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Child labor among farm households in Mozambique and the role of reciprocal adult labor

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ABSTRACT

We test the impact of a reciprocal adult labor program, Ajuda Mútua (AM), on child labor and schooling. AM was introduced into the province of Nampula in Mozambique, an area where farm production relies on child labor, potentially due to labor and financial market failures. Using difference in differences, we estimate that AM reduces child labor by eight percentage points. We argue that AM reduces child labor by providing low-cost adult labor and potentially increasing farm productivity. We benchmark the AM results against the impact of Village Saving and Loan Associations (VSLA) and AM and VSLA in combination (VAM). Neither VSLA nor VAM reduce child labor. If credit is used in a way that increases labor demand beyond what can be accommodated by AM labor, child labor may increase. We conclude that addressing labor market failures may be more successful at reducing child labor than addressing financial market failures. Results on schooling are mixed.

1. Introduction

In 2020, around one in 10 children worldwide and one in 4 children in sub-Saharan Africa were involved in child labor. While child labor rates have steadily declined between 2012 and 2020 worldwide, child labor rates in sub-Saharan Africa went up over the same period. In sub-Saharan Africa in 2020, 81.5 percent of child labor was in agriculture, with children often working unpaid on the family farm (ILO and UNICEF, ILO & UNICEF, 2021).

Labor market failures play an important role in the pervasiveness of farm child labor (Basu, Das, & Dutta, 2010; Benjamin, 1992; Bhalotra & Heady, 2008; Bhalotra & Heady, 2003; Bharadwaj, 2015; Dumas, 2007; Dumas, 2013; Dumas, 2020). Labor market failures occur when households are not able or willing to exchange labor through the labor market (De Janvry, Fafchamps, & and Sadoulet, 1991). Farm households may not be able to exchange labor if the agricultural cycles they experience are synchronized: labor demand and supply peak and trough at the same time. In this case households may experience excess labor demand in the peak season and use child labor as a buffer. Pressures to use child labor as a buffer will be greater if cash-based labor markets are absent or external (non–household) labor cannot be found. Even if households do not experience synchronised agricultural cycles and external labor is available, households may not be willing to use external labor, still preferring child labor. This can happen when there is no cash to pay for external labor or external labor is too costly, for example due to lower search and monitoring costs (Bharadwaj, 2015; Skoufias, 1995).[1] Proposed solutions that encourage external labor usage include long-term personalized contracts and sharecropping (Braverman & Stiglitz, 1982; Eswaran & Kotwal, 1985; Fehr & Gächter, 2000). However, empirical evidence on the impact of these programs on farm labor, including child labor, is scarce.

This paper tests how child labor is impacted by a program that directly addresses labor market failures. We test the introduction of a reciprocal adult labor program 'Ajuda Mútua' (AM) into the Nampula province of Mozambique. AM encourages neighboring households to exchange adult labor between themselves, not for a wage, but under the commitment that the labor will be recipro-

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[1] High monitoring costs are relevant for tasks carried out in the pre-harvest season where the output is not easily observable (Bharadwaj, 2015). With difficult to observe agricultural output, piece-wise contracts cannot be used and so rate-wise contracts are used in their place (Bharadwaj, 2015). Without supervision, it has been shown that shirking is likely to emerge when labor is hired on short-term rate-wise contracts (Eswaran & Kotwal, 1986).

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cated. Our main finding is that AM reduces child labor.[2] We argue that AM is likely to reduce child labor through two channels. First, AM can help cover labor shortages in periods where child labor is typically used as a buffer by providing adult labor that has low search costs, is free at the point of use, and can be temporarily allocated to periods in the agricultural cycle when it has the highest returns. Second, AM can reduce pressures on child labor by increasing adult labor productivity through economies of scale, information sharing of best practices, and lower shirking. These productivity increases may be enhanced by building trust among members, as members repeatedly work on each other's farms.

This paper is also the first to test the impact of AM on school absenteeism and enrollment. We find that AM decreases school absenteeism but does not impact school enrollment. There is a potential trade-off between child labor and schooling, as both activities can compete for children's time. Child labor is often associated with low school enrollment and attendance (ILO & UNICEF, 2021), and existing literature has shown that schooling can increase when child labor decreases (de Carvalho Filho, 2012; Duryea, Lam, & Levison, 2007; Edmonds, 2008; Edmonds & Schady, 2012; Soares, Kruger, & Berthelon, 2012). However, schooling is not the only alternative to child labor. Especially when school returns are low, children's time may also be spent in activities that are neither work nor schooling (Cigno & Rosati, 2005; Edmonds, 2008). Therefore, the trade-off between schooling and child labor may be weak (Baland, Demont, & Somanathan, 2020; Bandara, Dehejia, & Lavie-Rouse, 2015; Dammert, 2008; Kruger, 2007; Landmann & Frölich, 2015). Finally, there are cases where schooling and child labor are complements: when income from child labor is required to pay for school costs, child labor and schooling may increase (decrease) at the same time (De Hoop, Friedman, Kandpal, & Rosati, 2019; De Hoop, Friedman, Kandpal, & Rosati, 2019).

We benchmark the effects of AM against the effects of Village Saving Associations (VSLA) and the combination of AM and VSLA (VAM) where households have access to both AM and VSLA. AM, VSLA, and VAM were all introduced into Nampula by Save the Children as part of the same study allowing the programs to be compared. VSLA allows groups of households to pool incomes into a single saving fund which can then be borrowed at low interest rates. Before the introduction of VSLA, Nampula lacked formal and informal financial markets. VSLA addresses financial market failures by enabling households to both save and borrow in a safe and reliable environment.[3]

We find that VSLA and VAM do not reduce child labor, possibly due to high credit usage expanding household business, and, thus, labor demand. We also find that VSLA and VAM decrease school absenteeism but not to the same degree as AM. We find no effects of VSLA and VAM on school enrollment. This is coherent with existing literature concluding that addressing financial market failures has a limited impact on schooling (Angelucci et al., 2015; Attanasio et al., 2015; Beaman et al., 2014; Banerjee et al., 2015; Crépon et al., 2015; Dupas et al., 2018; Karlan et al., 2012; Tarozzi et al., 2015) and mixed effects on child labor (Angelucci et al., 2015; Attanasio et al., 2015; Baland et al., 2020).[4] In line with Dumas, 2020, we conclude that addressing labor market failures is more effective at reducing child labor than addressing financial market failures.

To identify the impacts of AM, VSLA, and VAM on child labor and schooling, we use a difference in differences design. Identification relies on the common trends assumption: in the absence of the treatment, the treated and control households would have followed the same trend in outcomes. To help satisfy the common trends assumption we do the following. First, we control for exogenous shocks between the baseline and endline. Second, we control for baseline covariates that are likely to be correlated with the dynamics of the outcomes. We do this parametrically and semi-parametrically using propensity score weights: both methods give qualitatively the same results.

Our paper contributes to the literature on the impact of labor market imperfections on child labor (Basu et al., 2010; Benjamin, 1992; Bhalotra & Heady, 2003; Bharadwaj, 2015; Dumas, 2007; Dumas, 2013; Dumas, 2020) and the literature on community-based programs where, like in AM and VSLA, beneficiaries are involved in the program's design and management. Community-based programs are cost-effective, especially when they help increase trust in post-conflict and insecure environments like Nampula Casey, 2018; Mansuri and Rao, 2004. We contribute to these literatures in at least three ways. First, by studying AM, we provide what we believe is the first evaluation of a community-based labor market organization. This is the first study that shows how child labor responds to an intervention that directly addresses labor market imperfections. Second, we provide evidence of relatively 'long-term' effects (three years after the program's introduction) compared to most estimates in the relevant literature (rare evidence of long-term effects can be found in Baland et al., 2020; Björkman Nyqvist, De Walque, & Svensson, 2017; Cassidy & Fafchamps, 2017). Third, we compare the effects of AM, VSLA, and their combination (VAM).

AM may be a viable and cheaper alternative to conditional cash transfers (CCTs). Our estimates of the AM impact on the probability that a child works are in line with the estimates obtained for some of the most promising CCTs, such as the Cambodian CESSP scholarship program (Ferreira & Schady, 2009), the Brazilian Bolsa Escola (Ferro & Kassouf, 2010), and the Mexican Oportunidades (Behrman, Parker, & Todd, 2011).[5] However, AM is likely to be cheaper to implement. For some of the CCTs that have been found to decrease the probability of child labor, for example, the CESSP scholarship in Cambodia, the amount of the transfers already exceeds our estimated costs for AM, even before considering the implementation costs. Moreover, AM only requires activation costs

[2] For a general description of AM in Mozambique see Chaiken, 2016. AM and the other program analyzed in this article, Village Saving Associations (VSLA), were the two programs introduced into Mozambique, Nampula, by a multi-country initiative called STRIVE. STRIVE was initiated by the USAID's Displaced Children and Orphans Fund (DCOF) and the USAID Micro-enterprise Development office, and developed in collaboration with several partner organizations, including - for the case of Mozambique - Save the Children. STRIVE's aims of employing market-led economic strengthening initiatives are discussed for the case of Mozambique in Brunie, Fumagalli, Martin, Field, and Rutherford, 2014.

[3] Literature on the impact of financial markets failures on child labor and schooling includes: Angelucci, Karlan, and Zinman, 2015; Attanasio, Augsburg, De Haas, Fitzsimons, and Harmgart, 2015; Augsburg, De Haas, Harmgart, and and Meghir, 2012; Augsburg, De Haas, Harmgart, and Meghir, 2015; Baland et al., 2020; Banerjee, Duflo, Glennerster, and Kinnan, 2015; Crépon, Devoto, Duflo, and Pariente, 2015; Dupas, Karlan, Robinson, and Ubfal, 2018; Hazarika and Sarangi, 2008; Shimamura and Lastarria-Cornhiel, 2010; Tarozzi, Desai, and Johnson, 2015; Wydick, 1999. Beaman, Karlan, and and Thuysbaert, 2014 and Karlan et al., 2012 analyze the effect on child labor/schooling of the introduction of VSLA. Other evaluations of VSLA, not explicitly considering child labor or schooling, are: Brunie et al., 2014; Bundervoet, Annan, and and Armstrong, 2011; Bundervoet, 2012; Cassidy and Fafchamps, 2017; Karlan, Savonitto, Thuysbaert, and Udry, 2017; Ksoll, Lilleør, Lønborg, and Rasmussen, 2016. The combination of AM and VSLA into VAM has similarities with programs combining a labor market component (such as vocational training) and interventions relaxing financial constraints, see, for example: Bertrand, Crépon, Marguerie, and and Premand, 2017; Crépon and Premand, 2018; Hicks, Kremer, Mbiti, and Miguel, 2013; J-PAL, 2013; Karlan and Valdivia, 2011. For the impact of these programs on child labor, see: Dammert, de Hoop, Mvukiyehe, and Rosati, 2018.

[4] Baland et al., 2020 finds positive effects of self-help groups on education, but argue that these effects come from increased social capital, rather than from improved access to credit. Effects on labor supply for teenagers and adolescents are ambiguous: Augsburg et al., 2012; Augsburg et al., 2015 finds that removing financial market frictions increases adolescents' labor supply and decreases adolescents' school enrollment; while Attanasio et al., 2015; Crépon et al., 2015 and Tarozzi et al., 2015 find some reduction in teenagers' labor supply.

[5] See de and Rosati, 2014 for a comprehensive summary of the impact of CCTs on child labor.

and then is expected to expand at no cost through word of mouth. In contrast, the costs of CCTs are expected to remain constant over time, as the transfers need to be paid to all beneficiaries, not only to those in the starting group.

2. How AM, VSLA, and VAM can impact child labor

2.1. Child labor in the study area

Save the Children introduced AM, VSLA, and VAM (the combination of AM and VSLA) into Nampula: a poor rural province in the North East of Mozambique with an economy based on subsistence agriculture, and weak formal labor and financial markets.[6] While there are no official statistics on child labor in Nampula, for the whole of Mozambique, at the time of the introduction of the programs, 22% of children between the age of five and 15 were involved in child labor, with the share of working children increasing with children's age. This is despite of the Child Labor Act of 2008, which banned all forms of labor for children under 15 years of age, and the Labor Law, which states that young people aged 15–18 should not be employed in tasks potentially detrimental to their health and well-being. Child labor was more prevalent in rural areas: the share of children between the age of five and 15 involved in child labor was 25% in rural areas and 15% in urban areas. Children mainly worked for their parents: over 70% of child labor was in the family business, and the residual share was in household chores. Child labor outside the family was negligible (UNICEF, UNICEF, 2009).

2.2. How AM can impact child labor

Our key hypothesis is that AM can reduce child labor by providing a pool of reciprocal adult labor that can displace child labor. In this section, we explain the reasoning behind this hypothesis by outlining the AM program and describing how AM may reduce pressures on child labor.

Ajuda Mútua (AM) is a reciprocal rotating labor scheme designed to encourage the sharing of adult labor. Participants self-select into groups of four to 15 households based on their needs. AM groups receive training from Save the Children field agents on how to rotate labor across households. Groups meet regularly, but the number of meetings is up to the households in question and varies with the agricultural cycle. Group members work together for the benefit of one household on a given day, for another on the next convenient day, and so on, until all members have reciprocated labor. The most common AM activities are farming duties such as seeding, tillage, weeding, and harvesting. The output derived from these activities stays with the household whose land has been cultivated and does not have to be shared among AM members. Less frequent AM activities include building and/or repair work of members' houses, like building improved toilets. The tasks to be performed through AM are left to the discretion of the participants, who are aware of their strengths and needs.

In Nampula, a constraint on farm production is the limited availability of labor (see Chaiken, Dixon, & and Herminio, 2012; Chaiken, 2016and Section 4). When adult labor is limited, child labor can provide a buffer. Further, farm households have minimal access to the food market and their food production is often insufficient to meet needs. In the harvest season, households do not produce enough to ensure that they stay above subsistence during the pre-harvest season. In the pre-harvest season, households seek off-farm jobs to support themselves and cannot afford to pay wage labor to work on their small-holding (Chaiken et al., 2012). This creates a vicious cycle (see also Fink, Jack, & Masiye, 2020): households often do not have sufficient labor to prepare their land during the pre-harvest season, which limits yield in the following harvest.

AM is designed to address the lack of external labor, which is a problem in the study area. Before the introduction of the programs by Save the Children, external labor was often limited to a few days per year and paid with cash (if available) as well as food and drinks (Chaiken, 2016). AM can help address labor shortages in two ways. First, holding productivity fixed, AM can allow households to optimally re-allocate adult labor at times when hired external labor is insufficient to meet demand. In the pre-harvest season this may occur when labor demand cannot be met by standard forms of wage farm labor, as farm laborers are seeking off-farm wage labor work, cannot be afforded by the local farms, cannot be paid due to a shortage of cash, or cannot be trusted to work efficiently. During harvest season similar labor shortages may occur simply due to the quantity of labor that is required. If child labor was previously used to cover adult labor shortages, increasing the availability of adult labor through AM can reduce child labor.

Second, AM workers may be more productive than wage workers, allowing households to cultivate more land. AM workers may be able to work together generating economies of scale. Productivity gains can also stem from sharing best practices between AM members, which has been documented by Chaiken, 2016 for similar community-based groups in Mozambique. Shirking may be lower among AM workers than among hired workers, as repeated interaction makes it easier to observe each other's productivity and to punish shirking workers by not reciprocating their work. Limiting shirking is particularly important during the pre-harvest season, where diligent and experienced judgment is required to give a better chance of good harvest yields (Bharadwaj, 2015; Eswaran & Kotwal, 1985). If AM workers are a closer substitute than wage workers for child labor, AM may further reduce the pressures on child labor.

AM may make use of a low but latent pool of trust in Nampula. In the past, farm households engaged in *mori*, a practice of incentivizing neighboring households to work together on each others' farms (Chaiken, 2016). However, this practice did not survive a prolonged period of war (independence war from 1961 to 1974 and civil war from 1977 to 1992) which weakened the interpersonal trust and traditional norms of reciprocity practices like *mori* relied on (Chaiken et al., 2012; Chaiken, 2016; Gallego & Mendola, 2013; Marsh, 2003). Therefore, in the absence of formal labor markets, as well as informal practices based on reciprocity, labor typically came from adults and children from within the household. By re-instigating reciprocal practices, AM can provide an alternative to child labor.

One of the major strengths of AM is that it is cheap and easy to implement. AM only requires start-up costs of providing information and it is then expected to expand through word of mouth. The cost incurred by Save the Children for the introduction of AM is not available separately from the cost of the implementation of the other programs. The average cost per beneficiary for the implementation of AM, VSLA, and VAM is estimated to be 30 dollars. This cost, however, is skewed towards the provision of VSLA that require trained facilitators with knowledge of the rules and the characteristics of the scheme. Therefore, 30 dollars is an upper limit for the cost of AM.

[6] In 2013 the population of Mozambique was approximately 25.8 million. With a population of approximately 4.8 million, Nampula is the country's second most populous province. Mozambique is divided into 10 provinces plus one capital city with provincial status. The provinces are divided into districts ('*Distritos*', 129 in total in the country), and districts are divided into Administrative Posts ('*Postos Administrativos*', 405 in total), and then into Localities ('*Localidades*'). In 2014 Mozambique was ranked 178th out of 187 countries in the UNDP's Human Development Index (UNDP, 2014).

2.3. How VSLA can impact child labor

The impact of micro-finance institutions on household and individual outcomes, such as child labor, is relatively well studied (see Sections 1 and 6.4). Our hypotheses follow the arguments in the literature. The impact of VSLA on child labor depends on the balance of three potentially competing effects: (i) a consumption smoothing effect, (ii) an income effect, and (iii) an economic-activity effect.[7]

The consumption-smoothing and the income effect are likely to reduce child labor. If VSLA savings and/or credit allow households to smooth consumption over the agricultural cycle or to increase household income, child labor will reduce. This is likely to occur either because (i) without dips in consumption, income from child labor is required less frequently, or (ii) if child labor is a bad in household preferences, as income increases parents choose to use less child labor. The economic-activity effect is likely to increase child labor. VSLA credit facilities may allow households to increase their farm capacity or diversify their production into non-farm activities. Depending on the scale and nature of the changes in economic-activity, an increase in farm capacity or non-farm business diversification may require more child labor. The net effect of the introduction of VSLA on child labor is *a priori unclear*.

As with AM, VSLA has roots in traditional reciprocal networks in Nampula's history. Informal financial practices such as *stigi*, which were rotating credit associations, also died out during the consecutive wars in Mozambique (Chaiken, 2016). VSLA acts as a structured, safe, and self-managed way for households to save money and receive credit.[8] Participants self-select into groups of 15 to 30 members. The groups receive training from Save the Children on financial literacy and account keeping. Groups meet around four times a month. At each meeting members pool a discretionary amount of money into a common fund.[9] The common fund can be lent out to group members. Money is lent only when all members are present at the group meeting to vote on the borrower's stated usage, amount, and interest rate (typically around $10-20\%$). The credited amount and any interest accrued are then invested back into the common fund. There is also an emergency fund, which cannot be lent, used free of interest to cope with unforeseen income shortfalls.

VSLA is cheap, flexible, and limits moral hazard. The costs of VSLA are essentially those of providing the initial information. Compared to AM, however, VSLA is more costly as it requires facilitators to be hired to explain the rules and provide materials. While more structured than AM, VSLA is still more flexible than Rotating Savings and Credit Association (ROSCA) as it is based on discretionary rather than fixed weekly contributions (Beaman et al., 2014). Finally, VSLA limits moral hazard, through a constitution that lists the reasons for expelling a member (Allen & Staehle, 2007).

2.4. How VSLA and AM in combination (VAM) can impact child labor

The impact of combinations of community-based programs, such as AM and VSLA, is rarely studied in the literature. We hypothesize that the impact of VAM on child labor depends on whether the two programs interact. An AM and VSLA interaction will be observable if having access to AM and VSLA in combination, rather than in isolation, changes: (i) whether households use the programs, and, conditional on using the programs, (ii) how intensely the programs are used (amount of savings, credit, and labor) and (iii) the composition of usage (for example, likelihood of using savings, relative to likelihood of using credit).

If there is no interaction between AM and VSLA, the effect of the programs on child labor in combination (VAM) will equal the sum of the effects of the programs in isolation. The impact of VSLA on child labor is *ex-ante* unclear (see Section 2.3), therefore, the impact of VAM on child labor is also unclear. However, if AM reduces child labor (see Section 2.2) we would expect VAM to either reduce child labor, or at least not increase child labor to the same extent as VSLA in isolation.

If there is an interaction between AM and VSLA, the effect of the programs in combination (VAM) on child labor is not necessarily equal to the sum of the effects of the programs in isolation. The interaction between AM and VSLA may impact whether households use the program and usage intensity. For example, if AM allows members to observe each other's work ethic, households may be more (or less) willing to use VSLA or may want to use it more (or less) intensely. Similarly, if VSLA allows members to observe each other's attitudes and reliability with money, households may be more (or less) willing to use AM or may want to use it more (or less) intensely. The interaction between VSLA and AM can also affect VSLA's usage composition. VSLA can be used for savings and/or credit and the balance between savings and credit may be affected by whether AM is available. If households can use AM to smooth labor supply and resulting income flows, consumption smoothing through VSLA savings may be required less. If AM allows households to meet labor demands, households may be more likely to use VSLA credit to make farm investments that require additional labor.

3. Program rollout, enrollment, and estimation sample

The programs were implemented in eight of Nampula's 15 districts. Programs were placed at the district level to limit: (i) possible spillover between treatment and control, (ii) management burden, and (iii) the sense of inequity among communities in the same areas excluded from the program. The treatment arms were constructed as follows. Of the 15 districts of Nampula, 12 were selected where Save the Children had some previous activities. Of these 12 districts, eight were selected such that once paired Save the Children perceived them to be similar in terms of demographics, market access, food availability, soil conditions and climate, access to services, previous presence of Save the Children, and average distance from the capital. Each pair of districts was randomly assigned one of the following treatment statuses: (i) control group, where neither AM nor VSLA was offered, (ii) AM, where only AM was offered, (iii) VSLA, where only VSLA was offered, and (iv) VAM, where both VSLA and AM were offered.

Program rollout was carried out in stages (see Fig. A.1). In stage 1, program facilitators were hired and trained, and information about the program was disseminated. Households interested in taking part in AM and/or VSLA signed up to enrollment lists. At this point, groups were formed but they were instructed by Save the Children to not start group activities. Once enrollment lists had been prepared, the sampling started. The sampling was stratified

[7] Save the Children's expectation was that VSLA would change the economic-activity of farms through asset building, income generation, and risk mitigation via improved access to credit (see: Brunie et al., 2014).

[8] For similar, earlier programs, see: Besley et al. (Besley, Coate, & Loury, 1993; Besley, Coate, & Loury, 1994); Banerjee et al. (Banerjee, Besley, & and Guinnane, 1994).

[9] The common fund is kept in a lock-box which requires different keys to open. These keys are each held by different group members and rotated. Contributions to the common fund are made with an end date in mind, at which point the fund is re-distributed to the members in proportion to their total contribution throughout the saving cycle. Saving cycles last between six and 12 months.

by district. In the control districts enumeration areas (EAs) from the 2007 census, containing an average of 100 households each, were first selected and households were then selected from each EA. Thus, the sampling frame in the control districts is representative of the population in those districts. In the treated districts, households were selected from the programs' enrollment lists. In stage 2, baseline data were collected in August 2009. In stage 3, after the program had been running for three years, endline data were collected in August 2012.[10] The estimation sample is children aged 10 to 15, inclusive. This is because labor questions are not asked to children under 10 and child labor above 15 is legal.[11]

4. Baseline descriptive statistics

The construction of the treatment arms and sampling design does not ensure comparability between treatment and control households at baseline. To help account for pre-existing differences, we use a difference in differences strategy, which is discussed in Section 5 alongside how we look for evidence to support the common trends assumption. Table 1 presents baseline descriptive statistics on: (i) household characteristics (size, proportion of children aged 10–15, total and cultivated area of plantation, and the total number of assets), (ii) head of household characteristics (occupation, age, gender, marital status, and education), and (iii) child information (age, gender, child labor, and schooling).

Table 1 column 1 presents descriptives statistics for control households, while column 2 presents descriptive statistics for AM households. The household and household head characteristics are mostly similar between control and AM households. Taken together, the characteristics illustrate that both sets of households are typical of households in Nampula: farming households who own land but fail to cultivate it all. Nearly all household heads in our sample are involved in farming as a primary or secondary occupation (see the eighth row). Almost 100% of households own a plantation and the average size of a plantation is approximately two hectares (third to fifth rows).[12] However, the plantation is often not completely cultivated, with the cultivated land area lying consistently below the total land area (compare the fifth and sixth row). Households have roughly 6 members, a third of whom are aged 10 – 15, household heads are in their forties (45 in control areas and 41 in AM areas), 90% are male and married, and the majority have primary school education (69% in control areas and 76% in AM areas). Tables A.1 and A.2 in the Appendix illustrate that these points can be carried across to VSLA and VAM households.

Fig. A.2 provides further evidence that not all land is cultivated. It shows the distribution of household plantation areas at the baseline and the amount of uncultivated land. The proportion of households who do not completely cultivate their land is indicated by the numbers above the bars. Uncultivated land exists even among households with little land. For example, 8% of the households owning less than 0.7 hectares of land and 15% of households owning between 0.7 and 1.4 hectares of land do not cultivate their land completely. Among households owning between 3.5 and 4.2 hectares of land, this share is close to 60%. These figures suggest that some constraints prevent all land from being cultivated.

The main reason households do not cultivate all their land is the lack of labor. Fig. A.3 plots the reasons why households do not cultivate all their land. The primary reason is the lack of labor (60% of those who give a reason for not cultivating all their land), followed by lack of money (22%). Other reasons, including reasons outside human control, such as resting land or lack of rain, are mentioned less often. Fig. A.3, therefore, suggests that constraints to cultivating all land come from labor market failures and - perhaps to a lesser extent - from financial market failures, that is the constraints AM and VSLA are designed to loosen.

While households and household head characteristics are similar, there are differences in child outcomes at baseline. The bottom panel of Table 1 shows that children in both control and AM areas are roughly the same age and gender, on average. Child labor is lower in control households compared to AM households: 48% in control and 65% in treatment. School enrollment is higher in control households compared to AM households: 83% compared to 74%. Conditional on attending school, the probability of having at least one day off from school in the last month is lower in control households compared to AM households: 14% compared to 44%. The difference in absenteeism is likely to result from the fact that, compared to children in AM households, children in control households are more likely to be enrolled in school and are less likely to be involved in child labor (see the joint school/labor proportions in the final four rows of Table 1).

The final four rows of Table 1 illustrate the relationship between child labor and schooling. We highlight three main points. First, there is minimal idleness in either control or AM households (no school and no labor is around 10%: bottom row, bottom panel). Second, cases where children only go to school are more likely than cases where children only work (compare sixth and seventh row, bottom panel). Third, child labor does not completely crowd out schooling, as child labor and schooling often occur together (see the eighth row of the bottom panel). Tables A.1 and A.2 in the Appendix illustrate that these points can be carried across to VSLA and VAM households.

The differences in baseline child outcomes highlight the importance of following a difference in differences strategy that compares outcome changes over time in treatment and control areas rather than at a single point in time. Supportive evidence for a difference in difference strategy comes from the similarity in household characteristics: if households who are observably similar share similar trends in child outcomes. The household and household head characteristics in panels 1 and 2 of Table 1 suggest that households are similar at baseline. Identification of program impacts is discussed in Section 5.

5. Empirical strategy

This paper uses a difference in differences strategy to estimate the causal impacts of the programs. The main estimating equation is:

$$Y_{chdt} = \alpha_t + \gamma_d + \mathbf{T}_{dt}\beta\prime + \mathbf{w}_{hdt}\tau\prime + \mathbf{s}_{hdt}\psi\prime + \upsilon_{chdt} \tag{1}$$

where Y_{chdt} is outcome Y (child labor, school attendance, and school enrollment) for child c, in household h, locality d and time period t. α_t and γ_d are time and locality fixed effects (the lowest available administrative level), respectively. $\mathbf{T}_{dt} = [AM_{dt}\ VSLA_{dt}\ VAM_{dt}]$ is a vector of treatment dummies that vary at the district-time level and $\beta = [\beta_{AM}\ \beta_{VSLA}\ \beta_{VAM}]$ is a vector of difference in differences treatment parameters. $\mathbf{w}_{hdt}$ is a vector of covariates and τ is the associated vector of parameters. $\mathbf{s}_{hdt}$ is a vector of time-varying shocks and ψ is the associated vector of parameters. υ_{chdt} is a composite error term. We present two sets of p-values using: (i) clustering at the treatment level and (ii) the Wild Bootstrap (see: Cameron,

[10] Administrative data show that there were approximately 500 AM participants in September 2009, 5000 in June 2010 and 11800 in December 2011, and approximately 2400 VSLA participants in September 2009, 6500 in June 2010, and 12200 in December 2011. While the growth of both programs is substantive, the programs' participants still represent a small fraction of the 4.8 million of inhabitants in Nampula.

[11] It is an unbalanced panel of children and households. Analyzing a balanced panel of children of said age would restrict the sample size given there are three years between the baseline and the endline.

[12] This figure is in line with national level data (see, for example USAID, 2010).

Table 1
Difference in means at baseline: control versus AM.

	obs	Control	obs	AM	Diff	s.e.	p-value
Household characteristics:							
Size	280	5.636	115	5.939	−0.303	0.212	0.153
Prop. aged 10–15	280	0.288	115	0.274	0.014	0.013	0.259
Own a plantation	280	0.993	115	1.000	−0.007	0.008	0.365
Number of plantations	280	2.682	115	2.878	−0.196	0.136	0.150
Area (hectares)	280	2.212	115	1.965	0.247	0.349	0.479
Cultivated area (hectares)	280	1.728	115	1.646	0.082	0.113	0.467
Total number of assets	280	2.525	115	3.043	−0.518	0.209	0.013
Head of household:							
Prop. farmers	280	0.989	115	1.000	−0.011	0.010	0.266
Age	280	44.607	115	40.678	3.929	1.377	0.005
Prop. male	280	0.929	115	0.913	0.016	0.029	0.598
Prop. married	280	0.925	115	0.870	0.055	0.032	0.082
Prop. no school	280	0.261	115	0.217	0.043	0.048	0.366
Prop. prim school	280	0.693	115	0.757	−0.064	0.050	0.206
	obs	Control	obs	AM	Diff	s.e.	p-value
Child (10–15, inclusive) information:							
Age	425	12.278	168	12.399	−0.121	0.155	0.435
Male	425	0.529	168	0.524	0.006	0.046	0.902
Child labor	425	0.478	168	0.649	−0.171	0.045	0.000
School enrollment	425	0.826	168	0.738	0.088	0.036	0.016
School absenteeism	349	0.138	121	0.438	−0.300	0.041	0.000
School and no labor	425	0.440	168	0.256	0.184	0.044	0.000
No school and labor	425	0.092	168	0.167	−0.075	0.029	0.009
School and labor	425	0.386	168	0.482	−0.096	0.045	0.032
No school and no labor	425	0.082	168	0.095	−0.013	0.026	0.615

Notes: Difference in means tests for baseline characteristics. Panel 1 is for all households in the baseline survey with at least one child aged from 10 to 15, inclusive. Panel 2 shows the characteristics of all children aged 10 to 15 in the households in the sample. Total assets (a proxy for wealth) are a summation of the following asset types: radio, bike, clock, cellphone, chair, aluminum pans, zinc roof panels, and improved toilet. Child labor is equal to one if the child has worked on the household plantation in the previous 12 months and zero otherwise. School enrolment is equal to one if the child is enrolled in school and zero otherwise. Absenteeism is equal to one if the child has had a day off school in the last 30 days and zero otherwise. By characteristic and cells from left to right: observations in control, mean of variable in control, observations in AM, mean of variables in AM, the difference in means between control and AM, the standard error for differences in mean, and p-value for the hypothesis that difference in means is equal to zero against the two-sided alternative.

Gelbach, & Miller, 2011; Roodman, Nielsen, MacKinnon, & Webb, 2019).

To identify the causal impacts of the programs, we rely on the common trends assumption: in absence of the treatment, control and treatment groups would have followed the same trend in outcomes. The assumption can fail for three reasons: (i) outcomes in different treatment arms were differentially affected by shocks, (ii) treatments were placed systematically in districts with higher expected returns (district selection), and (iii) households in treatment and control arms differ in a way that puts them on different trends (household selection). To help satisfy (i) we use the fact that our data contain detailed information about shocks.[13] We do not think reason (ii) is an issue in expectation: Save the Children did not choose which arm to assign each treatment based on the greatest expected returns. However, once the program placement was announced, households did self-select into the programs, which can mean (iii) is violated.

To do our best to satisfy (iii), we control for household characteristics ($\mathbf{w}_{hdt}$ in Eq. (1)). To model households' selection into the programs, we include baseline controls: (i) household composition, (ii) head of household characteristics, (iii) farm wealth, and (iv) trust. Controlling for household composition helps capture the targeting of households by Save the Children, who targeted households with children under the age of six and, in particular, households with children under two. Therefore, alongside household size, we control for the presence of children under two and children aged between two and six. Educated/wealthy households are more likely to be aware of campaigns, or less educated/wealthy households may have been targeted by Save the Children: education, age, wealth, and the principal job of the head of household are controlled for. Given the community-based nature of the programs, households with more trust in neighbors, local institutions, or third parties may be more likely to participate in the program (see: Durlauf & Fafchamps, 2005); therefore, we control for a composite measure of trust. In addition to the baseline characteristics (i)-(iv), we control for children's age and gender to capture compositional changes in age and gender between baseline and endline.[14]

We also control for the above characteristics semi-parametrically (see Appendix B). We estimate the propensity scores for the probability of treatment (see: Abadie, 2005; Hirano & Imbens, 2001) and we re-weight households on the common support by the inverse of their treatment probability. This choice of weights estimates the average treatment effect on the treated (see: Hirano & Imbens, 2001). The parametric results in Section 6 and the semi-parametric results in Appendix B are qualitatively the same. This suggests that our results are robust to different estimation methods. To identify effects, we still need to assume there are no unobservable differences that cause differences in child labor trends between treatment and control households. We cannot test this assumption. However, Save the Children did not

[13] We have shock data capturing whether or not the household experienced one or more of the following in the previous 12 months: drought, flood, erosion, cyclone, human illness, plant illness, animal illness, and price shock.

[14] These controls are also in line with the literature on the adoption of community based organizations (e.g., Arcand & Fafchamps, 2012; Fafchamps, 2009; Kurosaki & Fafchamps, 2002; Ferrara, 2002). To capture farm wealth we control for: baseline income (split by crop, animal, employment and other), total number of assets, and area of plantation. The questionnaire asks the respondents about their level of trust towards: people of the same ethnic/linguistic group, people of a different ethnic/linguistic group, the local store owner ('*lojista*'), officials of the local government, officials of the central government, police, teachers, nurses/doctors, and strangers. For each of these categories, the respondent is asked to assign a score ranging from 1 (very little trust) to 5 (very high trust). Our measures of trust are the mean of these scores across all categories.

advertise the program in treatment arms with an explicit mention of child labor (our main outcome variable). This suggests that households were unlikely to self-select into the programs based on the perceived benefits or costs of child labor.

6. Results

6.1. Main results

The main results are presented in Table 2. There is one panel for each outcome: child labor (first panel), school absenteeism (second panel), and school enrollment (third panel). Within each panel, there are three specifications. The first specification uses time and locality fixed effects. The second specification adds baseline controls. The third specification adds controls for shocks. The coefficients presented are from the fully interactive model where each treated group (AM, VSLA, VAM) is compared to the control group: these are the estimated coefficients $\hat{\beta} = [\hat{\beta}_{AM}\ \hat{\beta}_{VSLA}\ \hat{\beta}_{VAM}]$ of model (1). The sample is all children aged 10 to 15, inclusive. Clustered standard errors are presented in parentheses, and clustered and Wild Bootstrap p-values are given in the top and bottom square parentheses.

AM decreases child labor and school absenteeism and does not impact school enrollment. The full specification in the first panel of Table 2 suggests that AM decreases child labor by 8.4 percentage points (Wild Bootstrap p-value: 0.066). The full specification in the second panel of Table 2 suggests that AM decreases school absenteeism by 37 percentage points (Wild Bootstrap p-value: 0.066). Table A.3 presents an alternative measure for school absenteeism and shows that AM decreases the number of days of absenteeism in the previous four weeks of completed school by approximately 1.5 days. The full specification in the third panel of Table 2 suggests that AM does not change school enrollment: the point estimate is 9 percentage points, but the estimator is imprecise (Wild Bootstrap p-value: 0.487). All estimated impacts are robust to the inclusion of baseline controls variables and shocks: point estimates and p-values remain similar across specifications.

Table 2 also presents results for VSLA and VAM. Neither VSLA nor VAM reduce child labor. In fact, for both VSLA and VAM, the point estimate of the effect on child labor is positive: 4.4 percentage points for VSLA and 7.8 percentage points for VAM in the full specification. The estimates only reach conventional levels of statistical significance in the case of VAM. We cannot reject the hypothesis that the VSLA and VAM effects on child labor are equal. The point estimates for the effects of VSLA and VAM on school absenteeism are negative, suggesting that these programs may reduce school absenteeism. However, while AM reduces school absenteeism by over 30 percentage points, the decrease in school absenteeism is equal to 20 (17) percentage points in the full specification for VSLA (VAM) and the effect only reaches conventional levels of statistical significance for VSLA. We find no impact of VSLA or VAM on school enrollment.

6.2. Explaining the effect AM on child labor

In Sections 1 and 2 we suggest that AM can ameliorate pressures on child labor by addressing adult labor supply shortages. AM can do this by (i) expanding the available labor supply and (ii) increasing the productivity of workers. To investigate these two channels, Table 3 presents the effects of AM on internal labor (number of household members working on the household farm); external paid/non-paid labor (whether paid/non-paid external labor was used in the household farm in the 12 months before the interview); cultivated area of the plantation (in natural logs); and income (in natural logs). Effects are estimated for the main specification (1) in Section 5, at the household level, on the panel of all households with at least one child between 10 and 15, inclusive.

Table 3 provides evidence coherent with both an expansion of adult labor supply and higher desirability of AM workers compared to hired external workers. AM increases cultivated land area by 23% (Wild Bootstrap p-value: 0.075, see fourth panel of Table 3).[15] This increase does not lead to increased internal labor supply: the number of household members working on the farm remains constant.[16] Instead, Table 3 suggests that the external labor supply expanded: the proportion of households using non-paid external labor increases by 42 percentage points, and the proportion of households using paid external labor decreases by 28 percentage points only. This suggests that households are not completely synchronized and there is spare labor capacity that can be reciprocated. Paid-external workers are substituted with AM workers, which suggests that the latter are more desirable than the former. Due to an increase in the availability and desirability of external labor, AM is likely to make households less reliant on household labor. If children were used to cover labor shortages and/or were preferred over external hired workers, AM can provide a substitute for child labor, allowing child labor to decrease. There are various reasons why AM workers can be more desirable than hired workers. AM workers are free at the point of use and search costs are likely to be lower once AM groups have formed. AM workers may also be more productive than hired labor, for example, if they are less likely to shirk. We cannot distinguish between these possible reasons, however, we can show that trust increased in AM areas. Table 4 presents the results for regressions of measures of trust on variables as in the main specification (1) in Section 5. The dependent variable for the results in panels 1 and 2 are the median and mean values of aggregate counts from our battery of trust questions. All specifications lead to the same result: AM increases trust. An increase in trust may stem from repeated reciprocation among AM workers. Trust can boost the productivity of all workers through increased information sharing. Trust can boost the productivity of external workers making them less likely to shirk. In Nampula increased productivity may be particularly useful during pre-harvest when there is a wage labor shortage and completing farming tasks successfully is crucial for the next harvest yield.

6.3. How VSLA and VAM can affect child labor

Table 2, first panel, shows that VSLA and VAM do not decrease child labor and they may even increase it. This is not a fully surprising result, as null or mixed effects of VSLA and similar programs on child labor are standard in the literature (see Sections 1 and 2). Here we discuss the reasons behind the results on child labor in VSLA and VAM areas with a particular emphasis on the usage of VSLA and VAM.

Table 3 provides evidence that VSLA increased households' economic activity: cultivated farmland increased by 15% (Wild Bootstrap p-value: 0.048). There was no increase in trust in VSLA areas (see null effects in Table 4). This can explain why both external and internal labor increased: the former by roughly 8% and the latter by half a worker on average (see Table 3, first and second columns). The increase in both internal and external labor indicates

[15] Column five of Table 3 shows that results on income vary from a point estimate of 0.141 in the base model to 0.126 in the fully specified model but these results are imprecisely estimated. We do not place much emphasis on the income results, as calculating reliable income metrics in agricultural settings is notoriously difficult due to measurement error (see for example: Banerjee et al., 2015; Deaton, 1997).

[16] The point estimates are 0.037 and 0.065 with p-values of 0.918 and 0.870, see first panel of Table 3. Unfortunately, the data do not allow us to distinguish between adults and children.

Table 2
Main results for child labor, absenteeism and school enrollment.

	Child labor			Absenteeism			School enrolment		
	FE	FE + BL con.	FE + BL con. + shocks	FE	FE + BL con.	FE + BL con. + shocks	FE	FE + BL con.	FE + BL con. + shocks
AM	−0.104	−0.096	−0.083	−0.380	−0.382	−0.371	0.103	0.095	0.088
	(0.011)	(0.012)	(0.012)	(0.085)	(0.083)	(0.086)	(0.085)	(0.083)	(0.077)
	[0.000]	[0.000]	[0.000]	[0.003]	[0.002]	[0.004]	[0.262]	[0.289]	[0.290]
	[0.041]	[0.079]	[0.066]	[0.072]	[0.073]	[0.066]	[0.465]	[0.508]	[0.487]
VSLA	0.059	0.047	0.044	−0.191	−0.186	−0.203	0.027	0.015	0.014
	(0.096)	(0.099)	(0.099)	(0.027)	(0.020)	(0.024)	(0.061)	(0.066)	(0.067)
	[0.555]	[0.647]	[0.673]	[0.000]	[0.000]	[0.000]	[0.677]	[0.826]	[0.843]
	[0.605]	[0.602]	[0.614]	[0.043]	[0.033]	[0.037]	[0.734]	[0.829]	[0.836]
VAM	0.065	0.068	0.078	−0.178	−0.177	−0.171	0.110	0.102	0.097
	(0.013)	(0.012)	(0.011)	(0.115)	(0.112)	(0.100)	(0.046)	(0.051)	(0.057)
	[0.001]	[0.001]	[0.000]	[0.165]	[0.156]	[0.129]	[0.046]	[0.085]	[0.135]
	[0.057]	[0.065]	[0.062]	[0.476]	[0.470]	[0.379]	[0.054]	[0.199]	[0.461]
observations	2519	2519	2519	1930	1930	1930	2412	2412	2412
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Locality FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
BL controls	NO	YES	YES	NO	YES	YES	NO	YES	YES
shocks	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note: table output are the estimates of $\beta = [\beta_{AM}\ \beta_{VSLA}\ \beta_{VAM}]$ for model 1: $Y_{chdt} = \alpha_t + \gamma_d + \mathbf{T}_{dt}\beta\prime + \mathbf{w}_{hdt}\tau\prime + \mathbf{s}_{hdt}\psi\prime + \upsilon_{chdt}$. Three main outcomes ($Y$) with three specifications for each are presented. The outcomes by panel are the following. Panel 1: child labor is equal to one if the child has worked on the household plantation in the previous 12 months and zero otherwise. Panel 2: absenteeism is equal to one if the child has had a day off school in the last four weeks of completed school and zero otherwise. Panel 3: school enrolment is equal to one if the child is enrolled in school and zero otherwise. The three main specifications are models with: (i) time and locality fixed effects, (ii) addition of controls ($\mathbf{w}_{hdt}\tau\prime$), and (iii) addition of controls for shocks ($\mathbf{s}_{hdt}\psi\prime$). Within each cell, the top row is the point estimate, the second row the clustered standard error, the third row the p-value associated with the clustered standard error, and the fourth row is the p-value following the Wild Bootstrap procedure. All point estimates are estimated using OLS. The sample is an unbalanced panel of all children aged between 10 and 15, inclusive. The point estimates, standard errors, and p-values for the control variables are presented in Table A.2 in the Appendix. *Source*: authors' calculations.

Table 3
Possible mechanisms including labor responses, cultivated land and income.

	internal labor		external pay		external non-pay		area cult.		income	
	FE	FE + shocks + BL con.	FE	FE + shocks + BL con.	FE	FE + shocks + BL con.	FE	FE + shocks + BL con.	FE	FE + shocks + BL con.
AM	0.037	0.065	−0.237	−0.276	0.416	0.416	0.227	0.231	0.141	0.126
	(0.346)	(0.383)	(0.081)	(0.061)	(0.178)	(0.174)	(0.113)	(0.123)	(0.212)	(0.149)
	[0.918]	[0.869]	[0.022]	[0.003]	[0.053]	[0.048]	[0.084]	[0.101]	[0.526]	[0.427]
	[0.810]	[0.748]	[0.183]	[0.063]	[0.190]	[0.189]	[0.067]	[0.075]	[0.713]	[0.703]
VSLA	0.490	0.514	0.170	0.085	−0.035	0.022	0.150	0.145	0.423	0.207
	(0.183)	(0.172)	(0.021)	(0.025)	(0.053)	(0.050)	(0.020)	(0.027)	(0.315)	(0.188)
	[0.032]	[0.020]	[0.000]	[0.011]	[0.534]	[0.682]	[0.000]	[0.001]	[0.222]	[0.308]
	[0.062]	[0.064]	[0.057]	[0.074]	[0.694]	[0.720]	[0.048]	[0.048]	[0.361]	[0.533]
VAM	−0.267	−0.266	−0.205	−0.230	0.219	0.216	0.236	0.235	0.137	0.151
	(0.334)	(0.329)	(0.020)	(0.039)	(0.054)	(0.056)	(0.038)	(0.044)	(0.077)	(0.028)
	[0.451]	[0.446]	[0.000]	[0.001]	[0.005]	[0.006]	[0.000]	[0.001]	[0.119]	[0.001]
	[0.577]	[0.583]	[0.042]	[0.063]	[0.063]	[0.070]	[0.056]	[0.054]	[0.177]	[0.039]
observations	1638	1638	682	682	682	682	1654	1654	1663	1663
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Locality FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
BL controls	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
shocks	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Note: the table reports the estimates of $\beta = [\beta_{AM}\ \beta_{VSLA}\ \beta_{VAM}]$ for models: $Y_{hdt} = \alpha_t + \gamma_d + \mathbf{T}_{dt}\beta\prime + \mathbf{w}_{hdt}\tau\prime + \mathbf{s}_{hdt}\psi\prime + \upsilon_{hdt}$. Five main outcomes ($Y$) with two specifications for each are presented. The outcomes by panel are the following. Panel 1: number of internal household members used for labor on the household farm in the last 12 months. Panel 2: = 1 if the household, conditional on using external labor, has used paid external household labor on the household farm in the last 12 months, zero otherwise. Panel 3: = 1 if the household, conditional on using external labor, has used unpaid external household labor on the household farm in the last 12 months, zero otherwise. Panel 4: natural log of land area cultivated. Panel 5: natural log of household income per capita. Income per capita has been calculated by adding up: wage income, self-employment income, income from crops, income from livestock and eggs, remittances, transfers from private and public sources, and rental income (land or goods). The two specifications are: (i) time and locality fixed effects and (ii) then the addition of controls ($\mathbf{w}_{hdt}\tau\prime$) and shocks ($\mathbf{s}_{hdt}\psi\prime$). Within each cell, the top row is the point estimate, the second row the clustered standard error, the third row the p-value associated with the clustered standard error, and the fourth row is the p-value following the Wild Bootstrap procedure. All point estimates are estimated using OLS. The sample is an unbalanced panel of all households with children aged between 10 and 15, inclusive. *Source*: authors' calculations.

that, when external workers cannot be trusted, internal labor is needed to supervise their work (Feder, 1985; Frisvold, 1994). Taken together, these results suggest that, in VSLA areas, the increase in cultivated land was achieved through external paid labor and, potentially, child labor. Further, Table 5 illustrates that 39% of households in VSLA areas used VSLA for credit. This credit may have been used to invest in farmland (19% of households in VSLA areas used credit for agricultural purposes) or to expand households' off-farm business (41% of households in VSLA areas used credit for business). If farm production expands, children may be employed on the farm directly; if the off-farm business expands, children may take over activities previously carried out by adults (see also Dammert et al., 2018), particularly if there is a limited supply of adult labor. Overall, it appears that the economic activity effect (that may increase child labor) balanced, or overturned, other VSLA effects that can decrease child labor (such

Table 4
Possible mechanism: Trust.

	Median trust		Mean trust	
	FE	FE + shocks + BL con.	FE	FE + shocks + BL con.
AM	0.742	0.740	0.613	0.599
	(0.238)	(0.261)	(0.054)	(0.090)
	[0.017]	[0.025]	[0.000]	[0.000]
	[0.051]	[0.048]	[0.056]	[0.051]
VSLA	0.128	0.120	0.314	0.309
	(0.384)	(0.388)	(0.234)	(0.236)
	[0.749]	[0.766]	[0.221]	[0.232]
	[0.698]	[0.718]	[0.504]	[0.517]
VAM	0.198	0.202	0.380	0.374
	(0.093)	(0.105)	(0.029)	(0.063)
	[0.071]	[0.097]	[0.000]	[0.001]
	[0.139]	[0.202]	[0.047]	[0.037]
observations	1660	1660	1660	1660
Time FE	YES	YES	YES	YES
Locality FE	YES	YES	YES	YES
BL controls	NO	YES	NO	YES
shocks	NO	YES	NO	YES

Note: the table reports the estimates of $\beta = [\beta_{AM}\ \beta_{VSLA}\ \beta_{VAM}]$ for models: $Y_{hdt} = \alpha_t + \gamma_d + \mathbf{T}_{dt}\beta\prime + \mathbf{w}_{hdt}\tau\prime + \mathbf{s}_{hdt}\psi\prime + \upsilon_{hdt}$. Two main outcomes ($Y$) with two specifications for each are presented. The outcomes by panel are the following. Panel 1: median trust across a battery of trust questions. Panel 2: mean trust across a battery of trust questions. The two specifications are: (i) time and locality fixed effects and (ii) then the addition of controls ($\mathbf{w}_{hdt}\tau\prime$) and shocks ($\mathbf{s}_{hdt}\psi\prime$). Within each cell, the top row is the point estimate, the second row the clustered standard error, the third row the p-value associated with the clustered standard error, and the fourth row is the p-value following the Wild Bootstrap procedure. All point estimates are estimated using OLS. The sample is an unbalanced panel of all households with at least one child aged between 10 and 15, inclusive. *Source*: authors' calculations.

Table 5
Usage of AM and VSLA by treatment area.

	AM usage		VSLA usage	
	AM area	VAM area	VSLA area	VAM area
Median size of group	12.0	6.0	20.0	25.0
% of households who use AM for agriculture	93.6	90.2		
% of households who use AM for construction	12.8	4.0		
% of households who use AM for other	2.6	1.2		
Median number of months used for agriculture	5.0	5.0		
Median number of days used for agriculture	18.0	25.0		
% of household who use VSLA for saving			98.6	99.5
Median amount saved			2,500.0	3,821.5
% of household who use VSLA for credit			39.2	89.2
Median amount credited			1,000.0	900.0
% of household who used VSLA credit for business			41.2	32.8
% of household who used VSLA credit for illness			27.1	25.9
% of household who used VSLA credit for agriculture			18.8	40.2
% of household who used VSLA credit for family			9.4	17.2
% of household who used VSLA credit for education			5.9	22.4
Observations	126.0	221.0	222.0	221.0

Note: the median size of AM group and type of AM usage are conditional on using AM; the number of months and number of days are conditional on using AM in agriculture. The median size of VSLA group, the proportion who saved, the amount saved, the proportion who used credit, and the amount of credit used are conditional on using VSLA; reasons for using credit are conditional on using VSLA credit. For AM, when two pieces of information were reported for the same activity, we took the greater amount. For VSLA, we reported household level figures, namely the sum of all amounts across cycles and participants. *Source*: authors' calculations from the endline survey including all households with children aged from 10 to 15, inclusive. The average monthly exchange rate between January 2009 and May 2012 was 1MZN = 0.034USD. There was very little monthly variation, with a low of 1 MZN = 0.027USD in August 2012 and a high of 1MZN = 0.040USD in January 2009. Source http://oanda.com/currency/historical-rates/.

as consumption smoothing and income effects), resulting in an imprecisely estimated increase in child labor.

The economic activity effect may be larger in VAM areas compared to VSLA areas. Table 2, first panel, shows that the combination of VSLA and AM (i.e. VAM) may increase child labor (by roughly 8 percentage points). This suggests a caveat to the main AM result: while AM in isolation can reduce child labor, AM was not able to reduce child labor when in combination with VSLA. To explain why this may be the case, it is useful to compare VSLA usage in VSLA and VAM areas. Table 5 (columns three and four) shows that only 39% of households used VSLA for credit in VSLA areas, while in VAM areas the proportion of households that used VSLA for credit is nearly double (89%). In particular, the share of households that used credit in agriculture is much higher in VAM than in VSLA areas (40% vs 19%). Perhaps, as a result, the cultivated area increased by 24% in VAM areas, and only by 13% in VSLA areas (see the fourth panel of Table 3). This expansion in the economic-activity fueled by credit might have generated a greater labor demand in VAM areas compared to VSLA areas.

In principle, greater labor demand could have been compensated through AM labor. However, Table 3 (second and third panels) shows that, unlike in AM areas where total labor supply appears to increase, in VAM areas total labor supply does not increase. The substitution between external paid and external unpaid labor appears to be one-to-one: the probability that households use external unpaid labor increases by 22 percentage points, but the probability that households use external paid labor decreases by 23 percentage points. An increase in labor demand not compensated by an increase in labor supply might be the reason behind the increase in child labor. These results are in line with those from programs combining a labor market element (such as employability training) and a financial element (such as micro-credit) that have been found incapable of reducing child labor, due to the pressures on child labor created by the expansion of on/off-farm business (Dammert et al., 2018).

6.4. How AM, VSLA, and VAM can affect schooling

Table 2 presents evidence that AM reduces school absenteeism to the greatest degree out of three programs, possibly because AM in isolation reduces child labor. There is a link between the value of children's time on the family plantation and school attendance (Jacoby, 1994; Jacoby & Skoufias, 1997). AM reduces the opportunity costs of children not working on the plantation, and this can lead to increased school attendance.[17] We find no effects of AM on school enrollment: while school attendance is likely to vary with the opportunity cost of children's time, school enrollment and attainment are more likely to vary with household income and household's taste for education (Jacoby, 1994), which do not significantly change as an effect of the program. This is also the case for the impact of VSLA and VAM on school enrollment.

VSLA and VAM seem to reduce school absenteeism, although this effect only reaches conventional statistical significance levels in VSLA areas (Table 2, second panel). In theory, VSLA can reduce school absenteeism by (i) allowing households to use savings rather than child labor to smooth the effects of the economic cycle (see: Jacoby, 1994; Jacoby & Skoufias, 1997), (ii) helping households cope with day-to-day costs of education (transportation costs, uniforms school meals), and (iii) allowing households to use credit to invest in education. Despite these reasons, school absenteeism in VSLA areas decreases less than in AM areas, possibly due to the pressure on child labor generated by increased labor demand.

7. Conclusions

This paper adds to the fast-growing literature on the role labor market failures play in child labor decisions. We study the impact of the introduction of Ajuda Mútua (AM): a reciprocal labor program promoting labor exchange between adult members of neighboring households. Our novel finding is that AM reduces child labor. We argue that, by helping balance adult labor demand and supply over the agricultural cycle, AM directly addresses labor market failures in the study area, lessening the pressure on child labor. We benchmark the effects of AM with the effects of (i) VSLA: a program addressing the scarcity of formal saving and credit facilities by allowing neighboring households to save and borrow from each other, and (ii) VAM: the combination of VSLA and AM. We find that VSLA and VAM do not decrease child labor. In fact, when credit is used to invest in the family business, labor demand and, thus, child labor may increase. Like Dumas, 2020, we conclude that addressing labor market failures can be more effective than addressing financial market failures to reduce child labor.

Our analysis is the first evaluation of AM and also the first one that benchmarks the impact of AM against impacts of similar programs. The strength of AM, VSLA, and other community-driven programs is that they are shaped by the needs of the communities. However, this also means that the results of any program evaluation exercise are likely to be driven by how programs are used by a given community. It would be exciting to see if results are replicated elsewhere and we hope our results provide an instructive framework for new evaluations to come.

Acknowledgements

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[17] Similarly, increases in the returns in school attendance have been found to reduce child labor (see, for example: Edmonds & Shrestha, 2014).

Appendix A

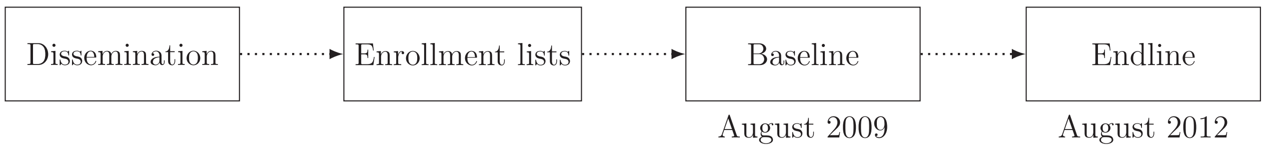

Fig. A.1. Timeline of the program rollout.

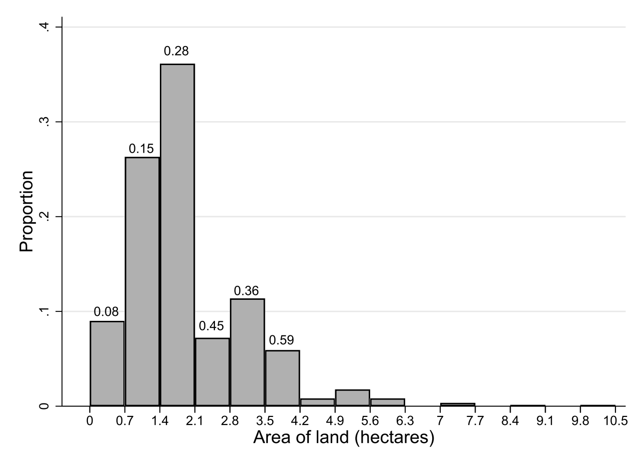

Fig. A.2. Household plantation area and proportion of area not cultivated. (*Note*: the numbers above the bars indicate the share of households who do not entirely cultivate all land. For example, the first bar indicates that just below 10% of the sample own less than 0.7 hectares of land. Of those, 8% do not cultivate all land. The shares are only reported for cases where valid data on not cultivated plantation area are available for more than ten households. *Source*: authors' own calculations across 844 households in the sample.).

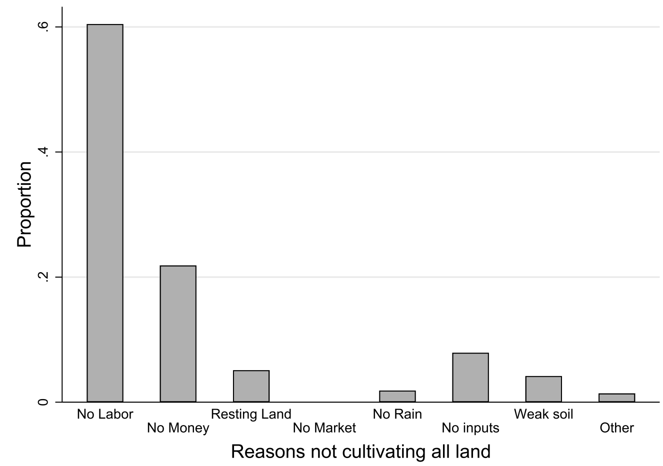

Fig. A.3. Main reasons for not cultivating all land. (*Note*: the sample is those households that have some uncultivated land, as described in Fig. A.2 and, further, provide a reason (215 households) for not cultivating that land. *Source*: authors' own calculations.).

Table A.1
Difference in means at baseline: control versus VSLA.

	obs	Control	obs	VSLA	Diff	s.e.	p-value
Household characteristics:							
Size	280	5.636	198	5.909	−0.273	0.174	0.117
Prop. aged 10–15	280	0.288	198	0.271	0.017	0.011	0.116
Own a plantation	280	0.993	198	0.995	−0.002	0.007	0.776
Number of plantations	280	2.682	198	2.167	0.515	0.108	0.000
Area (hectares)	280	2.212	198	2.090	0.122	0.271	0.652
Cultivated area (hectares)	280	1.728	198	1.796	−0.068	0.102	0.506
Total number of assets	280	2.525	198	3.096	−0.571	0.185	0.002
Head of household:							
Prop. farmers	280	0.989	198	0.955	0.035	0.014	0.017
Age	280	44.607	198	44.934	−0.327	1.169	0.780
Prop. male	280	0.929	198	0.934	−0.006	0.024	0.807
Prop. married	280	0.925	198	0.934	−0.009	0.024	0.696
Prop. no school	280	0.261	198	0.253	0.008	0.041	0.841
Prop. prim school	280	0.693	198	0.687	0.006	0.043	0.889
	obs	Control	obs	VSLA	Diff	s.e.	p-value
Child (10–15, inclusive) information:							
Age	425	12.278	281	12.192	0.085	0.131	0.515
Male	425	0.529	281	0.498	0.031	0.038	0.418
Child labor	425	0.478	281	0.512	−0.035	0.038	0.366
School enrollment	425	0.826	281	0.801	0.025	0.030	0.399
School absenteeism	349	0.138	215	0.270	−0.132	0.033	0.000
School and no labor	425	0.440	281	0.399	0.041	0.038	0.276
No school and labor	425	0.092	281	0.110	−0.019	0.023	0.420
School and labor	425	0.386	281	0.402	−0.016	0.038	0.666
No school and no labor	425	0.082	281	0.089	−0.007	0.021	0.758

Notes: Difference in means tests for baseline characteristics. Panel 1 is for all households in the baseline survey with at least one child aged from 10 to 15, inclusive. Panel 2 is characteristics for all children aged 10 to 15, inclusive of those households. Total assess (a proxy for wealth) are a summation of the following asset types: best, radio, bike, clock, cellphone, chair, aluminium pans, zinc roof panels, and improved toilet. Child labor is equal to one if the child has worked on the household plantation in the previous 12 months and zero otherwise. School enrolment is equal to one if the child is enrolled in school and zero otherwise. Absenteeism is equal to one if the child has had a day off school in the last 30 days and zero otherwise. By characteristic and cells from left to right: observations in control, mean of variable in control, observations in VSLA, mean of variables in VSLA, difference in means between control and VSLA, standard error for differences in mean, and p-value for hypothesis that difference in means is equal to zero against the two sided alternative.

Table A.2
Difference in means at baseline: control versus VAM.

	obs	Control	obs	VAM	Diff	s.e.	p-value
Household characteristics:							
Size	280	5.636	236	6.352	−0.716	0.167	0.000
Prop. aged 10–15	280	0.288	236	0.262	0.026	0.010	0.010
Own a plantation	280	0.993	236	0.992	0.001	0.008	0.864
Number of plantations	280	2.682	236	2.797	−0.114	0.143	0.424
Area (hectares)	280	2.212	236	1.686	0.527	0.254	0.039
Cultivated area (hectares)	280	1.728	236	1.464	0.264	0.109	0.016
Total number of assets	280	2.525	236	3.326	−0.801	0.177	0.000
Head of household:							
Prop. farmers	280	0.989	236	0.992	−0.002	0.009	0.796
Age	280	44.607	236	41.513	3.094	1.071	0.004
Prop. male	280	0.929	236	0.856	0.073	0.027	0.007
Prop. married	280	0.925	236	0.864	0.061	0.027	0.024
Prop. no school	280	0.261	236	0.161	0.100	0.036	0.006
Prop. prim school	280	0.693	236	0.729	−0.036	0.040	0.371
	obs	Control	obs	VAM	Diff	s.e.	p-value
Child (10–15, inclusive) information:							
Age	425	12.278	374	12.350	−0.073	0.121	0.549
Male	425	0.529	374	0.505	0.024	0.035	0.498
Child labor	425	0.478	374	0.388	0.090	0.035	0.010
School enrollment	425	0.826	374	0.837	−0.011	0.027	0.679
School absenteeism	349	0.138	310	0.165	−0.027	0.028	0.334
School and no labor	425	0.440	374	0.527	−0.087	0.035	0.014
No school and labor	425	0.092	374	0.078	0.014	0.020	0.473
School and labor	425	0.386	374	0.310	0.076	0.034	0.025
No school and no labor	425	0.082	374	0.086	−0.003	0.020	0.871

Notes: Difference in means tests for baseline characteristics. Panel 1 is for all households in the baseline survey with at least one child aged from 10 to 15, inclusive. Panel 2 is characteristics for all children aged 10 to 15, inclusive of those households. Total assess (a proxy for wealth) are a summation of the following asset types: best, radio, bike, clock, cellphone, chair, aluminium pans, zinc roof panels, and improved toilet. Child labor is equal to one if the child has worked on the household plantation in the previous 12 months and zero otherwise. School enrolment is equal to one if the child is enrolled in school and zero otherwise. Absenteeism is equal to one if the child has had a day off school in the last 30 days and zero otherwise. By characteristic and cells from left to right: observations in control, mean of variable in control, observations in VAM, mean of variables in VAM, difference in means between control and VAM, standard error for differences in mean, and p-value for hypothesis that difference in means is equal to zero against the two sided alternative.

Table A.3
Further absenteeism results: AM, VSLA, and VAM.

	Num. of school days in last month		
	FE	FE + BL con.	FE + shocks + BL con.
AM	−1.554	−1.573	−1.478
	(0.446)	(0.453)	(0.437)
	[0.010]	[0.010]	[0.012]
	[0.085]	[0.081]	[0.083]
VSLA	−1.256	−1.234	−1.333
	(0.376)	(0.361)	(0.392)
	[0.012]	[0.011]	[0.011]
	[0.045]	[0.035]	[0.040]
VAM	−1.054	−1.057	−0.992
	(0.519)	(0.493)	(0.471)
	[0.082]	[0.069]	[0.073]
	[0.249]	[0.171]	[0.183]
observations	1930	1930	1930
Time FE	YES	YES	YES
Locality FE	YES	YES	YES
BL controls	NO	YES	YES
shocks	NO	NO	YES

Note: table output are the estimates of $\beta = [\beta_{AM}\ \beta_{VSLA}\ \beta_{VAM}]$ for model 1: $Y_{chdt} = \alpha_t + \gamma_d + \mathbf{T}_{dt}\beta\prime + \mathbf{w}_{hd,t=0}\tau\prime + \mathbf{s}_{hdt}\psi\prime + \upsilon_{chdt}$. Three main outcomes ($Y$) with three specifications for each are presented. The outcomes by panel are. Panel 1: child labor is equal to one if the child has worked on the household plantation in the previous 12 months and zero otherwise. Panel 2: absenteeism is equal to one if the child has had a day off school in the last four weeks of completed school and zero otherwise. Panel 3: school enrolment is equal to one if the child is enrolled in school and zero otherwise. The three main specifications are models with: (i) time and locality fixed effects, (ii) addition of baseline controls ($\mathbf{w}_{hd,t=0}\tau\prime$), and (iii) addition of controls for shocks ($\mathbf{s}_{hdt}\psi\prime$). Within each cell, the top row is the point estimate, the second row the clustered standard error, the third row the p-value associated with the clustered standard error, and the fourth row is the p-value following the Wild Bootstrap procedure. All point estimates are estimated using OLS. The sample is an unbalanced panel of all children aged between 10 and 15, inclusive. *Source*: authors' own calculations.

Table A.4
Results for baseline control variables: AM, VSLA, and VAM.

	Child labor	Absenteeism	School enrollment
Household size:			
HH. size	0.017	−0.027	0.005
	(0.011)	(0.008)	(0.007)
children aged under 2	−0.024	0.024	−0.001
	(0.019)	(0.017)	(0.014)
children aged between 2 and 6	−0.025	0.037	0.008
	(0.017)	(0.014)	(0.011)
Child characteristics:			
age of child	0.083	−0.004	−0.009
	(0.006)	(0.007)	(0.006)
gender (=1 if male)	−0.030	−0.006	0.042
	(0.027)	(0.019)	(0.012)
Head of household characteristics:			
male (=1)	−0.082	−0.036	−0.035
	(0.044)	(0.050)	(0.029)
age	0.002	0.000	−0.000
	(0.001)	(0.001)	(0.001)
no educ. (=1)	0.032	0.041	−0.051
	(0.025)	(0.024)	(0.015)
prim. occ. agr. (=1)	0.262	0.146	0.042
	(0.057)	(0.076)	(0.073)
Household wealth:			
log(all income)	0.021	−0.012	0.011
	(0.007)	(0.009)	(0.007)
Area plantation	−0.000	0.001	−0.001
	(0.001)	(0.001)	(0.001)
Total number assets	−0.006	0.004	0.012
	(0.007)	(0.007)	(0.003)
Household trust:			
Trust	0.087	0.004	−0.027
	(0.027)	(0.025)	(0.011)
Shocks:			
Mean of total shocks	0.449	1.018	−0.003
	(0.252)	(0.384)	(0.141)
Mean of exogenous shocks	−0.224	−0.825	−0.125
	(0.216)	(0.173)	(0.204)
observations	2519	1930	2412
Time FE	YES	YES	YES
Locality FE	YES	YES	YES

Note: table output are the estimates of control variables in model 1: $Y_{chdt} = \alpha_t + \gamma_d + \mathbf{T}_{dt}\beta\prime + \mathbf{w}_{hd,t=0}\tau\prime + \mathbf{s}_{hdt}\psi\prime + v_{chdt}$. These are the control variables related to the full specification results presented in Table 2. The point estimates, standard errors and p-values for the control variables are presented. The sample is an unbalanced panel of all children aged between 10 and 15, inclusive. *Source*: authors' own calculations.

Appendix B. Robustness checks using propensity score weighting

We provide a semi-parametric estimation of the main empirical models to show that the results do not depend on parametric assumptions. We use propensity score weighting (see: Hirano & Imbens, 2001). Propensity scores for each treatment are based on a logit estimation of $T_{dt} = \pi_0 + X_{hdt}\prime\pi_1 + \epsilon$ where $T_{dt} \in [AM, VSLA, VAM]$ are a set of treatment dummies and X_{hdt} are the household controls explained in Section 5. The propensity scores for AM, VSLA, and VAM against the propensity scores for the control are plotted in Figs. B.1, B.2, and B.3. We drop control and treatment households outside the propensity score common support and we use the inverse of the propensity scores as regression weights (see: Hirano & Imbens, 2001).

The use of propensity score weights and the deletion of the households outside the common support attempt to make treated and control household more similar under the assumption that more similar households are more likely to follow the same outcome dynamics over time: the common trends assumption is more likely to be satisfied. To help assess the success of the weighting strategy, Tables B.2, B.3, B.4 compare weighted and unweighted baseline characteristics of treated and control households. Consider, for example, Table B.2. Before weighting, AM and control households were found to be different at least the 5% significance level in six of the 15 baseline characteristics considered and the standardized bias had an average of 24.22, a minimum of 2.76 and a maximum of 64.45. After weighting, none of the baseline differences are statistically different at the 5% significance level, and the standardized bias has an average of 6.67, a minimum of 0.05 and a maximum of 19.09. Table B.1 presents the results from the propensity score weighting estimation. Reassuringly, the semi-parametric results are in line with the parametric results presented in the main text: AM decreases child labor while VSLA and VAM may increase it.

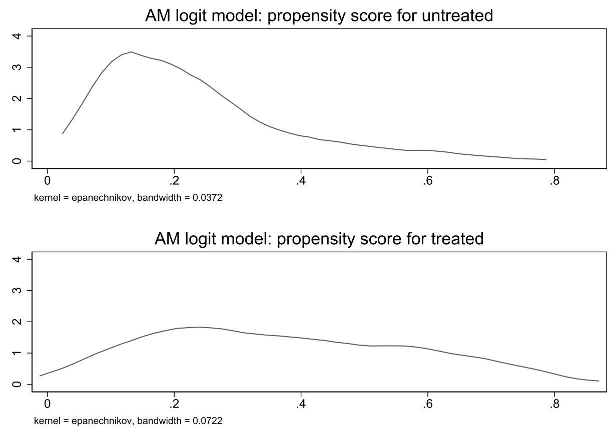

Fig. B.1. Common support for AM. (*Note*: The top panel represents the propensity score for the control group, which can be interpreted as the likelihood of entering the AM treatment. The bottom left panel is the propensity score histogram for all households that participated in the AM only treatment. *Source*: Authors' own calculations.).

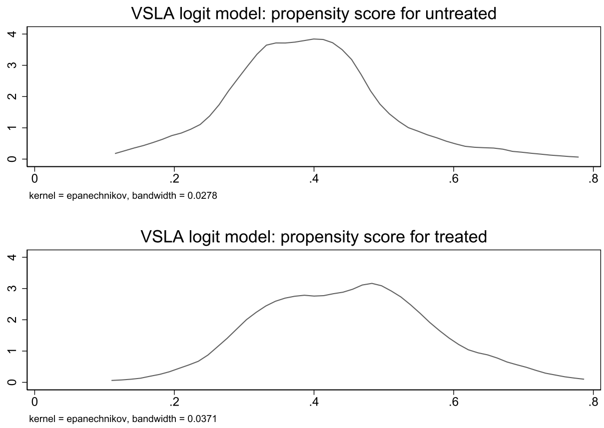

Fig. B.2. Common support for VSLA. (*Note*: The top panel represents the propensity score for the control group, which can be interpreted as the likelihood of entering the VSLA treatment. The bottom left panel is the propensity score histogram for all households that participated in the VSLA only treatment. *Source*: Authors' own calculations.).

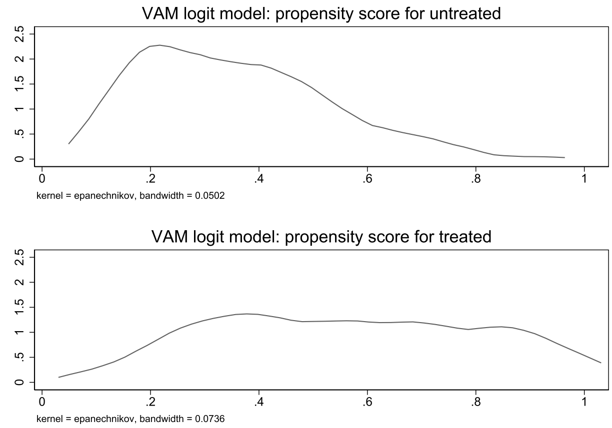

Fig. B.3. Common support for VAM. (*Note*: The top panel represents the propensity score for the control group, which can be interpreted as the likelihood of entering the VAM treatment. The bottom left panel is the propensity score histogram for all households that participated in the VAM only treatment. *Source*: Authors' own calculations.).

Table B.1
Propensity score weighted regressions: households on common support.

	Child labor			Absenteeism			School Enrolment		
	FE	FE + BL wgt	FE + BL wgt + shocks	FE	FE + BL wgt	FE + + BL wgt + shocks	FE	FE + BL wgt	FE + + BL wgt + shocks
AM MODELS:									
AM	−0.118	−0.171	−0.165	−0.406	−0.404	−0.415	0.024	0.001	−0.003
	(0.033)	(0.030)	(0.039)	(0.143)	(0.172)	(0.185)	(0.076)	(0.071)	(0.067)
	[0.038]	[0.011]	[0.024]	[0.066]	[0.101]	[0.110]	[0.770]	[0.988]	[0.966]
observations	830	830	819	627	627	617	800	800	789
R-squared	0.113	0.173	0.272	0.216	0.265	0.271	0.084	0.148	0.159
VSLA MODELS:									
VSLA	0.057	0.042	0.054	−0.175	−0.210	−0.214	−0.016	−0.024	−0.013
	(0.099)	(0.098)	(0.119)	(0.025)	(0.028)	(0.018)	(0.054)	(0.047)	(0.044)
	[0.608]	[0.699]	[0.679]	[0.006]	[0.005]	[0.001]	[0.787]	[0.647]	[0.781]
observations	1199	1199	1189	909	909	900	1170	1170	1160
R-squared	0.099	0.111	0.185	0.145	0.157	0.170	0.078	0.096	0.097
VAM MODELS:									
VAM	0.107	0.131	0.137	−0.167	−0.128	−0.112	0.089	0.093	0.109
	(0.027)	(0.008)	(0.040)	(0.108)	(0.131)	(0.130)	(0.061)	(0.062)	(0.070)
	[0.029]	[0.001]	[0.041]	[0.220]	[0.400]	[0.451]	[0.240]	[0.232]	[0.216]
observations	1217	1217	1206	942	942	932	1168	1168	1157
R-squared	0.124	0.170	0.230	0.136	0.220	0.246	0.102	0.132	0.143
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Locality FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Common Support	YES	YES	YES	YES	YES	YES	YES	YES	YES
PSWeights for BL	NO	YES	YES	NO	YES	YES	NO	YES	YES
shocks	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note: the top row presents nine different AM models, three for the child labor outcome, three for school absence, and three for school enrollment. The first model for child labor controls for time and local fixed effects, plus importantly only includes households in the propensity score common support. The top left cell contains a point estimate, the clustered standard error and p-value. Interpreting the top left cell, child labor in the AM areas reduced by 11.8 percentage points compared to the control areas, with an associated standard error of 0.033 and p-value of 0.038. The second model, re-weights for baseline characteristics using the propensity score weighting technique, and the third model controls for shocks between the baseline and endline. These models are repeated for VSLA and VAM models. *Source*: authors' own calculations.

Table B.2
Balancing of covariates between AM and control groups.

	Unweighted						Weighted						St. Bias (SB)	
	AM		Control		Difference		AM		Control		Difference			
	level	sd	level	sd	level	p-value	level	sd	level	sd	level	p-value	unweighted	weighted
HH size	6.33	2.03	6.06	1.97	0.27	0.13	6.26	1.99	6.38	1.84	−0.12	0.54	13.35	6.18
children aged under 2	0.43	0.55	0.38	0.56	0.05	0.29	0.39	0.52	0.39	0.58	0.00	1.00	9.50	0.05
children aged between 2 and 6	0.99	0.86	0.73	0.75	0.26	0.00	0.98	0.89	1.14	0.83	−0.17	0.06	31.60	19.09
mean age of children	12.42	1.26	12.28	1.22	0.14	0.21	12.42	1.23	12.41	1.21	0.01	0.91	11.22	1.11
total males children	0.94	0.75	1.00	0.85	−0.05	0.48	0.93	0.79	0.95	0.81	−0.01	0.87	6.56	1.59
hoh male (=1)	0.90	0.30	0.94	0.25	−0.03	0.16	0.92	0.27	0.92	0.28	0.00	0.89	12.03	1.38
hoh age	42.20	12.00	44.66	12.04	−2.46	0.02	42.84	12.55	41.03	9.59	1.81	0.13	20.50	16.22
hoh no educ (=1)	0.22	0.42	0.23	0.42	−0.01	0.76	0.25	0.43	0.22	0.42	0.02	0.59	2.76	5.51
hoh prim. occ. agr. (=1)	1.00	0.00	1.00	0.00	0.00		1.00	0.00	1.00	0.00	0.00			
log(hh income)	6.24	1.94	6.14	2.11	0.10	0.59	6.38	1.76	6.31	2.26	0.07	0.71	4.90	3.56
area plantation	1.99	1.33	2.20	3.01	−0.21	0.38	2.00	1.45	1.89	1.00	0.11	0.40	8.95	9.08
Total number assets	3.11	1.94	2.60	1.86	0.51	0.00	2.94	2.05	3.12	2.08	−0.18	0.38	26.76	8.73
Household trust	3.26	0.64	3.61	0.43	−0.34	0.00	3.28	0.63	3.32	0.43	−0.04	0.50	63.33	7.25
mean of total shocks	0.05	0.09	0.01	0.04	0.04	0.00	0.02	0.05	0.02	0.04	0.00	0.42	63.21	8.42
mean of exogenous shocks	0.05	0.10	0.00	0.02	0.05	0.00	0.01	0.03	0.01	0.04	−0.00	0.59	64.45	5.22

Notes: The SB prior to weighting and common support trimming is given as $SB_{before} = 100.\frac{(\bar{z}_T - \bar{z}_C)}{\sqrt{(0.5.(V_T(z)+V_C(z)))}}$, where $\bar{z}_T$ $(V_T(z))$ and $\bar{z}_C$ $(V_C(z))$ are the unweighted means (variances) in the treatment and control groups, respectively. Similarly, the SB after the weighting and common support trimming is given by: $SB_{after} = 100.\frac{(\bar{z}_{TW} - \bar{z}_{CW})}{\sqrt{(0.5.(V_{TW}(z)+V_{CW}(z)))}}$, where $\bar{z}_{TW}$ $(V_{TW}(z))$ and $\bar{z}_{CW}$ $(V_{CW}(z))$ are the propensity score weighted means (variances) in the treatment and control groups, respectively. *Source*: Authors' own calculations.

Table B.3
Balancing of covariates between VSLA and control groups.

	Unweighted						Weighted						St. Bias (SB)	
	AM		Control		Difference		AM		Control		Difference			
	level	sd	level	sd	level	p-value	level	sd	level	sd	level	p-value	unweighted	weighted
HH size	6.14	1.89	6.06	1.97	0.08	0.59	6.13	1.89	6.31	1.99	−0.18	0.22	4.07	9.38
children aged under 2	0.48	0.61	0.39	0.56	0.09	0.04	0.47	0.61	0.55	0.63	−0.08	0.09	15.56	13.08
children aged between 2 and 6	0.73	0.78	0.73	0.75	0.00	0.96	0.73	0.78	0.83	0.75	−0.09	0.11	0.34	12.15
mean age of children	12.17	1.32	12.28	1.22	−0.11	0.25	12.17	1.32	12.15	1.21	0.02	0.84	8.54	1.51
total males children	0.90	0.73	0.99	0.85	−0.09	0.13	0.91	0.73	0.92	0.82	−0.01	0.91	11.64	0.82
hoh male (=1)	0.92	0.26	0.94	0.24	−0.01	0.55	0.92	0.27	0.94	0.24	−0.01	0.44	4.44	5.90
hoh age	45.26	12.45	44.57	12.06	0.69	0.45	45.22	12.51	44.99	12.11	0.24	0.80	5.64	1.91
hoh no educ (=1)	0.24	0.43	0.23	0.42	0.01	0.76	0.24	0.43	0.22	0.41	0.02	0.47	2.34	5.52
hoh prim. occ. agr. (=1)	0.97	0.18	0.99	0.10	−0.03	0.02	0.98	0.14	0.97	0.16	0.01	0.56	17.24	4.43
log(hh income)	5.89	2.21	6.16	2.12	−0.27	0.10	5.90	2.22	5.99	2.28	−0.09	0.61	12.48	3.87
area plantation	2.19	1.49	2.18	3.00	0.01	0.97	2.21	1.49	2.02	2.13	0.19	0.16	0.30	10.25
Total number assets	3.15	2.14	2.62	1.86	0.53	0.00	3.10	2.07	3.16	2.01	−0.06	0.70	26.35	3.00
Household trust	3.63	0.58	3.61	0.43	0.02	0.59	3.61	0.57	3.65	0.44	−0.03	0.40	3.96	6.57
mean of total shocks	0.00	0.02	0.01	0.04	−0.01	0.01	0.00	0.02	0.00	0.02	−0.00	0.74	19.74	2.56
mean of exogenous shocks	0.00	0.02	0.00	0.02	−0.00	1.00	0.00	0.02	0.00	0.02	−0.00	0.37	0.01	6.56

Notes: The SB prior to weighting and common support trimming is given as $SB_{before} = 100.\frac{(\bar{z}_T - \bar{z}_C)}{\sqrt{(0.5.(V_T(z)+V_C(z)))}}$, where $\bar{z}_T$ $(V_T(z))$ and $\bar{z}_C$ $(V_C(z))$ are the unweighted means (variances) in the treatment and control groups, respectively. Similarly, the SB after the weighting and common support trimming is given by: $SB_{after} = 100.\frac{(\bar{z}_{TW} - \bar{z}_{CW})}{\sqrt{(0.5.(V_{TW}(z)+V_{CW}(z)))}}$, where $\bar{z}_{TW}$ $(V_{TW}(z))$ and $\bar{z}_{CW}$ $(V_{CW}(z))$ are the propensity score weighted means (variances) in the treatment and control groups, respectively. *Source*: Authors' own calculations.

Table B.4
Balancing of covariates between VAM and control groups.

	Unweighted						Weighted						St. Bias (SB)	
	AM		Control		Difference		AM		Control		Difference			
	level	sd	level	sd	level	p-value	level	sd	level	sd	level	p-value	unweighted	weighted
HH size	6.72	1.93	6.06	1.97	0.66	0.00	6.69	1.95	6.71	1.91	−0.02	0.86	33.62	1.28
children aged under 2	0.58	0.63	0.39	0.56	0.19	0.00	0.58	0.64	0.51	0.61	0.07	0.13	31.79	11.20
children aged between 2 and 6	1.03	0.91	0.73	0.75	0.30	0.00	0.99	0.89	1.02	0.74	−0.03	0.60	35.58	3.91
mean age of children	12.35	1.27	12.28	1.22	0.08	0.38	12.37	1.29	12.35	1.15	0.03	0.76	6.13	2.21
total males children	0.99	0.79	0.99	0.85	0.00	0.98	1.03	0.79	0.93	0.77	0.10	0.08	0.21	12.88
hoh male (=1)	0.85	0.36	0.94	0.24	−0.09	0.00	0.85	0.35	0.92	0.27	−0.07	0.00	28.29	21.68
hoh age	42.34	11.21	44.57	12.06	−2.23	0.01	42.62	11.55	43.04	10.22	−0.42	0.60	19.13	3.84
hoh no educ (=1)	0.16	0.37	0.23	0.42	−0.07	0.01	0.18	0.38	0.14	0.34	0.04	0.10	18.77	12.11
hoh prim. occ. agr. (=1)	0.99	0.07	0.99	0.10	0.00	0.50	0.99	0.08	0.98	0.12	0.01	0.20	4.77	9.14
log(hh income)	6.50	1.91	6.16	2.12	0.34	0.02	6.44	1.84	6.55	1.87	−0.12	0.38	16.71	6.42
area plantation	1.73	1.38	2.18	3.00	−0.45	0.01	1.72	1.11	1.96	1.01	−0.25	0.00	19.48	23.08
Total number assets	3.40	2.16	2.62	1.86	0.77	0.00	3.22	2.09	3.21	2.03	0.00	0.98	38.33	0.19
Household trust	3.70	0.49	3.61	0.43	0.09	0.00	3.70	0.50	3.74	0.43	−0.04	0.29	19.51	7.72
mean of total shocks	0.05	0.07	0.01	0.04	0.04	0.00	0.04	0.06	0.03	0.06	0.01	0.25	72.77	8.49
mean of exogenous shocks	0.05	0.09	0.00	0.02	0.05	0.00	0.03	0.07	0.02	0.07	0.00	0.52	71.83	4.72

Notes: The SB prior to weighting and common support trimming is given as $SB_{before} = 100.\frac{(\bar{z}_T - \bar{z}_C)}{\sqrt{(0.5.(V_T(z)+V_C(z)))}}$, where $\bar{z}_T$ ($V_T(z)$) and $\bar{z}_C$ ($V_C(z)$) are the unweighted means (variances) in the treatment and control groups, respectively. Similarly, the SB after the weighting and common support trimming is given by: $SB_{after} = 100.\frac{(\bar{z}_{TW} - \bar{z}_{CW})}{\sqrt{(0.5.(V_{TW}(z)+V_{CW}(z)))}}$, where $\bar{z}_{TW}$ ($V_{TW}(z)$) and $\bar{z}_{CW}$ ($V_{CW}(z)$) are the propensity score weighted means (variances) in the treatment and control groups, respectively. *Source*: Authors' own calculations.

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