Do different types of assets have differential effects on child education? Evidence from Tanzania[*]

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Abstract

In contrast to the traditional view of assets uniformly improving childhood development through wealth effects, this paper assesses whether different types of assets have differential effects on child education. Our analysis reveals that household durables and housing-quality characteristics have the expected positive effects, but agricultural assets have adverse effects on highest grade completed and test scores. We extend the standard agricultural-household model by explicitly including child labor, and use three waves of panel data from Tanzania to assess the effects of household assets on child education. We correct for the endogeneity of assets, and use a Hausman-Taylor instrumental variable (HTIV) panel data estimator to more efficiently control for time-invariant unobservables and to identify the effects of time-invariant observables. Further examination reveals that the negative effect of agricultural assets is more pronounced among rural children and children from farming households which may result from the higher opportunity cost of schooling.

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1. Introduction

A large body of evidence indicates that assets are a strong determinant of child educational outcomes, but review of the related literature reveals at least two important shortcomings. First, research on asset-child education relationship has been limited mostly to developed country settings (Elliott, Destin, & Friedline, 2011). Second, among the existing asset-child education studies, the notion that different types of assets can have differential effects on children's educational outcomes has been overlooked. Much of the existing literature corroborates the traditional view of assets uniformly improving child education through positive wealth effects (Chowa, Masa, Wretman, & Ansong, 2013; Conley, 2001; Deng, Huang, Jin, & Sherraden, 2014; Elliott et al., 2011; Elliott & Sherraden, 2013; Huang, 2011, 2013; Kim & Sherraden, 2011; Loke, 2013; Shanks, 2007; Zhan & Sherraden, 2003). Even though changes in the composition of asset holdings, apart from changing wealth, may affect child education in various ways, most studies monetize asset holdings at some arbitrary market price and find a positive relationship between the monetary value and child education. An undifferentiated view of assets as a wealth indicator ignores the potential for different types of assets to have differential effects on child education. For example, agricultural assets might raise the returns to child labor, discouraging education investment, while other assets could raise the efficiencies of time spent studying (e.g. electricity, bicycle, and close source of water) and increase returns to schooling. If there are heretofore unacknowledged differential effects across different types of assets, there could be scope to improve the design of asset transfer and public investment programs. A growing body of literature indicates that such programs usually transfer income generating assets such as livestock (Jodlowski, Winter-Nelson, Baylis, & Goldsmith, 2016; Kafle, Winter-Nelson, & Goldsmith, 2016; Rawlins, Pimkina, Barrett, Pedersen, & Wydick, 2014), agricultural inputs (Denning et al., 2009), and other in-kind physical assets (Banerjee et al., 2015; Muralidharan & Prakash, 2013). While physical asset transfers may provide a practical approach for programs aiming to improve livelihood outcomes in the short run, some assets could influence the returns to child labor in ways that discourage investment in formal education and hurt longer term economic development.

The net effect of asset holdings on children's educational outcomes may depend on whether the return to child labor using the specific physical assets is higher than the expected return to schooling. If owning an asset increases the returns to child labor and therefore the opportunity cost of schooling, then an asset transfer could encourage parents to pull their children out of school for household or farm activities. The opportunity cost of schooling is high when assets are complements to child labor; while the expected return on schooling is low in communities where schools are of poor quality and for children who tend to perform poorly in school. For agrarian households, agricultural assets are complementary to child labor and may increase the opportunity cost of schooling. In contrast, assets like household durables and improved housing structures do not complement child labor and may in fact improve educational outcomes. The differential effects of assets also may vary with children's gender (Burke & Beegle, 2004), rural or urban residence (Fafchamps & Wahba, 2006), credit constraints (Edmonds, 2006; Ranjan, 2001), transitory shocks (Beegle, Dehejia, & Gatti, 2006; Duryea, Lam, & Levison, 2007) and household poverty (Ersado, 2005). Nevertheless, if assets increase the opportunity cost of schooling, children with lower expected return to schooling are likely to be moved out of school to household or farm activities. As parental decisions govern most activities related to children, parental education may also play a key role in the intensity of these effects. Empirical evidence also suggests that parents invest favorably for high ability children or boys compared to girls, low ability children, and younger children because the later have lower expected return from education (Akresh, Bagby, de Walque, & Kazianga, 2012; Akresh, De Walque, & Kazianga, 2013). If this conceptual relationship between assets and child education persists, policy interventions that transfer assets or help build assets may have unfavorable ramifications on child education. Therefore, the 'asset-child education' nexus deserves further scrutiny.

Evidence of 'asset-child education' relationship in the context of developing countries is also limited and divided on its treatment of asset variables. While some studies examine the relationship between assets and child education by using household net worth or aggregated asset index as wealth indicator (Deng et al., 2014; Filmer & Pritchett, 2001), handful of others estimate the effects of asset ownership on educational outcomes (Chowa et al., 2013; Cockburn & Dostie, 2007). For example, Deng et al. (2014) finds positive relationship between household net worth and child educational attainment in China, but Chowa et al. (2013) finds similar relationship between asset ownership and test scores among Ghanian children; children from households that own at least one of the five key assets– TV, refrigerators, electric iron, electric or gas stoves, and kerosene – outperformed the control group in English test scores. Similarly, Filmer & Pritchett (2001) defines household's economic status based on aggregated wealth index and finds more than 30% gap in the school enrollment rate between rich and poor children in India, but Cockburn & Dostie (2007) finds a positive effect of having a close source of water on children's educational performance in Ethiopia. Despite some evidence of significant relationship between assets and children's educational outcomes, no rigorous evidence exists to support whether different types of assets have differential effects on child education.

The scant body of empirical evidence on asset-child education relationship also lacks a strong theoretical support. Cockburn & Dostie (2007) uses a variant of the agricultural household model and demonstrates that the effect of assets on child education varies with the type of assets. They argue that whenever expected return to schooling is less than return to child labor, providing households with more assets can have adverse effects on child education because child labor demand increases with asset holdings. That child labor adversely affects child education is a common finding in the existing literature on this issue and enjoys strong theoretical and empirical support (Basu, Das, & Dutta, 2010; Haile & Haile, 2012). Basu et al. (2010) also uses a variant of agricultural household model to examine the effect of land holdings on child labor in rural India and discovers that when the labor market is missing, land holding size and child labor have an inverted U-shaped relationship. The main message from these studies is that when the labor market is complete, increase in household wealth decreases child labor and as a result child education improves. However, when the labor market is missing or imperfect, the effect of land holding on child labor (hence child education) is ambiguous and may depend on the specification of underlying utility and production functions (Basu et al., 2010).

While Cockburn & Dostie (2007) and Basu et al. (2010) provide a theoretical understanding of the relationship between household wealth and child labor/education, they do not provide evidence on whether different types of assets can have differential effects on children's educational outcomes. Basu and colleagues estimated the effect of land holdings only and Cockburn & Dostie (2007) did not specifically test the hypothesis that different asset groups have differential effects on child education. The conceptual framework considered in this paper provides intuitively appealing theoretical and empirical bases for expecting different assets to have differential effects on child education. We examine the relationship between assets and child labor drawing from the basic framework of the agricultural household models described in Singh, Squire, & Strauss(1986). Under the assumption that child labor has a direct negative effect on child education, we demonstrate the assets-child education relationship by showing a relationship between assets and child labor. We also test whether the effect of labor complementary assets on child education is negative.

Unlike the theoretical exposition, our empirical approach estimates the effect of assets on children's educational outcomes, directly. Our empirical analysis uses data from three waves of

Tanzania National Panel Survey (NPS).[1] As opposed to the undifferentiated view of assets, we disentangle assets to three groups – household durables, agricultural assets, and housing quality characteristics – and estimate the effect of each type of assets on children's educational outcomes and show that different types of assets have differential effects on child education. One complication in empirical approach is the potential endogeneity of assets, which the existing literature has not addressed (Elliott et al., 2011; Lerman & McKernan, 2013). We correct for the potential endogeneity bias by using panel data estimators such as the Hausman-Taylor instrumental variable (HTIV) estimator for panel data. Our contribution to the literature is twofold. First, we establish a theoretical relation between different types of assets and child education under perfect and imperfect labor market conditions. Second, we provide empirical evidence to demonstrate that different types of assets have differential effects on child education; household durables and housing quality indicators have expected positive effects but agricultural assets negatively affect child education. As we demonstrate that the negative effect of agricultural assets is more pronounced among rural children and children of crop producers, we believe the negative effect stems from higher opportunity cost of schooling.

The rest of the paper proceeds as follows. In section 2, we present our theoretical model and summarize theoretical results. Then we present our empirical model, and describe key variables and the data used in the analysis. In section 4, we present and discuss both descriptive and empirical results. Section 5 discusses policy implications and conclusions.

2. Theoretical model and results

[1] The Tanzania NPS is part of the LSMS-ISA program which aims to marry complex consumption-based household surveys with plot-crop detailed agricultural surveys. For more details on the LSMS-ISA, see: http://go.worldbank.org/BCLXW38HY0. The Tanzania NPS data, along with details on the sample and instrument design, are publicly available at: http://go.worldbank.org/OOLZL0UIR0.

Our theoretical exposition builds on the model of child labor and landholding presented in Basu et al. (2010) who adopted the framework of the agricultural household model from Sing, Squire, and Strauss (1986). We start with the basic structure as described in Basu et al. (2010) and introduce an education production function which constrains the household's utility maximization problem. We consider two different scenarios under each of two labor market conditions; the perfect labor market and missing labor market. In one case, the household is constrained by an education production function and in the other case it is not. Our primary interest is in the interactions between assets and human capital investments in education and so in both cases we include education production functions. Nonetheless, for completeness, we summarize the results from all four cases – perfect and missing labor market with and without education production function – in Table 1. In this analysis, we first demonstrate the effect of asset holding on child labor and household consumption in the settings of a perfect labor market. We then switch to the case of missing labor markets. In either case, we explicitly assume that child labor adversely affects children's educational outcomes. Therefore, our theoretical analysis portrays the effect of assets on child education through child labor but does not attempt to find direct effects on child education.

Basic structure

Consider an economy where each household has one adult and one child. The adult always prefers to work and takes no leisure. The child either works or goes to school but takes no leisure. Suppose each household is endowed with the following utility function.

$$u = u(c, l) \tag{1}$$

where c is the total consumption and $l \in [0,1]$ is child labor hours, 0 indicates no child labor and 1 indicates no school/study hours. Since the adult always prefers to work, the total labor supply of the household is always 1+*l*. The aggregate consumption good *c* increases utility but labor accrues disutility. We assume that the utility function is smooth and quasi-concave and the following relationship holds: $u_c > 0, u_{cc} \leq 0, u_l < 0,$ and $u_{ll} \leq 0$. Similarly, we assume that the cross marginal utilities are negative; $u_{cl}, u_{lc} < 0$.[2] Each household faces a budget constraint, is engaged in some kind of household production activity, and owns agricultural assets (*K*) and non-agricultural assets (*A*). If a household has a school attending child, the household also faces an education production function, and is liable to the cost of schooling, p_q.

2.1. The perfect labor market case

When a well-functioning labor market exists, household can supply labor to off-farm activities and hire outside labor to work on its farm. All households are price takers and hire in/out labor at a market wage rate, *w*. Following Basu et al. (2010), we assume that both adults and children earn exactly the same wage. Suppose each household faces a production function, $Q(L, K)$, and an education production function, $q(s, A, \theta)$[3], where *L* is total labor used in household production, *K* is household's agricultural asset holding, *s=1-l* is total school/study hours, *A* is household's non-agricultural asset holding which may directly affect child education, and θ denotes 'other factors' that affect child education. For simplicity, we suppress θ and assume the education production function to be linear on school hours i.e. $q(s, A) = s + q(A)$. The household production function is quasi-

[2] These are a reasonable assumption because utility increases with consumption ($u_c > 0$) but at a decreasing rate ($u_{cc} < 0$) i.e. diminishing marginal utility. In case of labor, utility decreases with labor ($u_l < 0$) and it does so at an increasing rate ($u_{ll} < 0$). In other words, the marginal disutility from labor increases with additional labor. We also assume that the marginal utility of consumption decreases with additional labor i.e. $u_{cl}, u_{lc} < 0$.

[3] To the best of our knowledge, no previous studies introduced education production function in the settings of agricultural household model. Introducing education production function may make the model complicated but the added complications help us understand the potential effects of assets and tools that are not used in agricultural production and may have direct impact on child education. Models with child education functions are more realistic because most agricultural households face a decision of sending children to school or not, and this is increasingly so in developing countries.

concave and therefore, $Q_L, Q_K > 0; Q_{LL} < 0; Q_{LK} > 0$. We assume $q_s, q_A > 0$ and $q_{ss} = 0$. The household's problem is:

$$\max_{c,l} \quad u(c, l) \quad \text{subject to}$$

$$\begin{aligned} &Q = Q(L, K) \\ &q = q(s, A) \text{ and} \\ &c + p_q q = Q + y + w(H - L) \end{aligned} \tag{2}$$

where Q is output produced, q is children's educational outcomes, p_q is unit cost of child education, y is non-labor income, and $H = 1 + l$ is total labor supply of the household. Household supplies labor off-farm if $H > L$ and hires labor from outside if $H < L$. Since labor market is well-functioning and household can hire in/out labor as needed, production decision is separable from consumption decision. If a household possesses K units of agricultural assets, it can earn a profit of $\pi(w, K)$. Therefore, $c + p_q q = \pi(w, K) + wH$ + y. The household's problem simplifies to

$$u(c, l) - \lambda[c + p_q q - \pi(w, K) - w(1 + l) - y] \tag{3}$$

Rearranging the first order conditions from equation (3) gives us the following expressions

i.) $\frac{u_l}{u_c} \equiv Z = -(p_q + w)$

ii.) $c + p_q q = \pi(w, K) + w(1 + l) + y$

Totally differentiating the above expressions with respect to K and solving the resulting equations, we get

$$\frac{\delta l}{\delta K} = -\frac{z_c \pi_K}{z_c(p_q + w) + z_l} \text{ and } \frac{\delta c}{\delta K} = \frac{z_l \pi_K}{z_c(p_q + w) + z_l}$$

By assumption, $\pi_K > 0, q_s > 0$, and we can demonstrate that $z_c < 0, z_l < 0$.[4] Therefore, when the labor market is perfect, agricultural asset accumulation at the household level decreases child labor, i.e. $\frac{\delta l}{\delta K} < 0$ but increases household consumption i.e. $\frac{\delta c}{\delta K} > 0$. Similarly, differentiating expressions i.) and ii.) with respect to income *y* gives us the following conditions.

$$\frac{\delta l}{\delta y} = -\frac{z_c}{z_c w + z_l} < 0 \text{ and } \frac{\delta c}{\delta y} = \frac{z_l}{z_c w + z_l} > 0$$

This indicates that exogenous increase in income or assets unambiguously reduces (increases) child labor (consumption) when the labor market is perfect. This is consistent with previous findings that exogenous increase in land holdings decreases child labor when labor market is perfect (Basu et al. 2010 and Dostie and Cockburn 2007). However, further analysis shows that, unlike agricultural assets, increase in education-specific assets has negative effects on household consumption ($\frac{\delta c}{\delta A} < 0$) and positive effects on child labor ($\frac{\delta l}{\delta A} > 0$).[5] Results imply that, when the labor market functions perfectly, the income effect on child labor is always negative but the effect of assets depends on type of assets; agricultural assets decrease child labor but education-specific assets increase child labor. Since assets are likely to affect household income, the net effect of increase in assets is ambiguous. The ambiguity gets more complicated when the labor market is missing. Next, we provide a detailed analysis of the case of missing labor market when households face both production functions.

2.2. The missing labor market case

[4] We view this as a reasonable assumption because marginal rate of substitution between child labor and consumption may decrease with consumption, i.e. $z_c = \frac{\delta}{\delta c}\frac{u_l}{u_c} = \frac{u_{lc}u_c - u_l u_{cc}}{u_c^2} < 0$ because $u_c > 0, u_{lc} < 0$ and $u_l, u_{cc} < 0$, by assumption. Similarly, $z_l < 0$.

[5] Differentiating conditions i) and ii) with respect to non-agricultural assets (A), we get, $\frac{\delta l}{\delta A} = \frac{z_c p_q q_A}{z_c(p_q + w) + z_l} > 0$ and $\frac{\delta c}{\delta A} = -\frac{z_l p_q q_A}{z_c(p_q + w) + z_l} < 0$.

In this case each household's consumption decisions are non-separable from production decisions. No outside labor is hired and no household labor is supplied to off-farm activities. Since the market wage does not exist, the household's problem in (2) can be modified as

$$\max_{c,l} u(c,l) \text{ subject to}$$

$$Q = Q(L,K),$$

$$q = q(s,A) \text{ and } c + p_q q = Q + y \tag{4}$$

Because of non-separability, the household's problem simplifies to

$$u(c,l) - \lambda[c + p_q q(s,A) - Q(L,K) - y] \tag{5}$$

Solving the equation (5) gives us the following first order conditions (FOCs)

iii.) $\frac{u_l}{u_c} \equiv Z = -(p_q + Q_L)$

iv.) $c + p_q q = Q + y$

Differentiating the first order conditions with respect to agricultural assets, *K*, we get

$$\frac{\delta l}{\delta K} = -\frac{Q_K z_c + Q_{LK}}{\beta}$$

where $\beta = z_l + Q_{LL} + z_c(p_q + Q_{LL}) < 0$

The denominator (β) is always negative but the sign of numerator depends on the sign of the expression $Q_K z_c + Q_{LK}$. As we assume $Q_K, Q_{LK} > 0$ and $z_c < 0$, this implies that the effect of agricultural assets on child labor is ambiguous; it can increase or decrease child labor depending on the magnitude of the change in the marginal product of labor caused by additional agricultural assets. The ambiguous effect is further complicated because assets contribute to household income and the income effect on child labor may work on different direction than the direct effects of assets. To understand the income effect, we differentiate the FOCs with respect to non-labor income *y*; we get $\frac{\delta l}{\delta y} = -\frac{z_c}{\beta} < 0$. Unlike agricultural assets, increase in income decreases child labor, unambiguously. Similarly, the income effect on household consumption is always positive as $\frac{\delta c}{\delta y} = \frac{z_l + Q_{LL}}{\beta} > 0$.

We summarize our theoretical results in Table 1. Results in case 1 and case 3 are essentially replication of Basu et al. (2010) and Dostie and Cockburn (2007) except that we use agricultural assets in general as opposed to use of land ownership as the only asset in these studies. Case 2 and case 4 are novel and more realistic in that they consider both household and education production functions and explicitly model the cost of education. Overall, the results imply that, effects of exogenous increase in assets and income are clearly discernable when labor market is perfect. When no labor market exists and households have to make production and consumption decisions simultaneously, non-labor income and education-specific assets still have clearly discernible effects on child labor and consumption but the effects of assets used in agricultural production is more complicated to understand (Table 1).

If the expected return to schooling is higher, then increase in both agricultural asset holdings can decrease child labor and improve child education. This is consistent with economic theory of factor productivity in that child labor increases when returns to labor is higher than expected return to schooling and child school hours increase when expected return to schooling is higher. We resort to a rigorous empirical analysis to help unpack the ambiguous effect of assets on child education. Our empirical findings are consistent with the theoretical results in that household income always has positive effect on children's educational outcomes and the effect of assets depends on types of assets. The rest of the paper focuses on empirical analysis.

3. Data and method

3.1. Econometric model

Our empirical approach considers the missing labor market case explained in section 2.2 because our sample consists primarily of agricultural households in rural settings. As described in section 2.1, children's educational performance (*q*) is determined by school hours (*s*), non-agricultural assets (*A*), and other factors (θ). Assume that the other factors include parental characteristics, household income (*I*), and child's individual ability (QC_u) and school hours depends on agricultural assets (*K*), and household income. Parental characteristics consist of observed characters such as education (QP_e) and unobserved characters such as ability (QP_u). Conceptually, child education is a function of parental characteristics, income, assets, and child ability. That is,

$$q = QP_e + QP_u + QC_u + A + K + I + error \tag{6}$$

We know that certain parental characteristics such as hereditary trait and other abilities directly transmit to their children, i.e. $QC_u = f(QP_u) + error$. This implies that child education can be predicted by observed parental characteristics, child's ability, assets, and income.

$$q = QP_e + \widetilde{QC}_u + Z + I + error \tag{7}$$

where $\widetilde{QC}_u = QC_u + f^{-1}(QC_u)$ is unobserved ability that is both inherited from parents and specific to the individual child and Z indicates all household assets. Since the parental ability is correlated with parental education and household asset accumulation, the unobserved child ability (QC_u) is also correlated with both of them i.e. $corr(QC_u, QP_e) \neq 0$ and $corr(QC_u, Z) \neq 0$. Since the observed and unobserved variables are correlated and affect child education, we face the problem of endogeneity. We assume that these unobserved characteristics are time invariant and address the endogeneity problem empirically using panel data. We start with the following simple model for panel data.

$$q_{it} = X_{it}\Pi + u_i + \varepsilon_{it} \tag{8}$$

where *i* indicates individual and *t* indicates time, or survey round. Thus, q_{it} is child *i*'s education outcome at time *t*, X_{it} is a vector of explanatory variables which includes individual characteristics, parental characteristics, income, assets and other relevant controls, Π is matrix of coefficient estimates, u_i is a time invariant individual effect[6], and ε_{it} is idiosyncratic error term. We know that u_i consists of unobserved individual abilities which are correlated with both asset ownership and parental education. Estimating equation (8) with the random effects model yields inconsistent estimates because the 'zero correlation' assumption is clearly violated. The fixed effects model is consistent but it drops all time constant variables along with the individual effect (u_i). As all asset indexes are time varying, effect of asset endowment can be consistently estimated with the fixed effect model, but we would like to estimate the effects of time constant variables like parent's education and gender which cannot be included in a fixed effects model. Hausman and Taylor (1981) proposed an instrumental variable estimator (hereafter referred to as HTIV) to address this endogeneity problem. Specifically, replace (8) with:

$$q_{it} = x_{1it}\alpha + x_{2it}\beta + z_{1i}\theta + z_{2i}\gamma + u_i + \varepsilon_{it} \tag{9}$$

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[6] Note that u_i in equation (8) is equivalent to QC_u in equations (6) and (7).

where x_{1it} is a vector of time-varying exogenous variables such as age and household size, x_{2it} is a vector of time-varying endogenous variables such as assets, z_{1i} is a vector of time invariant exogenous variables such as gender and age started school, and z_{2i} is a vector of time invariant endogenous variables such as maximum parent's education. We assume that the idiosyncratic error term is correlated with no explanatory variables but the unobserved specific effect is correlated with both time-varying endogenous variables (x_{2it}) and time constant endogenous variables (z_{2i}). That is,

i.) $E(u_i|x_{2it}) \neq 0, E(u_i|z_{2i}) \neq 0$

ii.) $E(u_i|x_{1it}) = 0,\ E(u_i|z_{1i}) = 0$ and $E(\varepsilon_{it}|x_{1it}, x_{2it}, z_{1i}, z_{2i}) = 0$

The model specification in equation (9) provides a required framework for the HTIV model if conditions (i) and (ii) are satisfied. The HTIV model relies on instruments but the instruments come from within the model. In equation (9), z_{1i} serves as an instrument for itself, the within transformations $x_{1it} - \bar{x}_{1i}$ and $x_{2it} - \bar{x}_{2i}$ serve as valid instruments for x_{1it} and x_{2it}, respectively and the between transformation $\bar{x}_{1i}$ serves as a valid instrument for z_{2i}. With the instruments in hand, the final estimation of equation (9) with the HTIV method requires a generalized least squares (GLS) transformation of all the variables.[7] Conceptually, first, equation (9) is estimated with the fixed effects model saving the residual. The residual is used to run a regression on z_{1i} and z_{2i} by using x_{1it} and z_{1i} as instruments. All variables in the model are then transformed by using the estimated variance from the residual regression. The transformed model is estimated by using $x_{1it} - \bar{x}_{1i}, x_{2it} - \bar{x}_{2i}$, z_{1i} and $\bar{x}_{1i}$ as instruments. In practice, estimating equation (9) with the fixed effects model or the HTIV method both yield consistent estimates, but the HTIV approach is more efficient and can estimate coefficient estimates on time constant variables as well (Baltagi, Bresson, & Pirotte, 2003; Hausman & Taylor, 1981). For comparison purposes, we estimate

[7] In practice, estimating equation (9) with the STATA in-built command 'Xthtaylor'. We use the Xthtaylor command specifying asset indexes and maximum parent's education as endogenous.

equation (9) with three different panel data estimators – random effects model, fixed effects model, and the HTIV model but our preferred model is HTIV.

3.2. Outcome variables

This analysis assesses children's educational outcomes in the context of progression through the Tanzanian school system, represented in Figure 1. Tanzania follows a 2-7-4-2-3+ model of education that starts with 2 years of pre-primary school followed by 7 years of primary school which consists grades 1 to 7 and marks its completion with a national level examination – primary school leaving exam (PSLE) – at the end of the 7th grade (MoEVT, 2014). A pass score in the PSLE test is required to proceed to government secondary school. Those who fail the PSLE test can either retake the exam, proceed to private secondary school, or end their formal education. The first tier of secondary school ends after 4 years of schooling with another national level examination at the end of the 11th grade – Form IV exam (FIVE), alternatively O+ exam. Students passing the FIVE test can proceed to the second tier of secondary school and those who fail the FIVE test can either retake the exam or enroll in vocational courses (MS+). After 2 years of schooling at the higher secondary level, students take yet another national level examination, Form VI exam (also called A+ exam) at the end of the 13th grade. Students passing the A+ exam can directly go to university but those who fail the exam have to pass a diploma course before they can go to university. Students are selected for further formal or non-formal education based on their performance on A+ exam. Secondary school with A+ exam in Tanzania is equivalent to high school in the United States and students who pass the exam can attend universities which consists 3 plus years of formal education.

Based on the school system, outcome variables for this analysis are carefully chosen to estimate the effects of assets on both school enrollment and performance. Outcome variables for this analysis are the highest grade completed, the proportion of children in the household who pass the PSLE test (PSLE ratio), and the proportion of children who pass the FIVE test (FIVE ratio). The highest grade completed is a count variable ranging from 1 to 25. A grade of 25 marks the end of advanced university degree (eg. a PhD in the United States). For the highest grade completed, only the individuals who are 6-18 in the first round are included in the analysis. Individuals who have never attended school or only attended informal schools like adult education are excluded because both school outcome and school related explanatory variables are missing for them. As our empirical results on the effects of assets on highest grade completed are conditional on school attendance, inference from the results should be taken with caution.

While the highest grade completed is measured over individuals, the PSLE and FIVE ratios are measured at the household level because there is little to no variation in individuals' outcomes over time. The exam scores are binary variables recorded as pass or fail and individuals who pass the exam once will never retake the same exam. In our sample, about 65% of students pass the PSLE test in the first attempt and retake rate among unsuccessful students is very low; only about 13% of students unsuccessful in the first attempt succeed in the second attempt. As a result, we have a little variation to work with because 95% children have either 1 or 0 throughout and only 5% children see their scores change from 0 to 1 over time. Similar pattern applies to FIVE scores too. Assessing PSLE and FIVE performance at individual level also misses a large number of children who were not eligible to take the tests during wave 2 but became eligible well before wave 3 survey. The PSLE ratio is the number of children in the household who pass the PSLE test over the total number of children ages 6 to 18 in the same household. Similarly, the FIVE ratio is the proportion of the number of adolescents in the household who passed the FIVE test to the total number of adolescents ages 16 to 24 in the same household. As these proportions can represent performance of school age children at the household level only, using these ratios limits our ability to make direct inference about individual performance in the PSLE and FIVE tests.

3.3. Asset variables

Assets are broadly defined and they include household durables, housing quality characteristics, and agricultural assets. Table A1 in the Appendix enlists individual assets under each category. Household durables include 23 different tools and equipment used in the household such as television, radio, cellphone, bicycle etc. Housing quality characteristics include 14 different variables such as types of floor, roof, and wall materials, number of rooms, access to electricity, safe drinking water, toilet facility etc. Similarly, agricultural assets include 22 different farm tools and equipment, livestock, and livestock related assets giving us a total of 59 asset variables. Since each asset group consists of several individual assets, we run into a problem of finding appropriate weight for each asset variable. Including individual assets as explanatory variables in the regression equation correctly assigns weights but may not be pragmatic because we may run into problem of finding meaningful interpretation of the estimated coefficients. Several previous studies rely on the principal component analysis (PCA) approach which assigns weight to the asset variables based on their variance. The first principal component is considered to serve as a proxy for socioeconomic status as it captures the largest variation in assets (Filmer & Pritchett, 2001; Filmer & Scott, 2008; McKenzie, 2005; Vyas & Kumaranayake, 2006). We use the principal component approach to create asset indices for the three different types of assets – household durable assets, agricultural assets, and housing quality characteristics. Since this analysis uses longitudinal data, we pool the data across survey waves and calculate pooled weighting factors for each asset variable. Then we use the period-specific standardized asset variables to construct period-specific asset indexes. One could use period-specific weighting factors but allowing weights to change over time produces non-comparable asset indexes. Use of pooled weighting factors has been strongly supported by a more recent body of literature in this issue (Harttgen, Klasen, & Vollmer, 2013; Booysen, van der Berg, Burger, Maltitz, & Rand, 2008; Sahn & Stifel, 2003). The weighting factors for individual assets under each asset category are presented in Table A1 in Appendix.

Demographic variables included in the analysis as controls are both at individual level (age, sex, age started school, and number of siblings) and household level (age, sex, and marital status of household head and logarithm of total consumption expenditure). Other controls include maximum parent's education, binary indicators for school in local community[8], rural vs urban residence, economic shock in the last 12 months, and household's access to credit and saving facilities. Whenever outcome variable is at the household level, no individual level control variables are included in the model.

3.4. Data

We use the data from Tanzania LSMS, also called National Panel Survey (NPS). The NPS is a nationally representative survey that is implemented by the National Bureau of Statistics of Tanzania with technical support from the World Bank. It includes 3 survey rounds with 3265 households in the baseline (2008/09), 3924 households in the second wave (2010/11), and 5010 households in the third wave (2012/13). The increase in the sample size is due to household splits. The NPS maintains a relatively low attrition rate (4.8%) at the household level across all three waves of the survey. Number of observations at the individual level increased from 16,709 in the baseline to 20,599 and 25,412 in the second and third waves, respectively. The overall attrition rate at the individual level is 7.5%. In all the survey rounds, the NPS follows the same households and eligible members of the households. All household members of age 15 or older (excluding live-in servants) are considered eligible. Households and individuals are tracked to new locations when necessary. In this study, we use a balanced sample from the three survey rounds. The full panel contains 3082

[8] School in local community is coded 1 when the community has a primary school or a secondary school, or both, and 0 if no school.

households and 14,552 individuals but sample size for this analysis varies with outcome variables. For the highest grade completed, we use a panel of 4112 children from 2241 households who have once attended school and are 6-18 years old during the first wave. Similarly, for the PSLE variable, we use a panel of 3101 households having at least one PSLE eligible child of ages 6-18 and a panel of 2696 households with at least one FIVE eligible child of ages18-24 is used for the FIVE variable.

4. Results

4.1. Summary statistics

Summary statistics are presented in Tables 2-4. All point estimates are weighted to allow inferences to the population of either individuals or households, depending on the variable. Point estimates are accompanied by standard errors and number of observations. Table 2 presents demographic characteristics of sample in all three NPS waves. The first panel presents individual characteristics, middle panel presents household characteristics, and the last panel presents characteristics of the household head. Tanzania has a very young population with the average age of 21 years in baseline, 23 in the second wave, and 24 years in the third survey wave. Based on those who have attended school, the average school starting age is 8 which is higher than the regional average of 7 years for sub-Saharan Africa. The average household size is about 5 in all three waves and about half of them are children ages 6-18 years. Parental and household head's characteristics are very important for the analysis because effect of assets on child education mostly operates through parental decisions about child labor, schooling, intra-household resource allocation, and divisions of work. Parental education is measured with 'maximum parent's education', the maximum level of father and mother's level of education. As a vast majority of parents in our sample are not current students, we keep parental education constant across waves. On average, both parents and household heads have attended primary school but about 20% of the heads are still illiterate. Other characteristics of household head includes age, gender, and marital status. As household heads are changing over time (due to death, migration, marriage etc.) household head's characteristics such as gender, marital status, and literacy rate need not be constant across waves. Household heads are relatively young with the average age of 45 years in baseline, 47 in the second wave, and about 49 in the third wave. On average, household head's gender balance is skewed to males with only about 25% households headed by female, but more than 70% households have married heads.

Apart from individual and household head's characteristics, effects of assets may differ by income level, rural and urban areas, household's response to transitory shocks, and access to school in local community, so we discuss these variables too. As expected, more than 70% households reside in rural areas but more than 90% households have access to primary or secondary school in village. Although a majority (53%) of households reported to have experienced negative economic shock during baseline and the proportion was even lower for the following waves at 41% and 36%, 78% households experienced some kind of negative shock at some point of time. Consistent with reduction in national poverty rates (World Bank, 2015), average annual household consumption expenditure has increased over time from 2.5 million Tanzanian Shilling in baseline to 3.8 million Shilling in wave 3.

Children's educational outcomes are summarized in Table 3. As educational outcomes are not available for children who have never attended school, both our summary statistics and empirical results are conditional on attending school. Among the three educational outcomes, highest grade completed is based on the panel of 4112 children ages 6 to 18 years during the first NPS wave. We track the cohort of 6 to 18 year old children in baseline to estimate the effect of assets on 'highest grade completed'. On average, children in our sample have completed 5th grade in baseline, 7th grade in the second wave and 9th grade in the third wave. As the primary school leaving exam (PSLE) and Form IV exam (FIVE) data are not available for the first wave, we use the PSLE and FIVE data from the second and third NPS surveys only. Even though passing rate for both PSLE and FIVE tests is higher than 65% in both waves, only a small proportion of eligible children passed the tests because a majority of school-age children were not enrolled in school and had no opportunity to take the tests. Nevertheless, the proportion of school-age children passing PSLE test has increased over time from 18% 2010 to 23% in 2012. Similar pattern holds for the FIVE test too.

Descriptive statistics of asset indexes[9] across three waves are presented in Table 4. All asset indexes are constructed using the principal component analysis. To avoid non-comparability issues, loading factors for each asset variable are extracted from the pooled data. The aggregated asset index consists 59 asset variables but the disaggregated indexes – household durables, agricultural assets, and housing quality assets – consist 23, 22, and 14 variables, respectively. Table A1 in Appendix enlists all asset variables under each sub-category and pooled loading factor for each of them.

4.2. Empirical results

We first examine the data to verify that agricultural asset holding predicts child labor in agriculture. We pooled the data from the three waves and estimate a pooled probit regression of child labor on all three types of assets for various sub-samples. Results indicate that agricultural assets increase the likelihood of child labor among crop producers and rural households in general. But children are less likely to engage in any labor generating activity with increased ownership of household durables and housing quality assets (Table A2 in Appendix). This finding supports our assumption that effects of assets on child education operate through child labor. With this finding in hand, next we estimate the effect of asset holding on children's educational outcomes.

4.2.1. Effects of assets on highest grade completed

[9] Since we calculate asset indexes at the household level, we assume that all children within a household have equal access to household assets.

We use equation (9) to estimate the effects of assets on highest grade completed by children 6-18 years of age in baseline. In particular, equation 9 is estimated for two different model specifications using three different panel estimators; random effects, fixed effects, and HTIV models. Both specifications are exactly the same in all but the endogenous time-varying variables. The first specification includes aggregated asset index as the only time-varying endogenous variable (Table 5) and the second specification includes all three sub-indexes as time-varying endogenous variables (Table 6). Results in Table 7 also come from the second specification estimated with our preferred HTIV model for various subsamples.[10] Standard errors are clustered at the household level in all regressions. Tables are structured such that results in the first column are obtained from the random effects model which is inconsistent under conditions (i) and (ii) in section 3.3. Under the same conditions, results in the second and third columns are consistent as they are obtained from the fixed effects and HTIV models, respectively. Results in the third column are our preferred results because HTIV model is a more efficient estimator than the fixed effect model (Baltagi et al., 2003; Hausman & Taylor, 1981). Efficiency gain is particularly important for our analysis because our data comes from a comprehensive nationally representative survey which is likely suffered from unforeseen measurement errors.

Table 5 presents the effect of aggregated asset index on children's highest grade completed. The aggregated asset index has the expected sign suggesting positive wealth effects on children's education. Positive coefficient on consumption expenditure, proxy for household income, also suggests positive income effects, as expected. Among other controls, both having educated parents

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[10] The basic estimating equation is specified as: $Qc_{it} = x_{1it}\alpha + x_{2it}\beta + z_{1i}\theta + z_{2i}\gamma + u_i + \varepsilon_{it}$ where
Qc_{it}= highest grade completed,
x_{1it} = (household size, age, age of head, sex of head, marital status of head, number of children 0-18, and dummies for rural residence, and economic shock),
x_{2it} = (asset index or sub-indexes depending on specification),
z_{1i} = (sex, age started school), and
z_{2i} = max. parent's education

and access to a school in village help children achieve higher grades. In particular, about 5% increase in total expenditure and increase in parental education by one more level (such as primary to secondary school) have identical effect on child education in that both help children complete one more grade. Educated parents may see larger expected return from sending kids to school; so the opportunity cost of schooling may not be as high for their children and it may reduce child labor in agriculture. Similarly, children who live nearby a school may work on farm in the weekends or off-hours in weekdays and still attend school in the daytime. This would lead to the positive effect of 'school in village' even when child labor is employed in agriculture. Results indicate that, after controlling for endogeneity, effect of maximum parent's education on children's highest grade completed gets more than 4 times bigger than it was with the random effects model. This implies the potential endogeneity of parental education and shows the importance of using HTIV method over the fixed effect model. Interestingly, having a male head of household adversely effects children's grade level but girls are more likely to achieve higher grades than boys. This is consistent with existing evidence from developing countries that boys are more likely to forgo school for household agricultural activities in comparison to girls who usually take care of household and kitchen activities (Akresh et al., 2013; Burke & Beegle, 2004). The level of education increases with age but late school starters hurt their chances of achieving higher grades. Finally, household size has smaller but significant negative effect on child education suggesting any increase in household size reduces child education.

In Table 6, we disaggregate assets to three different groups – household durables, agricultural assets, and housing quality assets. Although results in Table 5 suggest that assets uniformly contribute to child education through positive wealth effects, results in Table 6 suggest different types of assets have differential effects on child education. Household durables and housing quality characteristics have the expected positive effects but agricultural assets have negative effects on children's highest grade completed. As agricultural assets include farm tools and equipment, land, and livestock, owning more agricultural assets may increase the opportunity cost of schooling and lead to higher child labor demand which contributes to school dropout. Overall, the adverse effect of agricultural assets is more than offset by household durables and good quality housing as the later have larger positive effects than agricultural assets. The estimated effects of other variables including access to school in village are qualitatively identical to the results presented in Table 5 and discussed above.

Results indicate that while the effect of aggregate wealth index on child education is unambiguously positive, disaggregating assets to different sub categories have significant differential effects. The evidence of negative effects of agricultural assets on the grade level completed is particularly striking because it is in contrast to the traditional view of positive wealth effect on education. Agricultural assets (or any productive assets) are a form of wealth, but they may behave differently than durable assets and housing quality assets in that the productive assets incur labor and other input cost to be operational. Ownership of agricultural assets may indicate wealth acquisition but it may increase the opportunity cost of schooling and child labor demand, especially among agrarian households which have no or limited access to labor market. The evidence points that an undifferentiated view of assets is misleading. Because ownership of agricultural assets increases the likelihood of child labor in own-farm activities (Table A2 in Appendix), the results also imply that the opportunity cost of schooling rises with agricultural assets presumably through an effect on child labor in farming.

That different assets have differential effects and agricultural assets increase child labor in agriculture is a striking result for policy makers and planners and deserves further exploration. In Table 7, we estimate our preferred HTIV model for various sub-samples to identify the potential mechanism behind the differential effects of different types of assets. We estimate the model for eight different sub-samples – rural, urban, crop producers, livestock keepers, boys, girls, poor, non-poor – and results indicate that different types of assets have differential effects among rural children or children from crop producers. Although aggregated asset index has positive effects on child education in both cases, we find no evidence of asset-specific effects on educational outcomes of urban children and children from livestock producers. Results for boys vs. girls, and poor vs. non-poor sub-samples are not presented here, but we find no evidence of differential effects in none of these cases. This indicates that while positive wealth effects on child education consistently holds in various scenarios, different types of assets have differential effects mostly among rural children and children from grain crop farmers. The results make a perfect sense in that the opportunity cost of schooling may not increase with agricultural assets if the household is not farming regardless of wealth status. In rural areas, labor markets are mostly absent and most households operate in agrarian settings so increased stock of agricultural assets increases opportunity cost of schooling.

4.2.2. Effects of assets on exam performance

We know from the earlier discussion that agricultural assets have negative effects on highest grade completed and the negative effects largely stem from child labor in agriculture because most agricultural assets are complement to child labor. While the 'highest grade completed' provides a valid measurement of school enrollment and grade completion, it still does not provide a measurement of individual performance in specific exams. We use the PSLE ratio to examine the effects of assets on school-age children's performance in the primary school leaving exam (Table 8). Similarly, FIVE ratio is used to assess the effects of assets on adolescent's performance in the form IV exam (Table 9). We still use the framework in equation (9) and estimate the same two model specifications, one with aggregated asset index and another with dis-aggregated indexes, using the random effects, fixed effects, and HTIV estimators but the analysis is carried out at the household level in contrast to individual level analysis for the highest grade completed. While the key variables of interest are still the same, the set of control covariates has been updated by deleting all individual level controls and adding some household level controls.[11] Results from the first specifications are not presented here, but as expected, we find positive wealth effects on children's performance in both PSLE and FIVE tests (See Table A3 and Table A4 in Appendix). Control variables are exactly the same in both specifications and the estimated coefficients on control variables from one specification are not qualitatively different from the other.

Table 8 presents the estimated effects of asset holdings on the PLSE ratio, proportion of school-age children passing the PSLE exam. Results from the second specification, where the asset index is disaggregated to three sub-indexes, reveals that the positive wealth effect on PSLE performance mainly comes from household durables and housing quality assets. However, in contrast to the 'highest grade completed', PSLE performance is not affected by agricultural assets at all. These results are robust in that similar results hold for performance in the FIVE test as well. Results in Table 9 indicate that like PSLE ratio, the aggregated wealth index has strong positive effect on FIVE ratio too. Again, the positive effect stems from effects of household durables and housing quality index, but agricultural assets have no effect on adolescent's performance in the FIVE test. This implies that the effect of agricultural assets is not homogenous among children from the same household and may depend on children's ability. To elaborate, children doing well in school may not be affected from agricultural assets as much because parents' expected returns from sending high ability children to school may be higher than the expected return from investment on low ability children's education. Because expected return from schooling is higher for high ability children, opportunity cost of schooling for high ability children may be not as high as compared to

[11] The new set of control variables include log(total expenditure), education of head, age of head, sex of head, marital status of head, household size, number of children, and binary indicators for residence in mainland or Zanzibar, and economic shock in the last 12 months.

children performing poorly in school. As a consequence, children who were not doing well in school may have had no opportunity to take the tests because they might have been taken out of school for farm activities. Since increased agricultural assets may incentivize parents to take out low ability children from school, agricultural assets adversely affect the highest grade completed but do not affect test performance because children taking the tests are mostly high ability students.

Among other variables, household consumption expenditure has a strong positive effect on PSLE and FIVE ratios, suggesting positive income effect on child educational outcomes. Similarly, maximum parents' education has a positive effect on both ratios. Specifically, having a parent with one more level of education contributes to 7% increase in the ratio of PSLE pass children and 8% increase in the ratio of FIVE pass children. Unlike the effect on 'highest grade completed', having a school in village has no effect on children's performance on either test. An implication is that students who are doing well and still in school may find it worthwhile to travel to nearby community for schooling, but students who are not doing well may drop out when school is far away.

5. Conclusion

A large body of empirical evidence indicates that household wealth helps improve child education (Deng et al. 2014; Chowa et al. 2013; Huang 2013; Elliott, Destin and Friedline 2011; Kim and Sherraden 2011; Shanks 2007; Zhan and Sherraden 2003; Conley 2001). Despite the positive effect of household wealth, there is extremely limited empirical evidence on how different components of the wealth (i.e. different assets) contribute to child education after controlling for household income. In this paper we developed a simple theoretical model that portrays a conceptual pathway for different types of assets to have differential effects on child education. Our model predicts, when labor market is perfect, increase in assets contributes to child education, but when labor market is missing, the effect of assets can go either way depending on types of assets and other conditions. Under the assumption of missing labor market, our empirical results confirmed the theoretical findings and revealed that different assets have differential effects on child education presumably through child labor.

We showed that agricultural assets have adverse effect on the highest grade completed but have no effect on performance in the primary school leaving exam and the form IV exam. This implies that agricultural assets may increase the opportunity cost of schooling for children but the increment may not be homogenous among siblings or other children in the same household. For children who are doing well in school, the opportunity cost of schooling is warranted because they have higher expected return from education than other children. As child schooling largely depends on parental decision about when and which child to send to school, parents may choose to take the low ability children out of school and invest more in high ability children's education. This is likely the case in many developing countries and it certainly leads to negative effect of agricultural assets on grade completed or school enrollment but no effect on school performance because children who are still in school are not affected by household's endowment of agricultural assets. That agricultural assets have negative effects on child education because they are labor using technology and increase opportunity cost of schooling is well justified with the evidence of larger negative effect of agricultural assets for children working in household agricultural activities. Our finding that the negative effects of agricultural assets is amplified for rural children or children of crop producers also backs up the evidence that the negative effect of agricultural assets operates through child labor in agriculture.

Household durable assets such as radio, TV, bicycle and housing quality assets such as better toilet facility, access to electricity, and good quality house have positive effects on both 'grade completed' and exam performance for children of age 6-18 and youth of age 18-24. Unlike agricultural assets, household durables and good quality housing are not labor using technology and they are unlikely to increase the opportunity cost of schooling. Instead, a large endowment of household durables and good hosing conditions are perceived as household wealth or higher socioeconomic status that contribute to better education for children via wealth effect. In addition, these assets may provide enhanced economic security and reduced economic stress among parents which usually leads to better child education through good parenting. The positive effect of housing quality assets is a part of wealth effect on child education, but some assets such as access to electricity, safe drinking water, and good toilet facility may have a direct effect on child education; electricity increases efficiency studying, and access to safe water and good toilet facilities may improve school performance through improved health of children.

Results imply that even though assets serve as a good predictor of child educational performance, asset based interventions that capitalize in agricultural assets may not be favorable for child education. From policy perspective, if child education is an intended goal of the intervention, transferring agricultural assets or other resources to build agricultural asset holding may not yield the desired result. In the context of Tanzania, program interventions that transfer livestock or help increase livestock herd size may be favorable for child education than providing other agricultural assets to crop producers and households in rural areas. Despite the potential negative effect of agricultural assets on child education, there may be ways to increase agricultural asset holdings without compromising child education. Since the negative effect of agricultural assets essentially boils down to child labor in agriculture, asset based intervention conditional on 'no child labor in agriculture' policy may help increase household welfare without hurting child education; although implementing such a policy may be extremely difficult. Another implication of our findings is that transferring agricultural assets in combination with awareness training or adult education to parents, or establishing a public school in the target community also may help mitigate the potential adverse effects of agricultural assets on child education.

Programs that help accumulate household durables or improve housing quality characteristics contribute to child education and therefore may be incorporated in policy interventions aiming to improve both household welfare and child education. Although policy interventions that transfer household durables or housing quality assets are rare in practice, empirical findings in this study suggest that interventions that combine agricultural asset transfers with household durables or housing quality assets may contribute to household socioeconomic status as well as temper the potential negative effect of agricultural assets on child education. Since we control for household income, our findings should still hold regardless of the level of household income. One caveat is that this study does not consider the threshold level of income or asset holding above which change in asset ownership may have no effect on child education. In other words, if the demand for child education is inelastic to the opportunity cost of schooling, which may be the case for wealthy people, then our findings may not hold anymore. Otherwise, the effect of assets on child outcomes are based on type of assets and policy interventions that help accumulate assets or directly transfer assets should be implemented with caution.

Overall, the key implication of this study is that assets are an important element of social policies that focus on improving both household and individual welfare. The traditional method of considering all assets under household's possession as an aggregated measure of household wealth may be misleading because different type of assets have differential effects on child education and this may be true for other outcomes too. The evidence that, even after controlling for household income, asset holding has a significant positive effect on child education but the effect differs by the type of assets is a novel finding and deserves further exploration. If similar findings hold for other countries and contexts, it should help researchers and policymakers to design asset based interventions or all other policy interventions that help accumulate assets in a more meaningful way.

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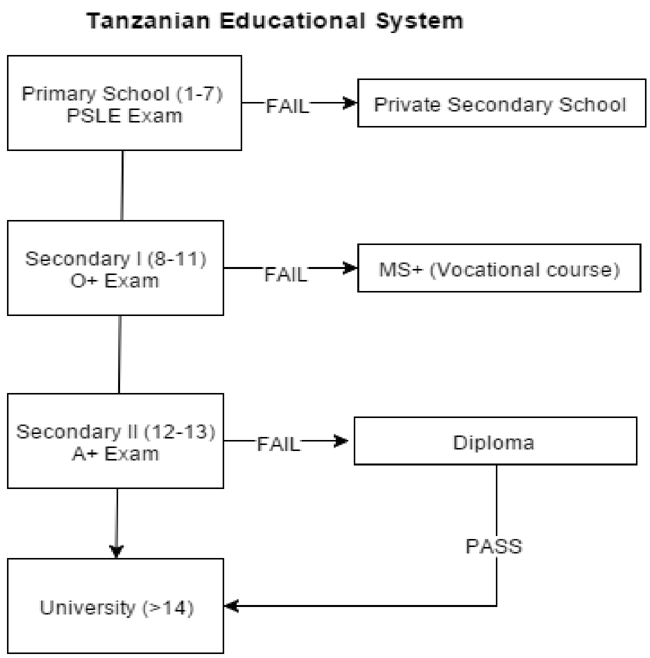

Figure 1. Educational system in Tanzania

Table 1. Effects of exogenous increase in assets and income on child labor and household consumption

	Perfect labor market				No labor market			
	Case 1		Case 2		Case 3		Case 4	
	l	*c*	*l*	*c*	*l*	*c*	*l*	*c*
Agricultural Assets (K)	-ve	+ve	-ve	+ve	±	+ve	±	+ve
Assets specific to child education (A)	.	.	+	-ve	.	.	+ve	-ve
Income (y)	-ve	+ve	-ve	+ve	-ve	+ve	-ve	+ve
Education production function (q)	No		Yes		No		Yes	

Notes. *l* indicates child labor, and *c* indicates household consumption. Similarly, -ve, +ve, and ±, indicate negative, positive, and ambiguous effects of assets or income, respectively, on child labor and household consumption.

Table 2: Summary statistics of individual and household characteristics

Characteristics	Wave 1 (2008/09)	Wave 2 (2010/11)	Wave 3 (2012/13)	Observations
Individual				
Age	20.97	22.76	24.48	14552
	(0.150)	(0.150)	(0.144)	
Gender (1=male,0=female)	0.49	0.49	0.49	14552
	(0.004)	(0.004)	(0.004)	
Age started school†	8.01	8.01	8.01	9645
	(0.021)	(0.021)	(0.021)	
Household				
Expenditure, real (million TSZ)	2.50	2.91	3.84	3069
	(0.042)	(0.046)	(0.062)	
Maximum parent's education‡	2.23	2.23	2.23	3064
	(0.023)	(0.023)	(0.023)	
Household size	5.01	5.27	5.26	3073
	(0.048)	(0.049)	(0.049)	
Number of children 6-18	2.79	2.89	2.84	3073
	(0.038)	(0.039)	(0.039)	
Shock in last 12 months (1=Yes,0=No)	0.53	0.41	0.36	3073
	(0.009)	(0.009)	(0.009)	
Rural	0.72	0.71	0.71	3069
	(0.008)	(0.008)	(0.008)	
School in village (1=Yes, 0=No)	0.89	0.94	0.96	3073
	(0.003)	(0.004)	(0.003)	
Household Head				
Age	45.3	47.1	48.7	3073
	(0.28)	(0.276)	(0.27)	
Gender (1=Male, 0= Female)	0.76	0.75	0.74	3073
	(0.008)	(0.008)	(0.008)	
Education level (grade)	2.27	2.27	2.27	3073
	(0.022)	(0.022)	(0.022)	
Marital status (1= Married, 0 else)	0.75	0.74	0.72	3073
	(0.008)	(0.008)	(0.008)	

Notes. Point estimates are population weighted means. Standard errors are in parentheses.
†Number of observations of 'age started school' is much smaller than other variables because about 35% of the population has never attended school
‡Maximum parent's education is maximum education level of father or mother. It is coded as follows: 1= no education, 2= primary not finished, 3= primary, 4= secondary not finished, 5= secondary, and 6= higher than secondary.

Table 3: Summary statistics of child educational outcomes across three waves

Educational outcomes	Wave 1 (2008/09)	Wave 2 (2010/11)	Wave 3 (2012/13)	Observations
Highest grade completed	5.86	7.64	9.14	4112
	(0.050)	(0.053)	(0.054)	
PSLE pass ratio‡	-	0.18	0.23	3101
		(0.005)	(0.006)	
FIVE pass ratio‡	-	0.10	0.13	2696
		(0.005)	(0.006)	

Notes. Point estimates are population weighted means. Standard errors are in the parentheses.
‡Primary school leaving exam (PSLE) and Form IV exam (FIVE) are national level examinations administered after 7th and 11th grades, respectively. The PSLE and FIVE ratios are the proportions of children passing the PSLE and FIVE tests to total children of ages 6-18 and 16-24, respectively. Because test scores data are not available for the first wave, both PSLE and FIVE ratios are presented for the second and third waves only.

Table 4: Summary statistics of asset indexes across three waves

Asset indexes	Wave 1 (2008/09)	Wave 2 (2010/11)	Wave 3 (2012/13)
Aggregated Asset index†	-0.227	0.020	0.207
	(0.058)	(0.060)	(0.059)
Household durable index	-0.128	0.082	0.046
	(0.043)	(0.044)	(0.043)
Agricultural asset index	0.067	0.025	-0.091
	(0.047)	(0.046)	(0.011)
Housing quality index	-0.155	-0.028	0.182
	(0.038)	(0.040)	(0.041)
Observations	3082	3082	3082

Notes. Point estimates are population weighted means. Standard errors are in the parentheses. All asset indexes are constructed using the Principal Component Analysis (PCA) and the same loading factors obtained from the pooled data are used across three waves.
†Aggregated asset index consist of 59 variables, and three sub-indexes – household durable index, agricultural asset index, and housing quality index – consist 23, 22, and 14 variables, respectively.

Table 5. Effects of aggregated asset index on highest grade completed of children ages 6 to 18

	Dep variable: Highest grade completed		
	RE	FE	HTIV
Log(Total expenditure)	0.263***	0.152***	0.164***
	(0.035)	(0.040)	(0.034)
Aggregated Asset index	0.098***	0.038**	0.051***
	(0.011)	(0.016)	(0.012)
School in village (1=Yes,0=No)	0.145**	0.239***	0.248***
	(0.063)	(0.086)	(0.073)
Max. parent's education	0.224***	-	0.843***
	(0.025)		(0.077)
Gender (1=Male, 0=Female)	-0.275***	-	-0.293***
	(0.053)		(0.060)
Head's gender (1=Male, 0=Female)	-0.229***	-0.289**	-0.046
	(0.076)	(0.114)	(0.056)
Age (Years)	0.810***	0.814***	0.814***
	(0.008)	(0.010)	(0.006)
Age started school	-0.463***	-	-0.431***
	(0.025)		(0.024)
Household size	-0.080***	-0.079***	-0.074***
	(0.014)	(0.017)	(0.013)
Observations	11992	11992	11992

Notes. Standard errors are in parentheses. Significance level: * $p < .10$, ** $p < .05$, *** $p < .01$. Results are based on panel of children who have attended school and were 6 to 18 years old in 2008. Results are presented for key variables only, estimated model includes additional variables.

Table 6. Effects of different assets on highest grade completed of children ages 6 to 18

	Dependent variable: Highest grade completed		
	RE	FE	HTIV
Log(Total expenditure)	0.241***	0.146***	0.157***
	(0.035)	(0.040)	(0.034)
Household durable index	0.073***	0.020	0.026*
	(0.014)	(0.018)	(0.015)
Agricultural asset index	-0.009***	-0.012***	-0.013***
	(0.003)	(0.004)	(0.004)
Housing quality index	0.096***	0.053**	0.066***
	(0.017)	(0.021)	(0.017)
School in village (1=Yes, 0=No)	0.150**	0.242***	0.248***
	(0.063)	(0.086)	(0.073)
Max. parent's education	0.213***	-	0.827***
	(0.025)		(0.078)
Gender (1=Male, 0=Female)	-0.275***	-	-0.292***
	(0.053)		(0.060)
Head's gender (1=Male, 0=Female)	-0.243***	-0.287**	-0.149**
	(0.076)	(0.114)	(0.071)
Age (Years)	0.810***	0.811***	0.812***
	(0.008)	(0.010)	(0.006)
Age started school	-0.459***	-	-0.429***
	(0.025)		(0.024)
Household size	-0.079***	-0.078***	-0.074***
	(0.014)	(0.017)	(0.013)
Observations	11992	11992	11992

Notes. Standard errors are in parentheses. Significance level: * $p < .10$, ** $p < .05$, *** $p < .01$. Results are based on panel of children who have ever attended school and were 6 to 18 years old in 2008. Results are presented for key variables only, estimated model includes more variables.

Table 7. Effects of different assets on highest grade completed of children ages 6 to 18, under various scenarios

	Model: HTIV			
	Rural	Urban	Grain crop farmers	Livestock keepers
Log(Total expenditure)	0.152***	0.258***	0.221***	0.191***
	(0.040)	(0.071)	(0.040)	(0.044)
Household durable index	0.068***	0.021	0.057***	0.081***
	(0.023)	(0.021)	(0.022)	(0.025)
Agricultural asset index	-0.026***	-0.007	-0.012*	0.002
	(0.008)	(0.005)	(0.007)	(0.008)
Housing quality index	0.123***	0.010	0.102***	0.109***
	(0.024)	(0.028)	(0.023)	(0.026)
School in village (1=Yes, 0=No)	0.241*	0.074	0.314***	0.327***
	(0.134)	(0.091)	(0.101)	(0.119)
Max. parent's education	0.581***	0.470**	0.837***	0.759***
	(0.139)	(0.192)	(0.133)	(0.145)
Gender (1=Male, 0=Female)	-0.313***	-0.185*	-0.289***	-0.298***
	(0.065)	(0.102)	(0.065)	(0.070)
Head's gender (1=Male, 0=Female)	-0.224***	-0.065	-0.144*	-0.075
	(0.086)	(0.128)	(0.085)	(0.096)
Age (years)	0.764***	0.902***	0.782***	0.792***
	(0.007)	(0.012)	(0.007)	(0.008)
Age started school	-0.420***	-0.437***	-0.422***	-0.405***
	(0.031)	(0.054)	(0.030)	(0.033)
Household size	-0.073***	-0.084***	-0.078***	-0.068***
	(0.016)	(0.024)	(0.016)	(0.016)
Observations	8095	3897	8796	7217

Notes. Standard errors are in parentheses. Significance level: * $p < .10$, ** $p < .05$, *** $p < .01$. Results are based on panel of children who have ever attended school and were 6 to 18 years old in 2008. Results are presented for key variables only, estimated model includes more variables.

Table 8. Effect of different assets on Primary School Leaving Exam (PSLE) performance of children ages 6 to 18

	Dependent variable: PSLE pass ratio		
	RE	FE	HTIV
Log(Total expenditure)	0.051***	0.035***	0.040***
	(0.007)	(0.009)	(0.008)
Household durable index	0.012***	0.008*	0.010***
	(0.003)	(0.005)	(0.004)
Agri. asset index	0.001*	0.000	-0.000
	(0.001)	(0.001)	(0.002)
Housing quality index	0.018***	0.003	0.010*
	(0.003)	(0.006)	(0.005)
School in village	0.007	0.012	0.011
	(0.009)	(0.012)	(0.009)
Max parent's education	0.006	-	0.073***
	(0.005)		(0.019)
Head: age	0.003***	0.004***	0.005***
	(0.000)	(0.001)	(0.001)
Head: Gender (1=male, 0=female)	-0.036***	-0.075***	-0.033**
	(0.013)	(0.025)	(0.014)
Household size	-0.024***	0.002	-0.021***
	(0.002)	(0.004)	(0.003)
Observations	6029	6029	6029

Notes. Standard errors are in parentheses. Significance level: * $p < .10$, ** $p < .05$, *** $p < .01$. As the dependent variable is at the household level, no individual characteristics are included in the model.

Table 9. Effect of different assets on Form IV Exam (FIVE) performance of youth ages 18 to 24

	Dependent variable: FIVE pass ratio		
	RE	FE	HTIV
Log(Total expenditure)	0.036***	0.024***	0.031***
	(0.006)	(0.008)	(0.008)
Household durable index	0.018***	0.004	0.009***
	(0.003)	(0.004)	(0.003)
Agri. asset index	-0.000	-0.001	-0.002
	(0.001)	(0.002)	(0.001)
Housing quality index	0.019***	0.009*	0.015***
	(0.003)	(0.006)	(0.005)
School in village	0.008	0.007	0.010
	(0.009)	(0.011)	(0.008)
Max parent's education	0.011***		0.077***
	(0.004)	-	(0.019)
Head: age	0.001***	0.001	0.003***
	(0.000)	(0.001)	(0.001)
Head: Gender (1=male, 0=female)	-0.029**	-0.033	-0.018
	(0.013)	(0.035)	(0.013)
Household size	-0.010***	-0.000	-0.006***
	(0.001)	(0.003)	(0.002)
Observations	5219	5219	5219

Notes. Standard errors are in parentheses. Significance level: * $p < .10$, ** $p < .05$, *** $p < .01$. As the dependent variable is at the household level, no individual characteristics are included in the model.

Appendix

Table A1. Pooled scoring factors and baseline summary statistics of asset variable

Household durables	Mean	Scoring factors	Agricultural assets	Mean	Scoring factors	Housing quality characteristics	Mean	Scoring factors
Radios	0.79	0.15	Hoes	2.27	0.03	Own dwelling (1=Yes 0=No)	0.78	-0.26
TVs	0.24	0.36	Spraying machines	0.04	0.10	Rent dwelling (1=Yes 0=No)	0.14	0.26
Telephones	0.02	0.12	Water pumps	0.02	0.13	House wall (1=cement/concrete, 0=else)	0.28	0.34
Mobile phone	1.11	0.30	Reapers	0.00	0.31	House roof (1=metal sheets 0=else)	0.66	0.25
Refrigerators	0.14	0.33	Tractors	0.00	0.31	House floor (1=concrete/cement/tiles 0=else)	0.43	0.36
Sewing machines	0.13	0.19	Trailers	0.00	0.31	Number of rooms (=1 if 3 or more 0=else)	0.55	0.01
Video/DVDs	0.19	0.26	Ploughs	0.07	0.08	Safe water (1=boiled/bottled/treated 0=else)	0.33	0.17
Computers	0.07	0.05	Harrows	0.00	0.31	Water source (1=protected, 0=open source)	0.53	0.24
Irons	0.36	0.29	Milking machines	0.00	0.40	Water hauling time(1=less than average, 0 else)	0.62	0.00
Electric/gas stoves	0.08	0.26	Harvesters/threshers	0.00	0.40	Access to toilet (1=Yes 0=No)	0.90	0.04
Other Stoves	0.69	0.24	Hand miller	0.01	0.22	Toilet type (1=modern, 0=Vault/Pit)	0.13	0.26
Water heaters	0.04	0.23	Coffee pulper	0.00	0.25	Electricity (1=Yes 0=No)	0.23	0.37
Cassette players	0.02	0.07	Fertilizer distributors	0.00	0.38	Fuel(1=electricity/gas/generator/solar,0=else)	0.24	0.37
Music systems	0.03	0.12	Livestock	3.84	0.03	Cooking fuel (1=firewood 0=else)	0.71	-0.36
Cars	0.05	0.23	Poultries	5.81	0.01			
Motor cycles	0.05	0.14	Donkeys	0.06	0.04			
Carts	0.54	0.05	Plots	1.61	0.02			
Bicycles	0.02	0.09	Outboard engines	0.03	0.03			
Wheel barrows	0.03	0.07	Land owned (1=Yes, 0=No)	0.64	0.01			
Boats/canoes	0.01	0.02	Land rented (1=Yes)	0.06	0.00			
Houses	1.17	-0.03	Land shared (1=Yes)	0.01	0.00			
Fan/ACs	0.23	0.30		0.13	0.00			
Dish antennas	0.13	0.26						
Observations	3082	3082		3082	3082		3082	3082

Notes. All asset variables are in count, unless otherwise indicated. Asset indexes calculated by using binary indicators of asset ownership are not qualitatively different from the indexes resulting from count variables. Scoring factor is the weight that is used to calculate the first principal component. The first component explains 26% of the variance in durable assets

Table A2. Likelihood of child labor on own-farm agricultural activities

	Model: Pooled Probit			
	Rural	Urban	Crop producers	Livestock keepers
Log(Total expenditure)	0.165***	0.053	0.123***	0.143***
	(0.033)	(0.064)	(0.031)	(0.034)
Household durable index	-0.014	-0.011	-0.004	-0.025
	(0.016)	(0.021)	(0.015)	(0.017)
Agricultural asset index	0.016**	-0.005	0.011*	0.008
	(0.006)	(0.004)	(0.006)	(0.006)
Housing quality index	-0.222***	-0.192***	-0.168***	-0.133***
	(0.018)	(0.026)	(0.017)	(0.018)
School in village (1=Yes, 0=No)	0.807***	0.404***	0.693***	0.549***
	(0.117)	(0.105)	(0.090)	(0.105)
Max. parent's education	-0.112***	-0.030	-0.100***	-0.079***
	(0.020)	(0.030)	(0.018)	(0.018)
Gender (1=Male, 0=Female)	0.154***	0.218***	0.169***	0.152***
	(0.035)	(0.069)	(0.033)	(0.035)
Head's gender (1=Male, 0=Female)	0.005	-0.120	-0.065	-0.062
	(0.060)	(0.133)	(0.060)	(0.063)
Age (years)	0.094***	0.049***	0.093***	0.096***
	(0.005)	(0.010)	(0.005)	(0.005)
Age started school	-0.022	-0.045	-0.019	-0.015
	(0.013)	(0.029)	(0.013)	(0.014)
Household size	-0.058***	-0.111***	-0.063***	-0.069***
	(0.013)	(0.024)	(0.012)	(0.012)
Observations	8097	3897	8798	7219

Notes. Standard errors are in parentheses. Significance level: * $p < .10$, ** $p < .05$, *** $p < .01$. Dependent variable is child labor in agriculture (1= yes, 0 = no) and the results are obtained from pooled probit model.

Table A3. Effect of asset ownership on primary school leaving exam performance

	Dependent variable: PSLE pass ratio		
	RE	FE	HTIV
Log(Total expenditure)	0.056***	0.036***	0.041***
	(0.007)	(0.009)	(0.008)
Asset index	0.019***	0.011**	0.016***
	(0.002)	(0.005)	(0.003)
School in village	0.008	0.013	0.014
	(0.009)	(0.011)	(0.009)
Max parent's education	0.006	-	0.063***
	(0.005)		(0.019)
Head: age	0.003***	0.004***	0.005***
	(0.000)	(0.001)	(0.001)
Head: Gender (1=male, 0=female)	-0.032**	-0.072***	-0.030**
	(0.013)	(0.025)	(0.014)
Household size	-0.023***	0.002	-0.020***
	(0.003)	(0.004)	(0.003)
Observations	6029	6029	6029

Notes. Standard errors are in parentheses. Significance level: * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A4. Effect of asset ownership on Form IV Exam (FIVE) performance

	Dependent variable: FIVE pass ratio		
	RE	FE	HTIV
Log(Total expenditure)	0.042***	0.025***	0.029***
	(0.006)	(0.007)	(0.008)
Asset index	0.025***	0.008*	0.018***
	(0.002)	(0.005)	(0.003)
School in village	0.010	0.007	0.013
	(0.009)	(0.011)	(0.008)
Max parent's education	0.011***	-	0.078***
	(0.004)		(0.018)
Head: age	0.002***	0.001	0.004***
	(0.000)	(0.001)	(0.001)
Head: Gender (1=male, 0=female)	-0.022*	-0.032	-0.014
	(0.013)	(0.035)	(0.013)
Household size	-0.009***	0.000	-0.005**
	(0.001)	(0.003)	(0.002)
Observations	5219	5219	5219

Notes. Standard errors are in parentheses. Significance level: * $p < .10$, ** $p < .05$, *** $p < .01$.