistically significant. Beneficiary children also worked for more hours in total and in agriculture work for 2010/2011 and 2013/2014.

4 | RESULTS

4.1 | Overall effect of FISP on child labour

Table 3 shows the effect of FISP on child labour in Malawi. The table contains an analysis of the probability of child labour in (1)–(4). As described in equation (6), the models include the averages of all the time-varying control variables. However, their coefficients are omitted to conserve space. $\hat{v_{it}}$ is the predicted residual from the first-stage regression of FISP on the total number of coupons allocated to the district. The variable was significant in all but the two models for commercial work. $\hat{v_{it}}$ is statistically significant, which indicates endogeneity between FISP and child labour. Column (1) shows that FISP positively affected child labour. The probability of child labour increased by

TABLE 1 Descriptive statistics

FISP	2010/11 Mean	2012/13 Mean	2016/17 Mean	2019/20 Mean	2010/20 Mean
Child-level variables					
Child work in last 7 days (Yes = 1; No = 0)	0.46	0.51	0.47	0.50	0.49
Work agriculture (Yes = 1; No = 0)	0.18	0.23	0.19	0.24	0.21
Domestic work (Yes = 1; No = 0)	0.37	0.39	0.35	0.36	0.37
Commercial work hours	0.03	0.04	0.09	0.11	0.07
Total work hours	2.50	2.90	2.83	3.46	2.99
Total agriculture work hours	1.83	1.99	1.50	1.92	1.81
Total hours on domestic work	0.34	0.38	0.49	0.46	0.43
Total hours on commercial work	0.33	0.53	0.84	1.09	0.75
Male child (Male = 1; Female = 0)	0.49	0.49	0.49	0.48	0.49
Child in school (Yes = 1; No = 0)	0.80	0.82	0.83	0.81	0.82
Child's age (years)	10.41	10.62	10.81	10.92	10.73
Orphan child (Yes = 1; No = 0)	0.22	0.22	0.21	0.20	0.21
Household-level variables					
Number of coupons received	1.08	1.11	0.89	0.45	0.84
Age of household head	44.31	45.13	45.54	45.42	45.18
Household head has been to school (Yes = 1; No = 0)	0.77	0.81	0.88	0.85	0.83
Household size	4.37	6.64	6.66	6.38	6.15
Accessed credit (Yes = 1; No = 0)	0.14	0.26	0.29	0.30	0.26
Male-headed household (Yes = 1; No = 0)	0.78	0.77	0.74	0.71	0.74
HH suffered an adverse shock (Yes = 1; No = 0)	0.00	0.00	0.08	0.02	0.03
PCA asset index	−0.12	−0.26	−0.32	−0.29	−0.26
Size of cultivated land (acres)	2.10	2.02	2.16	2.07	2.08

about 12 percentage points due to FISP. This represents about 24% of the child labour incidence in the sample. The likelihood of agricultural work also increased by ten percentage points for an additional coupon explaining 52% of agricultural child labour in Malawi. FISP was also associated with an 11 percentage point change in the probability of domestic work (fetching water and firewood). However, there was no statistically significant effect of FISP on the likelihood of commercial work.

Columns (5)–(8) give the effect of FISP on child labour hours conditional on having positive hours of work. Column (5) shows that an additional coupon in the household intensified total child labour hours by about 0.84 hours (50 minutes). The effect on agriculture work hours was about 1.19 hours (72 minutes) of additional agricultural work per unit increase in the FISP coupon. The hours of domestic work increased by a marginal 0.15 hours (9 minutes) when a household got one more coupon. Effectively, FISP explains 27% of the mean child labour hours and 67% of the total time spent on agriculture work. The effects of FISP on child labour are consistent with the a priori expectation that the inputs may have made agriculture relatively profitable and increased demand for child farm labourers. Indirectly, the coupons could also increase the likelihood of domestic work for children to allow adult household members to have more time on the farm.

Boys were less likely to work in general. However, consistent with the expectation that boys are more productive on the farm, the probability of agriculture work was about three percentage points higher for boys than girls. However, a boy had about 28 percentage points lower chance of doing domestic work. Compared

TABLE 2 Test of mean difference of child labour between beneficiary and non-beneficiary household

Variables	Non-beneficiary	Beneficiary	Difference
Panel A: Year = 2010/11	n = 1018	n = 1241	n = 2259
Worked in last 7 days	0.44	0.48	−0.04*
Agriculture work	0.15	0.21	−0.06***
Domestic work	0.37	0.37	0.00
Commercial work	0.03	0.03	0.00
Total work in 7 days (Hours)	2.06	2.86	−0.80***
Agriculture work (Hours)	1.36	2.21	−0.86***
Domestic work (Hours)	0.37	0.32	0.04
Commercial work (Hours)	0.34	0.33	0.01
Panel B: Year = 2013/14	n = 1670	n = 1299	n = 2969
Worked in last 7 days	0.48	0.54	−0.06***
Agriculture work	0.20	0.27	−0.08***
Domestic work	0.38	0.42	−0.04**
Commercial work	0.05	0.03	0.02**
Total work in 7 days (Hours)	2.68	3.19	−0.52**
Agriculture work (Hours)	1.71	2.36	−0.65***
Domestic work (Hours)	0.34	0.42	−0.08***
Commercial work (Hours)	0.63	0.41	0.22
Panel C: Year = 2016/17	n = 2125	n-1150	n = 3271
Worked in last 7 days	0.46	0.49	−0.03*
Agriculture work	0.18	0.22	−0.03**
Domestic work	0.35	0.35	0.00
Commercial work	0.08	0.11	−0.03**
Total work in 7 days (Hours)	2.79	2.91	−0.13
Agriculture work (Hours)	1.53	1.43	0.11
Domestic work (Hours)	0.51	0.46	0.05
Commercial work (Hours)	0.74	1.03	−0.28*
Panel D: Year = 2019/20	n = 3210	n = 749	n = 3959
Worked in last 7 days	0.49	0.55	−0.06***
Agriculture work	0.23	0.28	−0.05***
Domestic work	0.35	0.40	−0.05***
Commercial work	0.11	0.08	0.03***
Total work in 7 days (Hours)	3.47	3.43	0.04
Agriculture work (Hours)	1.87	2.09	−0.22
Domestic work (Hours)	0.44	0.54	−0.10***
Commercial work (Hours)	1.15	0.79	0.36*

to girls, boys worked for 0.36 hours (22 minutes) in agricultural activities, but they spent less time on domestic work.

Age was a positive predictor of both the probability and intensity of child labour. Orphan children had a lower likelihood and intensity of work in Malawi. Larger household size was associated with an increased likelihood of agri-

TABLE 3 Effect of FISP on child labour in Malawi

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probability of child labour				The intensity of child labour			
	Work	Agriculture	Domestic	Commercial	Work	Agriculture	Domestic	Commercial
FISP	0.12***	0.10***	0.11***	−0.01	0.84***	1.20***	0.15***	−0.41
	(0.02)	(0.02)	(0.02)	(0.01)	(0.19)	(0.22)	(0.03)	(0.31)
Male child	−0.17***	0.03***	−0.28***	0.00	−0.62***	0.36***	−0.37***	0.22*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.08)	(0.09)	(0.02)	(0.12)
The child is in school	0.09***	0.05***	0.09***	−0.02*	0.16	0.52***	0.11***	−0.57**
	(0.02)	(0.01)	(0.02)	(0.01)	(0.16)	(0.17)	(0.02)	(0.23)
Age of child	0.05***	0.04***	0.03***	0.02***	0.48***	0.44***	0.05***	0.41***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.04)
Orphan child	−0.04*	0.01	−0.05**	−0.01	−0.12	0.13	−0.09***	−0.22
	(0.02)	(0.02)	(0.02)	(0.01)	(0.18)	(0.20)	(0.03)	(0.29)
Age of household head	−0.00	0.00	−0.00	−0.00	0.00	0.01	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
The household head has been to school	−0.01	−0.02	−0.01	0.01	−0.20	−0.31	−0.02	0.17
	(0.02)	(0.02)	(0.02)	(0.01)	(0.20)	(0.20)	(0.03)	(0.29)
Household size	−0.00	0.01**	−0.01**	−0.00	0.02	0.12***	−0.01**	−0.09
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.05)	(0.01)	(0.06)
Accessed credit	0.04**	0.03***	0.02	0.02**	0.29**	0.27*	0.02	0.46**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.13)	(0.14)	(0.02)	(0.18)
Male-headed household	−0.01	−0.01	−0.01	−0.02	0.02	−0.01	−0.00	−0.21
	(0.02)	(0.02)	(0.02)	(0.01)	(0.19)	(0.22)	(0.03)	(0.27)
HH suffered an adverse shock	−0.08*	0.02	−0.06	0.00	0.17	0.28	−0.06	0.33
	(0.04)	(0.03)	(0.04)	(0.02)	(0.43)	(0.41)	(0.06)	(0.54)
PCA asset index	−0.02**	−0.00	−0.01*	−0.00	−0.11*	−0.05	−0.01	−0.08
	(0.01)	(0.01)	(0.01)	(0.00)	(0.06)	(0.07)	(0.01)	(0.09)
Size of cultivated land	0.00	0.01***	0.00	−0.00**	0.04*	0.08***	0.00	−0.10**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.04)
Year = 2013	0.04**	0.01	0.04***	0.01	0.20	−0.02	0.04**	0.43*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.12)	(0.15)	(0.02)	(0.22)
Year = 2016	0.02	−0.01	0.01	0.05***	0.15	−0.29*	0.09***	1.43***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.14)	(0.17)	(0.02)	(0.23)

TABLE 3 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probability of child labour				The intensity of child labour			
	Work	Agriculture	Domestic	Commercial	Work	Agriculture	Domestic	Commercial
Year = 2019	0.09***	0.07***	0.07***	0.05***	0.87***	0.61***	0.14***	1.43***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.19)	(0.23)	(0.03)	(0.28)
Residuals	−0.12***	−0.11***	−0.11***	0.01	−0.94***	−1.29***	−0.14***	0.32
	(0.02)	(0.02)	(0.02)	(0.01)	(0.19)	(0.22)	(0.03)	(0.30)
Observations	12,462	12,462	12,462	12,462	12,462	12,462	12,462	12,462

Bootstrap standard errors with 1000 repetitions in parenthesis. Standard errors are clustered around the child to take care of serial correlation. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

cultural work and a decreased probability of domestic and agricultural work. Children in households with access to credit and those affected by adverse economic shocks were more likely to work.

4.2 | The effect of FISP on child labour by child characteristics

Table 4 examines the impact of FISP on child labour for different groups of children in two panels. Columns (1) and (2) provide results for boys and girls. In Panel 1, the average effects of FISP on child labour among boys and girls are 15 and 9 percentage points, respectively. These results mean that boys were about six percentage points more likely to work than girls. But there was no meaningful difference between boys' and girls' work intensities in columns (4) and (5).

Columns (3) and (4) show the subsidy's effect on child labour for 5–14 and 15–17 year groups. For 5–14-year-olds, child labour increased by about 12 percentage points for an additional coupon. The coefficients imply that FISP was associated with approximately 0.60 hours (36 minutes) of additional child work. However, 15–17-year-olds were about 17 percentage points more likely to work because of FISP, and they worked for about 2.22 hours (133 minutes).

Finally, columns (5) and (6) estimate the effect of FISP on child labour among school-going and out-of-school children. Intuitively, we would expect a higher impact among out-of-school children. However, the results show that FISP only increased both the probability and intensity of child labour the among school-going group. Children in school were about 13 percentage points more likely to work if the household got a coupon. And they worked for an additional 0.97 hours (58 minutes) when their household got one more coupon. The models did not show any statistically significant effect of FISP on child labour among out-of-school children in the sample. This result is potentially due to the small size of this sub-sample. Only about 18% (2286) of the children were not in school for all the sample years.

4.3 | The effect of FISP on child labour by household characteristics

Table 5 examines the impact of FISP on child labour for different household characteristics. Column (1) of Panel 1 shows that children in female-headed households (FHH) and male-headed households (MHH) were 12 percentage points more likely to work due to an additional FISP coupon. The respective intensities for FHH and MHH are 0.85 hours (46 minutes) and 0.80 hours (51) of additional child labour.

The effects on educated and non-educated household heads are presented in columns (3) and (4). FISP did not affect child labour among households whose heads had been to school. However, the probability of child labour increased by about 11 percentage points and intensity by 0.85 hours (51 minutes) if the head had not had formal schooling. The subsidy did not affect the incidence and intensity of child labour among households that cultivated

TABLE 4 Effect of FISP on child labour by child characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Child's sex		Child's age		Enrolment status	
	Boys	Girls	5–14 years	15–17 years	In school	Not in school
***Panel 1**: Probability of child labour (CRE-CF Probit)—Marginal effects*						
FISP	0.15***	0.09***	0.12***	0.17***	0.13***	−0.01
	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)	(0.05)
Mean FISP	−0.00	0.02**	0.00	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Child and household controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6381	6081	9894	2568	10,176	2286
***Panel 2**: Child labour hours (CRE-CF Tobit)—Marginal effect conditional on positive child labour*						
FISP	0.95***	0.57*	0.59***	2.22***	0.97***	−0.63
	(0.23)	(0.31)	(0.18)	(0.54)	(0.18)	(0.87)
Mean FISP	0.06	0.24**	0.12**	0.20	0.15***	0.11
	(0.07)	(0.09)	(0.06)	(0.19)	(0.06)	(0.19)
Child and household controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6381	6081	9894	2568	10,176	2286

Bootstrap standard errors with 1000 repetitions in parenthesis. Standard errors are clustered around the child to take care of serial correlation. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Child and household controls and time average are the same as in Table 3.

less than the average farm plot. However, column (6) shows that child labour incidence increased by 15 percentage points for an extra coupon among those who cultivated more than the average plot size. The intensity of child labour increased by about 1.26 hours (76 minutes) among this group of farmers.

4.4 | Additional results

I examined the effects of the different coupons—maize seed, fertilizer, other coupons—on child labour. The results in Table 6 show that an extra maize seed coupon increased the probability of general child labour by about 62 percentage points and agriculture and domestic work by about 60 and 58 percentage points. The effects of fertilizer coupons were, however, smaller in magnitude. General child labour and domestic work increased by 17 and 16 percentage points if the household received a fertilizer coupon. Other coupons, in turn, also increased the probabilities of child labour in all work, agriculture and domestic. Table A5 in Appendix A contains the effects of the different coupons on work intensities.

Table 7 contains the effects of FISP on the shares of child labour in different activities. The child labour share of a particular activity was defined as the ratio of work hours and the total work hours. Columns (1)–(3) are estimated with the Tobit model. From column (1), agriculture labour as a proportion of total work hours increases by about nine per cent when the household gets one more coupon. This represents about 15% of the share of agriculture child labour. Domestic work increased by about 6% (43% of the share of domestic work). As in Table 3, FISP did not affect commercial activities.

TABLE 5 Effect of FISP on child labour by household characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Head's sex		Head's education		Farm size	
	FHH	MHH	Educated	Not educated	Less than average	More than average
***Panel 1**: Probability of child labour (CRE-CF Probit)—Marginal effects*						
FISP	0.12***	0.12***	0.05	0.11***	−0.05	0.15***
	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)
Mean FISP	0.02	0.00	0.00	0.01	0.00	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Child and household controls	Yes	Yes	Yes	Yes	Yes	Yes
The time average of controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3195	9267	2103	10,359	1844	10,618
***Panel 2**: Child labour hours (CRE-CF Tobit)—Marginal effect conditional on positive child labour*						
FISP	0.85**	0.80***	0.22	0.85***	−1.11***	1.26***
	(0.36)	(0.22)	(0.43)	(0.20)	(0.40)	(0.22)
Mean FISP	0.10	0.14**	0.05	0.15**	0.32**	0.08
	(0.11)	(0.07)	(0.16)	(0.06)	(0.16)	(0.06)
Child and household controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3195	9267	2103	10,359	1844	10,618

Bootstrap standard errors with 1000 repetitions in parenthesis. Standard errors are clustered around the child to take care of serial correlation. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Child and household controls and time average are the same as in Table 3.

The relationship between the programme and schooling outcomes in Malawi is in Tables 8 and 9. I generated two dummy variables for children aged 6–14 years – (1) enrolment status (1 = enrolled; 0 = not enrolled) and (2) Absenteeism (1 = withdrew from school for two consecutive weeks in the past 12 months; 0 = did not withdraw from school). The results in Table 7 show that the programme did not affect school enrolment and absenteeism rates in Malawi. However, according to Table 9, FISP may have increased the enrolment rate by about 11 percentage points among households whose heads had been to school. FISP also appears to have increased enrolment among households that cultivated less than average plots by about seven percentage points. Children from these households were about five percentage points less likely to be absent if their household got a coupon. This is contrary to what we expect according to Tables 3 and 4. It would, therefore, be helpful to study pupils' academic performance since child labour can adversely affect test scores. However, the dataset does not contain any information on academic performance.

5 | CONCLUSION

The article has evaluated the effect of agricultural input subsidy programmes on child labour using data from Malawi, which has implemented one of Africa's most extensive and long-running input subsidy programmes in recent times. I deal with the potential endogeneity by employing district coupon allocation as an instrument for a

TABLE 6 Effect of maize, fertilizer, and other coupons on child labour

	(1)	(2)	(3)	(4)
	Work	**Agriculture**	**Domestic**	**Commercial**
***Panel A**: Effect of maize coupons on the probability of child labour*				
Number of maize seed coupons	0.62***	0.60***	0.58***	−0.05
	(0.08)	(0.08)	(0.08)	(0.05)
Mean maize coupons	0.03	0.05***	−0.04*	−0.00
	(0.02)	(0.02)	(0.02)	(0.01)
Child and household controls	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	12,462	12,462	12,462	12,462
***Panel B**: Effect of fertilizer coupons on the probability of child labour*				
Number of fertilizer coupons	0.17***	0.16***	0.15***	−0.02
	(0.03)	(0.03)	(0.03)	(0.02)
Mean fertilizer coupons	0.02	0.03***	−0.00	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Child and household controls	Yes	Yes	Yes	Yes
The time average of controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	12,462	12,462	12,462	12,462
***Panel C**: Effect of other coupons on the probability of child labour*				
Number of other coupons	0.76***	0.78***	0.67***	−0.08
	(0.13)	(0.12)	(0.13)	(0.07)
Mean other coupons	0.00	0.07***	−0.07**	0.02
	(0.03)	(0.02)	(0.03)	(0.02)
Child and household controls	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	12,462	12,462	12,462	12,462

Bootstrap standard errors with 1000 repetitions in parenthesis. Standard errors are clustered around the child to take care of serial.

household's number of coupons. The results suggest that the FISP increased the incidence and intensity of child labour. The article additionally provides evidence of the child labour effect of the coupons for different socioeconomic and demographic groups. Children in male-headed, uneducated, and smallholder households are worse affected. These findings mean that a general input subsidy programme could have unintended negative consequences on child labour.

In the broader context, the child labour effect of FISP appears marginal compared to the success of the FISP as a food insecurity and poverty alleviating strategy. This notwithstanding, policymakers must take steps to address the child labour effects of the programme in accordance with the SDGs' principle of leaving no one behind. This study finds that children in households that cultivate less than the average farm plot are worse affected. This means that children from impoverished households may be disproportionately affected. Thus, this may potentially hamper the country's overall poverty-reduction programmes and efforts in the long run.

TABLE 7 Effect of FISP on child labour shares

	(1) Agriculture share	(2) Domestic share	(3) Commercial share
FISP	0.09***	0.06***	−0.02
	(0.02)	(0.01)	(0.02)
Mean FISP	0.02***	−0.01*	−0.00
	(0.00)	(0.00)	(0.01)
Child and household controls	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	12,462	12,462	12,462

Bootstrap standard errors with 1000 repetitions in parenthesis. Standard errors are clustered around the child to take care of serial correlation. *p < 0.1, **p < 0.05, ***p < 0.01. Child and household controls and time average are the same as in Table 3.

TABLE 8 Effect of FISP on school enrolment and temporary withdrawal

	(1)	(2)	(3)	(4)	(5)	(6)
	School Enrolment			Withdrew for two consecutive weeks		
	All children	Girls	Boys	All children	Girls	Boys
FISP	0.02	0.03	0.01	−0.01	0.02	−0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Mean FISP	0.00	−0.01	0.01*	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Child and household controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8797	4541	4256	7798	4049	3749

Bootstrap standard errors with 1000 repetitions in parenthesis. Standard errors are clustered around the child to take care of serial correlation. *p < 0.1, **p < 0.05, ***p < 0.01. Child and household controls and time average are the same as in Table 3.

The study's findings have policy implications for the future design and implementation of input subsidy programmes in developing countries. The government and the implementing agencies should attempt to reduce the child labour impact of the programme. One policy option is to condition FISP on the academic performance of pupils of beneficiaries. This will ensure that children contribute toward family welfare without jeopardizing their education and human capital. This recommendation is premised on studies that have found a negative relationship between child labour and academic performance. Fortunately, the analysis shows that FISP did not negatively affect school enrolment and dropout rates. However, for a complete understanding of the Malawian case, there must be further research on the relationship between the programme and educational attainment and academic performance in the country.

The programme did not significantly affect child labour among children whose parents have formal education, suggesting that parental education could effectively mitigate the programme's adverse effects. Authorities could, therefore, exploit education as a means of reducing the problem. This could be done by educating parents about the negative impact of child labour. Such education could be incorporated into training programmes for beneficiary households.

TABLE 9 Effect of FISP on school enrolment and temporal withdrawal by household characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Head's sex		Head's education		Farm size	
	FHH	MHH	Educated	Not educated	Less than average	More than average
Panel A: Probability of enrolment						
FISP	0.03	0.01	0.11**	0.01	0.07**	0.02
	(0.04)	(0.02)	(0.05)	(0.02)	(0.03)	(0.02)
Mean FISP	0.01	0.00	−0.01	0.00	−0.02	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Child and household controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2227	6570	1475	7322	1275	7522
Panel B: Probability of temporary withdrawing from school						
FISP	−0.04	−0.00	−0.03	−0.00	−0.05**	0.01
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Mean FISP	0.01	0.00	−0.01	0.01	−0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Child and household controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1939	5859	1182	6616	1095	6672

Bootstrap standard errors with 1000 repetitions in parenthesis. Standard errors are clustered around the child to take care of serial correlation. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Child and household controls and time average are the same as in Table 3.

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DATA AVAILABILITY STATEMENT

The data supporting this study's findings are available from the corresponding author upon reasonable request.

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APPENDIX A

TABLE A1 Effect of total district coupon allocation on the number of coupons received by the household

	FISP
District coupon allocation	−2.41***
	(0.38)
District coupon allocation	1.07***
	(0.17)
Male child	0.01
	(0.03)
The child is in school	−0.01
	(0.05)
Age of child	−0.00
	(0.01)
Orphan child	0.04
	(0.06)
Age of household head	−0.00
	(0.00)
The household head has been to school	0.01
	(0.05)
Household size	0.00
	(0.01)
Accessed credit	0.00
	(0.04)
Sex of household head (Male = 1)	0.06
	(0.06)
HH suffered an adverse shock	0.01
	(0.09)
Asset index PCA	0.02
	(0.01)
Size of cultivated land	0.04***
	(0.01)
Year = 2013	0.08*
	(0.05)
Year = 2016	−0.10**
	(0.05)
Year = 2019	−0.50***
	(0.05)
District population	−0.00
	(0.00)
Constant	2.25***

(Continues)

TABLE A1 (Continued)

	FISP
	(0.29)
Mean of time-varying controls	Yes
Observations	12,462

TABLE A2 Correlated random effects Tobit-control function estimate of the effect of FISP on child labour marginal effect—zero or positive child labour

	(1)	(2)	(3)	(4)
	All work	Agriculture	Domestic	Commercial
FISP	1.05***	1.13***	0.17***	−0.21
	(0.24)	(0.21)	(0.03)	(0.15)
Mean FISP	0.17**	0.21***	−0.01	0.01
	(0.07)	(0.06)	(0.01)	(0.04)
Child and household controls	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	12,462	12,462	12,462	12,462

Bootstrap standard errors with 1000 repetitions in parenthesis. Standard errors are clustered around the child to take care of serial correlation. *p < 0.1, **p < 0.05, ***p < 0.01. Child and household controls and time average are the same as in Table 3.

TABLE A3 Correlated random effects Tobit-control function estimate of the effect of FISP on child labour marginal effect—zero or positive child labour

	(1)	(2)	(3)	(4)	(5)	(6)
	Child's sex		Child's age		Enrolment status	
	Boys	Girls	5–14	15–17	In school	Not in school
FISP	1.24***	0.69*	0.71***	3.10***	1.25***	−0.74
	(0.29)	(0.37)	(0.22)	(0.75)	(0.23)	(1.02)
Mean FISP	0.08	0.28**	0.14**	0.28	0.19***	0.13
	(0.09)	(0.11)	(0.07)	(0.26)	(0.07)	(0.23)
Child and household controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6381	6081	9894	2568	10,176	2286

Bootstrap standard errors with 1000 repetitions in parenthesis. Standard errors are clustered around the child to take care of serial correlation. *p < 0.1, **p < 0.05, ***p < 0.01. Child and household controls and time average are the same as in Table 3.

TABLE A4 Correlated random effects-control function Tobit estimate of the effect of FISP on child labour marginal effect—zero or positive child labour

	(1)	(2)	(3)	(4)	(5)	(6)
	Head's sex		Head's education		HH Farm size	
	MHH	Educated	Not educated	Educated	Less than average	More than average
FISP	1.09**	1.00***	0.29	1.06***	−1.42***	1.58***
	(0.47)	(0.27)	(0.55)	(0.25)	(0.52)	(0.27)
Mean FISP	0.13	0.18**	0.06	0.19**	0.41**	0.10
	(0.14)	(0.09)	(0.21)	(0.08)	(0.21)	(0.08)
Child and household controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3195	9267	2103	10,359	1844	10,618

Bootstrap standard errors with 1000 repetitions in parenthesis. Standard errors are clustered around the child to take care of serial correlation. *p < 0.1, **p < 0.05, ***p < 0.01. Child and household controls and time average are the same as in Table 3.

TABLE A5 Effect of maize, fertilizer, and other coupons on child labour time

	(1) Work	(2) Agriculture	(3) Domestic	(4) Commercial
***Panel A**: Effect of maize coupons on child labour time*				
Number of maize seed coupons	2.35***	2.67***	0.40***	−0.73**
	(0.59)	(0.41)	(0.08)	(0.32)
Mean maize coupons	0.20	0.19	−0.01	0.01
	(0.17)	(0.12)	(0.02)	(0.09)
Child and household controls	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	12,462	12,462	12,462	12,462
***Panel B**: Effect of fertilizer coupons on child labour time*				
Number of fertilizer coupons	0.44*	0.64***	0.10***	−0.29**
	(0.25)	(0.18)	(0.03)	(0.13)
Mean fertilizer coupons	0.18**	0.16***	−0.00	0.01
	(0.07)	(0.05)	(0.01)	(0.04)
Child and household controls	Yes	Yes	Yes	Yes
The time average of controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	12,462	12,462	12,462	12,462
***Panel C**: Effect of other coupons on child labour time*				
Number of other coupons	2.01**	2.67***	0.43***	−1.04**
	(0.94)	(0.68)	(0.12)	(0.49)
Mean other coupons	0.73***	0.59***	−0.02	0.11

TABLE A5 (Continued)

	(1) Work	(2) Agriculture	(3) Domestic	(4) Commercial
	(0.25)	(0.19)	(0.03)	(0.12)
Child and household controls	Yes	Yes	Yes	Yes
Mean of time-varying controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	12,462	12,462	12,462	12,462

Bootstrap standard errors with 1000 repetitions in parenthesis. Standard errors are clustered around the child to take care of serial correlation. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. Child and household controls and time average are the same as in Table 3.

TABLE A6 Determinants of sample attrition

	(1) All attrits	(2) Attrits (5–14 years)
FISP coupon in HH	0.00	−0.00
	(0.00)	(0.00)
Age of child	−0.15***	−0.08***
	(0.00)	(0.00)
Worked in last 7 days	0.02***	−0.01*
	(0.01)	(0.01)
Age of household head	0.00	−0.00
	(0.00)	(0.00)
The household head has been to school	0.01	0.01
	(0.02)	(0.01)
Household size	0.01**	0.01***
	(0.00)	(0.00)
Accessed credit	−0.01	−0.00
	(0.01)	(0.01)
Gender of household head (Male = 1)	0.00	−0.02
	(0.02)	(0.02)
HH suffered an adverse shock	0.01	0.01
	(0.03)	(0.02)
Scores for component 1	−0.00	−0.01*
	(0.00)	(0.00)
Size of cultivated land	0.00	0.00
	(0.00)	(0.00)
year = 2013	0.07***	0.03**
	(0.01)	(0.01)
year = 2016	0.19***	0.14***
	(0.01)	(0.01)
Observations	8503	6815

Standard errors in parentheses.
$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

APPENDIX B

Households reported the number of assets that they had. There were 32 durable assets, which give 32 variables containing quantities owned. These were combined into an asset index using the principal component analysis (PCA). I checked that there is enough basis for performing the PCA with the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO). The KMO values in Table A7 show that the KMO values were high enough to generate a low-dimensional representation of the asset data.

I performed a PCA on the correlation matrix and all principal components with greater eigenvalues in the second stage. I retained the first PCA for the regression analysis since it had the most expected correlation with the variables. Finally, I generated the asset index as standardized units of the principal component scores.

TABLE B1 Kaiser-Meyer-Olkin measure of sampling adequacy

Year	KMO values	Interpretation (Kaiser, 1974)
2010/11	0.89	Meritorious
2012/13	0.90	Marvellous
2016/17	0.91	Marvellous
2019/20	0.91	Marvellous