Stuck exchange: can cash transfers push smallholders out of autarky?

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Abstract

This paper focuses on the role of Unconditional Cash Transfer in helping smallholder overcome barriers to trade by mitigating transaction costs. We use data from a Randomized Controlled Trial collected for the evaluation of the Child Grant Program (CGP) - Zambia's flagship social protection cash transfer program. We employ a Heckman correction model that allows us to capture the effects of the program on the propensity to engage in trade and on the traded quantities while correcting for the selectivity bias that may result from farmers' self-selection into a certain market regime. We find that the program significantly contributes to pushing farmers out of autarky and to increase their market participation both as buyers in input markets and as sellers in output markets. Another interesting finding is that the program produced greater benefits for those household that leave further away from markets or that lack telecommunication technology, or in other terms for those that face more binding transaction costs from transportation of information gathering.

1. Introduction

The majority of small farmers in Sub-Saharan Africa live in poverty and are engaged in subsistence farming aimed at self-sufficiency, with little or no connection to output and input markets. The issue of smallholders' participation in markets has topped the sub-Saharan policy makers' agenda in the last couple of decades due to its role in reducing poverty and increasing living standards and the even spread of economic growth. During the eighties, Africa went from being a world's great crop exporter to being a net food importer, with the entire region's agricultural exports overtaken by a single country: Thailand. In the nineties, the situation deteriorated further when many governments dismantled the state-owned agricultural monopolies that had guaranteed the connection of farmers to markets by gathering their crops at centrally fixed prices. These liberalization moves left no time for markets to develop and no alternative institutions were put in place to link farmers to markets, with negative repercussions on agricultural production and poverty (Simatele, 2006). Due to the exacerbated inadequacies in marketing systems following the 1991 agricultural liberalization reform in Zambia, maize production fell by 32% in the following five years and maize sales by a staggering 53% (Seshamani, 1999; Bwalya et al., 2013). These drops in farm output production and marketing were attributed to the fact that smallholders experienced difficulties in marketing their crops, getting a fair price and accessing adequate and timely inputs. The fact that farmers had to not only produce but also find the right buyers and sellers, negotiate prices and deliver their produce lead to a steep rise in transaction costs which cut many smallholders out of the markets forcing them to a state of self-sufficiency farming (Kahkonen and Leathers, 1999). Transaction costs are the observable and unobservable costs associated with arranging and carrying out a market transaction, in particular, with transportation of products, searching and screening of trading partners, bargaining, gathering of prices and other market information, contract monitoring and enforcement (de Janvry et al., 1991; Goetz, 1992; Key et al, 2000; Alene et al., 2008). They tend to be household-specific and stem from the differential access to assets, market infrastructure and information causing some households to be completely excluded from the markets. Despite the Zambian markets are widely pervaded by transaction costs the attention of policy makers has concentrated more on measure to increase production, such as subsidized inputs. Much less effort has been dedicated to analysing the role that ease of access to markets plays in stimulating production and market participation with a clear risk of adopting misguided policies. This paper evaluates the impact of a quintessential social protection policy measure, such as unconditional cash transfers, in increasing smallholder commercialization by mitigating transaction costs. Unconditional cash transfer (UCT) programs aim to reduce poverty by providing welfare programs without any conditions upon the receivers' actions. Such programs can also have significant productive impacts on rural livelihoods by inducing investments in agricultural activities. While the impact of UCTs on various aspects of farm production decisions has been widely analysed, little attention has gone to their effect on marketing decisions (Asfaw et al., 2014; Daidone et al., 2015; Boone et al., 2013). From an economic point of view they constitute an increase in exogenous income that may allow liquidity-constrained farmers to bear part of the transaction costs related to marketing their product or procuring a certain input. To the best of our knowledge this is the first paper in the literature to look at the relationship among these three variables in the context of agricultural markets.

Previous studies have used transaction costs theory to explain farmers' response in terms of output supply and input demand and their commercialization. Agriculture commercialization can take many different forms. Commercialization can occur on the output side of production with increased marketed surplus, or on the input side with increased use of purchased inputs. More in general, commercialization involves transition from traditional self-sufficiency goals towards income and profit-oriented decision making (Pingali and Rosegrant, 1995). Goetz (1992) studies food marketing behaviour in Senegal and focuses on the role of several proxy measures for transaction costs on the decision of whether to participate in the grain market and on how much to trade for both buyers and sellers. The study uses a Heckman selection model to address farmers' self-selection into sellers and non-sellers and buyers and non-buyers. The author finds that transaction costs determinants, such as ownership of transportation and information means, play a significant role in the farmers marketing decisions concerning participation and quantities. Key et al., (2000) focus on participation in maize markets in Mexico when there are monetary transaction costs in accessing markets as sellers or buyers. They estimate structural supply functions and production thresholds based on a censored outcome model with unobserved censoring threshold. They introduce a distinction between fixed and variable transaction costs which both influence market participation decisions while supply decisions, conditional on market participation, only depend on variable transaction costs. They find that ownership of transport equipment reduces participation thresholds thus inducing switching from autarky to market participation at higher rates. Heltberg and Tarp (2000) analyse the role of fixed and variable transaction costs in farmers' output marketing decisions in Mozambique. They use a standard Heckman selection to analyse the impact of transaction costs proxies on the value of sales of agricultural output and on the participation choice between autarky and selling regime. Alene et al., (2008) access the effects of transaction costs on the amounts of sold output and purchased inputs for Kenyan smallholders. Output supply and input demand responses to changes in transaction costs are decomposed into market entry decisions and quantity decisions using a Heckman selection model. The results showed that while transactions costs have significant negative effects on market participation, institutional innovations - such as group marketing – can in fact mitigate the costs of accessing markets. Omamo (1998) used the transaction costs approach to explain households' decisions on whether to devote resources to low-yielding food crops or to cash crops with higher market returns in Kenya. The results show that relatively more land is devoted to cash crops and less to food crops the closer the households are to markets, highlighting the role of transport costs. In Zambia, Bwalya et al., (2013) in their study quantify the impact of transaction costs on the likelihood and extent of participation of smallholders in maize markets. Results show that ownership of assets such as radios increased the likelihood of market participation while, on the intensive margin, ownership of oxcarts and experience in maize marketing were the factors that increased quantities of sold maize.

In this study we look at commercialization on both output and input markets and analyse farmers' marketing behaviour in terms of revenues from crop sales and expenditure for seeds purchases. We use data from the impact evaluation study of the Zambia Child Grant Program (CGP), a randomized cash transfer program implemented in three of the poorest districts of the country between 2010 and 2012. Mean impacts are estimated with a standard Heckman selection model that distinguishes between the decision of the farmer on whether to participate in a certain market regime as a buyer or seller and the decision on how much to buy or sell of a good. A special focus is dedicated to two dimensions of treatment effect heterogeneity, namely, heterogeneity of impacts across subgroups defined by the farmers' observed characteristics and heterogeneity across the outcome distribution. We use interaction of the treatment dummy with selected covariates to analyse the first aspect and quantile regression with a semi-parametric correction for sample selection to estimate the effects of CTs at different points of outcome distribution. We find that cash transfers induce greater commercialization of smallholders both in output and input markets. The program increased the likelihood of beneficiary farmers to move from self-sufficiency to selling crops in the market by a significant 12.7 percentage points and induced an average increase in the volume of sales by 67.3%. On the input side UCTs have an effect only on the extensive margin with an increase in the share of farmers that move from autarky to buying seeds in the market of 8.3 percentage points. The program produces heterogeneous effects and benefits more those farmers that face more binding transaction costs.

The rest of the paper is organized as follows. In section 2 we present a theoretical framework that describes the relationship among market regime choice, transaction costs and cash transfers. Section 3 illustrates some institutional aspects of the program and descriptive statistics of the data. Section 4 presents the econometric methodology. We discuss our empirical findings in section 5 while section 6 gives some conclusions of this study.

2. Theoretical framework

In this section we describe the theoretical model that guides our empirical analysis. The role of transaction costs in the production and marketing behavior of farm-households was first developed in several works such as Minot (1999), Key et al. (2000), Makhura et al., (2001). The focus here is to describe how the decisions on whether to participate in the market and on the amount of marketed surplus are affected by transaction costs and by the introduction of a cash transfer.

Consider a farm-household that is both a consumer and a producer of a certain good *i*, and expresses, therefore, both a supply of the good given by the quantity produced q_i and a demand for the same good, as input x_i or as consumption for its own subsistence c_i. The farm-household has also to decide how much of the good to market m_i. The marketed surplus, defined as the difference between supply and demand for the good, will be positive if household supply exceeds demand for the good and negative in the opposite case (i.e. $m_i > 0$ when the good is sold as an output while $m_i < 0$ when it is bought as an input or for own consumption) (Edmeades, 2006). Let also p_i^mbe the market price for good *i*. If there were no transaction costs the farm-household decides whether to take part in market transactions by comparing the market price of the good with its shadow price, say $\tilde{p}_i$, defined as the price that would equate demand and supply of the household for good *i*. The household decides to produce in excess of its own demand and participate as a seller if the market price of the good is higher than the shadow price, while it will decide to buy the commodity if the market price is lower than the household's shadow price. Therefore, in absence of transection costs households face a single market price both for buying and selling the commodity and will all take part in one of the two possible market regimes, namely as buyer or sellers. In the limit case when the shadow price is equal to the market price the household will be indifferent between not participating in market transaction and participating as either a buyer or a seller. The problem of the farm-household can be cast formally as a maximization problem:

$$\max_{q_i, c_i, x_i, m_i} u(c; z_u) \tag{1}$$

$$\sum_{i=1}^{N} p_i^m m_i + R = 0 \tag{2}$$

$$q_i - c_i - x_i + A_i = m_i, \quad i=1,2\ldots N \tag{3}$$

$$G(q, x; z_q) = 0 \tag{4}$$

$$q_i, c_i, x_i > 0 \tag{5}$$

where *R* is other non-farm income and exogenous transfers, $z_u$and $z_q$are household exogenous characteristics that act as utility and production shifters, respectively, $A_i$is the endowment in good *i*, and *G* is the production technology. The relationship in (2) is the cash constraint which states that expenditure for all purchases on the market must be at most equal to the revenues from sales in the market plus the amount of other income. Relationship (3) is the resource balance which says that for each of the *N* goods the amount consumed and used as input should not exceed the amount produced plus the endowment. Possible difference are settled in the market by selling (m_i>0) or buying (m_i<0) the good.

Transactions costs are introduced in this framework as proportional (PTCs) and fixed (FTCs). PTCs increase proportionally with the amount of good traded so they can be modelled as an increase of the effective unitary price payed by buyers and a decrease of the effective unitary price received by sellers of the same good. Therefore, PTCs introduce a price band between the price effectively received by sellers and the price effectively payed by buyers. PTCs include per-unit costs of transporting goods to and from the market and costs related to the gathering of information on prices (imperfect information). FTCs, on the other hand, are invariant to the traded quantity of the good, so once the decision to participate in the market has been made, and the related costs incurred, they become irrelevant as far as decisions on the quantities produced and marketed are concerned. FTCs may include the costs of: search for the best price; negotiation and bargaining when there is imperfect information regarding prices; screening, enforcement, and supervision of counterparts. Farmers may have to screen potential input sellers when there is asymmetric information as to the quality of the inputs. Due to their very nature transaction costs are unobservable or hard to record at best. Therefore, they are modeled as a function of the farm-household's observed characteristics. In general, while information variables are expected to determine FTCs, measures of distance to markets, quality of infrastructure and ownership of transportation means are expected to determine PTCs. Formally, let $t_p^b(z^b)$, $t_p^s(z^s)$, $t_f^b(z^b)$, $t_f^s(z^s)$ be PTCs for buyers, PTCs for sellers, FTCs for buyers and FTCs for sellers, respectively, and z^b, z^s their observable determinants.

Since transaction costs impact unitary prices and the overall expenditure and revenues of market transactions they modify the cash constraint that can be written as:

$$\sum_{i=1}^{N} \left[\left(p_i^m - t_{pi}^s(z^s)\right)\delta_i^s + (p_i^m + t_{pi}^b(z^b))\delta_i^b\right] m_i - t_{fi}^s(z^s)\delta_i^s - t_{fi}^b(z^b)\delta_i^b + T = 0 \tag{6}$$

where δ_i^s is equal to 1 if the farm-household participates in the market as a seller and is zero otherwise. Analogously, δ_i^b is one for buyers and zero otherwise. Hence, when transactions costs are present the farm-household's problem is expressed by equations (1), (3) and (6). In order to derive the supply and demand equations one needs to solve an optimization problem based on the following Lagrangian:

$$\begin{aligned}
\mathrm{L} &= u(c; z_u) \\
&+ \sum_{i=1}^{N} \mu_i(q_i - c_i - x_i + A_i - m_i) \\
&+ \phi G(q, x; z_q) \\
&+ \lambda\left[\sum_{i=1}^{N} \left[\left(p_i^m - t_{pi}^s(z^s)\right)\delta_i^s + (p_i^m + t_{pi}^b(z^b))\delta_i^b\right] m_i - t_{fi}^s(z^s)\delta_i^s - t_{fi}^b(z^b)\delta_i^b + R\right]
\end{aligned}$$

where μ_i, ϕ, λ are Lagrange multipliers. Algebraically, the solution follows two steps, finding first the optimal quantities conditional on the market participation regime, and then choosing the market participation regime that leads to the highest level of utility (Key at al., 2000; Sadoulet and de Janvry, 1995). We follow a logical sequence and illustrate first the choice of the market regime in the presence of transaction costs.

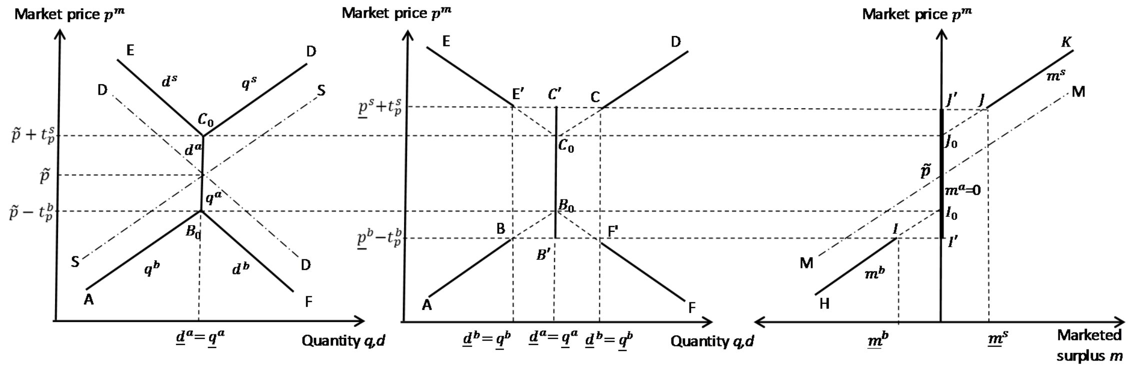
Market participation is determined by comparing the utility obtained in each market regime. We show this by using the indirect utility function $V(p, y, z_u)$ where p is the price applicable in a given market regime. When there are only PTCs, which only alter the unitary price effectively paid or received by the farm-household, the problem of the household is similar to the one with no transaction costs. The household only needs to compare its shadow price with the effective market prices. In this case, the price band induced by the PTCs, $p^m - t_p^s$, $p^m + t_p^b$, produces a third market regime in which the shadow price is higher than the price a household would effectively receive as a seller in the market and lower than the price it would effectively pay as a buyer. Households whose shadow price falls in this price band will have a greater utility by being self-sufficient, i.e. by producing the good themselves instead of buying it, or by producing just the amount needed for their subsistence instead of producing more and marketing the surplus. A household will be indifferent between participating in the market as a seller and being self-sufficient in the limit case when the shadow price is equal to the price received as a seller, $\tilde{p} = p^m$- t_p^s. We can also define this threshold level in terms of observable market prices, $p^m = \tilde{p}$ + t_p^s. Since indirect utility is increasing in the effective price for sellers, a household will be better-off selling the good if its effective price is higher than the shadow price $\tilde{p} \ < p^m$- t_p^s, or in terms of market prices, $p^m > \tilde{p} \ + t_p^s$. Similarly, the household will be indifferent between buying and self-sufficiency at the threshold market price $p^m = \tilde{p}$ - t_p^b. Since indirect utility is decreasing in the effective price for buyers, the household will choose to buy the good on the market if $p^m < \tilde{p}$ - t_p^b. When FTCs enter the analysis, it is clear from (6) that they do not impact unitary prices directly, but reduce a household's income and consequently lower utility at any given price. Hence, the indifference price threshold for sellers, say $\underline{p}^s$, is found by equating utility in autarky and utility as a seller, i.e.

$$V(\tilde{p}_i, y_0\left(\underline{p}^s\right), z_u) = V(\underline{p}^s, y_0\left(\underline{p}^s\right) - t_f^s, z_u) \tag{7}$$

where we have defined y_0 as total income before incurring FTCs to make explicit the influence of the latter in the indirect utility function, i.e. $y_0(p)$=$\sum_{i=1}^{N} p_i(q_i - x_i + A_i) + T$. Formally, since indirect utility is increasing in prices for sellers, the reduced utility due to the incurring of FTCs must be compensated by a higher selling price to keep the right-hand side of equation (7) equal to the left-hand side. Intuitively, since now the household is incurring both fixed and proportional transaction costs, the threshold price above which it becomes convenient to sell the good in the market, must be higher than before, i.e. $p^m > \underline{p}^s + t_p^s > \tilde{p} + t_p^s$. Specularly, the threshold price below which the household finds it is convenient to buy the good, solves the following utility equation $V(\tilde{p}, y_0\left(\underline{p}^b\right), z_u) = V(\underline{p}^b, y_0\left(\underline{p}^b\right) - t_f^b, z_u)$. The new threshold price, $\underline{p}^b$, will be lower compared to a situation with only PTCs, i.e. $p^m < \underline{p}^b + t_p^b < \tilde{p} + t_p^b$.

Given the choice of the market regime, Figure 1 illustrates the behavior of the farm-household in terms of quantities demanded and supplied, in the first and second panel respectively. The third panel shows the marketed surplus, i.e. the horizontal difference between supply and demand, as a function of market price. The lines SS and DD in the first panel represent the household's supply and demand for the good, respectively, when there are no transaction costs. Their intersection determines the household's shadow price ($\tilde{p}$) for this given good. The corresponding market surplus is shown by the line MM in the third panel. The household is indifferent between trading and being autarchic when $p^m = \tilde{p}$, a net buyer of the good ($m < 0$) when $p^m < \tilde{p}$, and a net seller ($m > 0$) when $p^m > \tilde{p}$.

Figure 1: Household demand, supply and marketed surplus under transaction costs



To see the effects of transaction costs on the quantities demanded, supplied and marketed we combine the market participation decisions and the corresponding price thresholds with the supply and the demand curve under each regime. When only PTCs are present the price at which selling begins, shifts up by t_p^s. This implies that the whole upper portions of the original supply and demand curves shift upward by t_p^s. Similarly, the household will not buy until the price reaches $\tilde{p}$ - t_p^b, so the lower portion of the curves shifts down by t_p^b (Minot, 1999). Therefore, with PTCs, the supply and the demand curves are made of three portions. For market prices such that $p^m > \tilde{p} + t_p^s$ the household is a net seller and the supply curve is given by $q^s = q(p^m - t_p^s, z_q)$ while the demand curve is $d^s = d(p^m - t_p^s, z_u)$. For price levels such that $p^m < \tilde{p}$ - t_p^b the household is a net buyer and the supply curve is given by $q^b = q(p^m + t_p^b, z_q)$ while the demand curve is $d^b = d(p^m + t_p^b, z_u)$. For price levels that fall inside the band $(\tilde{p} - t_p^b, \tilde{p} + t_p^s)$, the household is self-sufficient and unaffected by market prices. This is represented graphically by a vertical line where supply and demand coincide, $d^a = d(\tilde{p}, z_q) = q^a = q(\tilde{p}, z_q)$, and the autarchic quantity produced and used as input or for own consumption is $\underline{d}^a = \underline{q}^a$. The overall supply curve will then be given by the curve AB_0C_0D and overall demand by EC_0B_0F. As a result, for net sellers the corresponding marketed surplus is positive and is given my $m^s = m(p^m - t_p^s, z_q, z_u)$. For net buyers marketed surplus is negative and given by $m^b = m(p^m + t_p^b, z_q, z_u)$. Finally, in autarky, the farm-household does not trade, therefore the marketed surplus is zero for market prices that fall in the autarchic price band, $m^a = m(\tilde{p}, z_q, z_u) = 0$. This is represented by the I_0J_0 portion of the thick vertical line superimposed to the y-axes in the third panel. Hence, the overall marketed surplus schedule when only PTCs are present is given by the line HI_0J_0K.

The introduction of FTCs widens the autarky price band by pushing upwards the price when selling begins and pushing downwards the price where buying begins. Therefore, selling and buying are delayed until the market prices reach $\underline{p}^s + t_p^s$ and $\underline{p}^b - t_p^b$, respectively. This is shown in the second panel by the longer vertical section $B'C'$common to both the autarchic demand and supply curves. However, once in the market the quantities supplied and demanded are not affected by FTCs, because they are determined by marginal returns to production and marginal utility, respectively. Hence, FTCs only create a discontinuity in the supply and demand curves compared to the otherwise equivalent curves of the situation with only PTCs. The seller's supply curve now is given by the segment CD in the second panel and the overall supply curve is given by the broken line $ABB'C'CD$. Similarly the overall demand curve is $FF'B'C'EE'$. In the third panel, the corresponding marketed surplus schedule is given by the segment JK for sellers, by HI for buyers and by $I'J'$ for self-sufficient households. Hence, the overall marketed surplus curve is the broken line $HII'J'JK$.

Hence FTCs do not affect the position of the curves, while PTCs shift them upward for sellers and downward for buyers.

Under PTCs and FTCs, supply, demand and market surplus also have three regions, but the transition between autarky and buying or selling is accompanied by a discrete jump in quantities. The jump occurs because, at the point at which it becomes profitable to either sell or buy, the decision price faced by the household changes discretely to cover for FTCs (Key et al., 2000). The selling threshold quantity that corresponds to the threshold selling prices is $\underline{q}^s \equiv q(\underline{p}^s, z_q) = \underline{d}^s \equiv d(\underline{p}^s, z_u)$, while the buying threshold quantity is given by $\underline{q}^b \equiv q(\underline{p}^b, z_q) = \underline{d}^b \equiv d(\underline{p}^b, z_u)$. Since the jump in market prices is generated in order to cover for FTCs, the threshold quantities will also depend on FTCs but not on PTCs.[1] In particular, since the selling (buying) price is an increasing (decreasing) function of FTCs, so will be the selling and buying threshold quantities. The other variables that determine the threshold quantities are: on the supply side, farm-household characteristics that act as production shifters $z_q$and the endowment in goods *A*; on the demand side farm-household characteristics that act as utility shifters z_u, the endowment in goods A, and exogenous income *R*. Considering that marketed surplus is the result of the joint decisions on production and consumption, the corresponding thresholds will depend on FTCs and the rest of characteristics that determine the demand and supply threshold quantities, namely $\underline{m}^s = m(t_f^s, z_q, z_u, R, A)$ and $\underline{m}^b = m(t_f^s, z_q, z_u, R, A)$ (Edmeades, 2006).

We can now characterize the decision of the agricultural household to engage in market transaction by comparing the desired quantities with the threshold quantities, instead of comparing shadow prices with market prices.

$$m(\mathrm{p^m} - \mathrm{t_p^s}, \mathrm{z_q}, \mathrm{z_u}) > \underline{\mathrm{m}}^{\mathrm{s}}(\mathrm{t_f^s}, \mathrm{z_q}, \mathrm{z_u}, \mathrm{R}, \mathrm{A}) \quad <=> \text{ household is a seller.} \tag{8}$$

The marketed supply is given by $m^s = m(p^m - t_p^s, z_q, z_u)$.

$$m(p^m + t_p^b, z_q, z_u) > \underline{m}^b(t_f^b, z_q, z_u, R, A) \quad <=> \text{ household is a buyer.} \tag{9}$$

The marketed supply is given by $m^{\mathrm{b}} = m(p^m + t_p^b, z_q, z_u)$.

$$m(\mathrm{p^m} - \mathrm{t_p^s}, \mathrm{z_q}, \mathrm{z_u}) < \underline{m}^s(t_f^s, z_q, z_u, R, A) \text{ and} \tag{10}$$

$$m(p^m + t_p^b, z_q, z_u) > \underline{m}^b(t_f^b, z_q, z_u, R, A) \quad <=> \text{ household is autarchic.}$$

The market supply is null in this case $m^a(\tilde{p}, z_q, z_u) = 0$.

We model the policy at hand, given by the introduction of an unconditional cash transfer, as an exogenous increase in other income, $\Delta R > 0$ and analyze its effects both on the quantity of marketed surplus (*intensive margin*) and on the decision to participate in market transactions (ex*tensive margin*). The idea behind this comparative statics exercise is that differential access to services and means to mitigate transactions costs may be a driving factor of market participation patterns among smallholders (Alene et al., 2008). The higher income from the CT increases demand for goods at any given price, thus shifting the demand curve to the right. On the other hand, CTs

[1] Formally, since the threshold prices $\underline{p}^s$and $\underline{p}^b$ implicitly defined by (7) and (8) are functions of FTCs but not of PTCs, given the one-to-one relationship between prices and quantities, the threshold selling and buying quantities are also a function of FTCs but not of PTCs.

puts the farm-household in a better position to buy better inputs, increase access to mechanized tools and, ultimately, increasing the scale of production. Also, in a world of risk-averse farmers that face uncertainty in the output and factor markets an increase in liquidity may increase the farmers' willingness to take on more risks which in turn stimulates production (Hennessy, 1998; Lovo 2011). All this leads to an increased supply at any given price thus shifting the supply curve to the right. As a result, the net effect on the amount of marketed surplus, given by the interplay of the demand and supply effects of the CT, is indeterminate and its sign remains an empirical issue. On the extensive margin, CTs can influence the decision to trade as a buyer or a seller by altering the relevant price thresholds, and, consequently, the quantity thresholds. The extra income offered by CTs may be used by farmers to cover FTCs and overcome entry barriers to goods markets. It may allow them to purchase communication tools and services, such as cell phone, top-ups, televisions and other technological devices and the relevant subscriptions. These entail better and timely access to market information. Cash transfer may enhance the social status of the beneficiary in the community fostering access to local social networks in which ideas and information are exchanged. CTs may be used to buy membership in formal marketing and farming organizations that help farmers increase their leverage with counterparts and facilitate market interactions in general. In all these cases farmers use the CTs to bear part of the fixed transaction cost incorporated in the threshold prices $\underline{p}^b$and $\underline{p}^s$, thus narrowing the autarchic price band and the corresponding gap between threshold quantities, $\underline{m}^b$and $\underline{m}^s$. Since $\underline{m}^b$ is a decreasing function of FTCs and $\underline{m}^s$ is an increasing function of FTCs, a CT-induced contraction of fixed costs will result in a higher buying threshold ($\underline{m}^b$) and lower selling threshold ($\underline{m}^s$). These results simply in a higher participation rate in market transaction by smallholders.

3. Data, programme and descriptive statistics

In 2010, the Zambia's Ministry of Community Development and Social Services (MCDSS) started to implement the Child Grant Programme (CGP). The stated goal of the programme is to alleviate poverty among the poorest households and block its intergenerational transmission by stimulating progress in a number of intermediate objectives: supplementing and not replacing household income; increase in the number of children enrolled in and attending primary school; reduction of the rate of mortality and morbidity among children under 5 years old; reduction in stunting and wasting among children under 5 years old; increase in the number of households owning assets such as livestock; and increase in the number of households that have a second meal a day.

The pilot evaluation of the CGP was implemented in three districts that had never received any CTs and with highest rates of mortality, morbidity and stunting among children under 5 years of age. The three districts are located in very isolated and remote areas. They include Kaputa, located in Northern Province and Shongombo and Kalabo, located in Western Province. The CGP was based on a categorical targeting mechanism, reaching any household with a child under 5 years old. Only households with children under three years old were enrolled in the programme to ensure that every recipient household receives the transfers for at least two years after the programme is introduced to that area. A continuous enrolment system was implemented in which households were immediately enrolled after having a newborn baby. Beneficiary households received 60 new kwacha (ZMK) a month. The planned transfer size is constant regardless of household size and amounts on average to about 25 percent of a household's monthly consumption expenditure. Payments are unconditional of income, wealth or labour market status leaving households entirely free in how to spend the money. The designated recipient of the cash is the female head of household, who could be a mother or a grandmother. During the 2-year period, payments were made on time for all three districts, following a bimonthly schedule.

CGP's impact evaluation was designed as a longitudinal randomized controlled trial (RCT) with random assignment at the community level. There were two levels of random selection of participants, at the Community Welfare Assistance Committees (CWACs) and household level. The first stage of the randomization process was carried out by the Ministry by selecting and ordering 30 CWACs within each of the three districts (out of roughly 100 CWACs in each district) through a lottery. After the 90 CWACs were randomly selected for the study, the Ministry identified all eligible households with at least one child under 3 years old. In the second stage 28 households were then randomly sampled from each CWAC for inclusion in the study. Random assignment of the communities to treated and control groups occurred only after baseline data were collected, thus avoiding anticipation effects in the baseline data, as neither the respondent nor the enumerator knew their future treatment status. The final assignment to treatment and control groups was implemented by flipping a coin to determine whether the first half of the list of randomly selected CWACs would be treated or not. The final sample has 2515 households which amounts to 14,565 people.

Baseline data were collected during the lean season that spans from September through February, during which people have little food left from the previous harvest and hunger is most felt. The 24-month follow-up data collection occurred in September and October 2012 exactly 24 months from the baseline study, ensuring that households are being compared in the same season as at the baseline, avoiding seasonal effects.

In this paper we are interested in estimating the effects of the CGP program by comparing the participation rate and marketed surplus measured in monetary terms for the treated and control group. The binary randomization mechanism of the RCT design should ensure comparability along every observed and unobserved dimension between treated as a whole and the controls. This allows attribution to the intervention of any observed post-treatment differences resulting from the binary comparison of the average outcome between the treatment and control groups.

Table A1 shows descriptive statistics of our estimation sample at baseline. We estimate the sample means by treatment arm for all covariates used in estimation and use t-tests for the difference in means of continuous variables and a test of proportions for categorical variables. There are 8 covariates (out of 21) that are unequally distributed in the two treatment arms at the 95% level of confidence, which is more than we would expect to happen by pure chance. For example, households in the treated communities appear to live nearer to the main market but further away from the input market compared to control households. The choice of the covariates in our study is not random though, but is informed by the economic model. The official Baseline Report uses the full set of observed characteristics providing evidence of success of the binary randomization process that foreran the implementation of the CGP programme (Seidenfeld et al., 2011). The report establishes that treated and controls are observationally equivalent in terms of observed characteristics. To reduce the variance in the residuals, increase the statistical precision of the estimates and, at the same time, control for the observed differences at baseline between the treated and control group, we include these covariates in all our regressions. Table A2 shows descriptive statistics for our four outcome variables, namely, the revenues from crop sales, the share of sellers, the expenditures for seeds purchases and the share of seeds buyers. What stands out is the relatively low share of farmers that sell any of their crops in the market (19.8%-23.9%), and the even lower share of those who buy seeds in input markets (12.8%-13.4%). At baseline, there are no statistically significant differences in any of the four outcome variables at the 95% level of confidence.

4. Empirical strategy

The aim of this paper is to estimate the causal effects of unconditional cash transfers on the marketing behaviour of smallholders in terms of the decision on whether to engage in market transactions and on how much to trade. Our goal is to capture the role of CTs in spurring a greater degree of commercialization in both the output and input markets. To achieve this we focus on revenues from sales of all crops in the previous 12 months and the expenditures for purchases of all seeds in the same period. For both crops and seeds the household expresses, on one hand, a demand for own consumption and input use and, on the other hand, a household supply, since both goods can be produced in-house. Therefore, for crops, the household has to decide whether to produce the self-sufficient amount that just meets its own demand or to produce more and market the resulting surplus. For seeds, the household has to decide whether to produce enough to meet its own input demand or to produce less than its needs and buy the extra quantity on the market. Previous studies have used as a dependent variable sold quantities of a single crop (Goetz, 1992; Key et al., 2000) or of a single input (Alene et.al, 2008). Another strand of the literature uses the value of crop sales (Heltberg and Tarp, 2002) or of tropical livestock units sales (Bellemare and Barret, 2006). Here we follow the latter strand since it allows the analyst to use all available information instead of focussing on a single crop or animal. Moreover, aggregate supply rather than single crop supply is what ultimately matters to policy. On the downside, aggregation conceals possible causal mechanisms that act at the level of the single crop.

The main estimation issue in our context is similar to the one in the prototypical example that motivated the Heckman's selection model in which a women is observed working only if the market wage is higher than her shadow price of labour (reservation wage), thus leading to a sample of working women that is not randomly selected and, therefore, not representative of the women population. Smallholders who decide to take part in market transactions as sellers (buyers) do so only if the market price of the good is higher (lower) than the threshold shadow price inclusive of transactions costs. The effects of CTs on the marketed quantities, estimated on the self-selected sample of smallholders observed taking part in transactions will, in general, be biased and inconsistent for the population of smallholders. Moreover, if there is random assignment of the "treatment", the programme may increase the volume of market sales or purchases of beneficiary smallholders either by increasing the likelihood for them to engage in market transactions or, given the market participation rate, by raising the marketed quantities. Therefore, even a randomized experiment cannot guarantee that treatment and control individuals will be comparable *conditional on being on the market* (Lee, 2009). As a result, treated-control differences must be corrected for the possible effects of selection into a certain market regime. This motivates our use of a standard Heckman selection model which jointly estimates the amount of marketed surplus and the market regime choice. Formally, for sellers the joint choice may be expressed by the following system of equations:

$$m^{s*} = T\alpha_s + D\tau_s + DT\beta_s + X'\pi_s + \varepsilon_s \tag{11}$$
$$\equiv V'\Psi_s + \varepsilon_s$$
$$I^{s*} = T\mu_s + D\theta_s + DT\gamma_s + Z'\delta_s + \upsilon_s \tag{12}$$
$$\equiv W'\Gamma_s + \upsilon_s$$
$$I^s = \mathbf{1}[I^{s*} > 0] \tag{13}$$
$$m^s = m^{s*} * I^s \tag{14}$$

For buyers the system of equations is:

$$m^{b*} = T\alpha_b + D\tau_b + DT\beta_b + X'\pi_b + \varepsilon_b \tag{15}$$
$$\equiv V'\Psi_s + \varepsilon_b$$
$$I^{b*} = T\mu_b + D\theta_b + DT\gamma_b + Z'\delta_b + \upsilon_b \tag{16}$$
$$\equiv W'\Gamma_s + \upsilon_b$$
$$I^b = \mathbf{1}[I^{b*} > 0] \tag{17}$$
$$m^b = m^{b*} * I^b \tag{18}$$

where D is the treatment dummy that equals 1 for beneficiary households and zero otherwise and T is the post-treatment dummy that equals 1 if the household is observed at follow-up. X and Z include a set of exogenous covariates. We rewrite the set of regressors in the quantities and participation decision compactly as $V = (T, D, DT, X)$ and $W = (T, D, DT, Z)$. Ψ_j=$(\alpha_j, \tau_j, \beta_j, \pi_j)$ and Γ_j=$(\mu_j, \theta_j, \gamma_j, \delta_j)$ for *j*={*b,s*} are the vector of coefficients in the quantities and participation equation, respectively. The coefficient on the treatment dummy identifies the difference between the average outcome of the treated at follow-up and the average outcome they would have experienced without the treatment at follow-up. The coefficient on the time dummy identifies the average outcome change in the untreated group between baseline and follow-up, i.e. the pure effect of time. Finally, the coefficient on the interaction term identifies the causal impact as the extra change in the average outcome of the treated over the change that this group would have experienced had they not received the cash transfer. The coefficients on X and Z identify the impact of the rest of the covariates. Further, m^{s*} is the latent or desired amount of marketed surplus of sellers and it is observed when it is higher than the corresponding threshold for market participation $\underline{\mathrm{m}}^{\mathrm{s}}$. I^{s*} is the latent propensity to participate in the market as a seller and I^s is the observed binary indicator that is 1 when the household chooses to sell over being autarchic, i.e. $\mathbf{1}[I^{s*} > 0]$=$\mathbf{1}\left[m^{s*} > \underline{\mathrm{m}}^{\mathrm{s}}\right]$. We assume that errors in the choice equation and in the marketed quantities equation are jointly normal with mean zero and covariance $\sigma_{\varepsilon_s \upsilon_s}$. The variance in the quantities' equation is left as a parameter to estimate ($\sigma^2_{\varepsilon_s}$) while the variance in the participation equation is set equal to one since it refers to a latent variable that has no scale ($\sigma^2_{\upsilon_s}$=1). The corresponding variables for buyers, namely, m^{b*}, I^{b*}, m^b, I^b, $\sigma_{\varepsilon_b \upsilon_b}$, $\sigma^2_{\varepsilon_b}$, $\sigma^2_{\upsilon_b}$ are defined similarly.

If market participants were randomly selected into a given market regime we might estimate the causal effect of interest simply by comparing the change in marketed quantities for the treated to the change for the controls with a plain difference-in-differences approach. However, if the quantities equation was estimated separately by OLS on the sample of market participants only, the conditional expectation of the error term would not be zero $E\left[\varepsilon_j \middle| V, I^j = 1\right] = E\left[\varepsilon_j \middle| V, \upsilon_j > -W'\Gamma_j\right] \neq 0$ for *j*={*b,s*}, which translates into omitted variable bias. To correct for this we adopt a two-step control function approach. Given the assumption of joint normality, the conditional expectation of the error term is equal to $\sigma_{\varepsilon_j \upsilon_j}\left(\frac{\phi(W'\Gamma_j)}{\Phi(W'\Gamma_j)}\right)$ where $\phi(\cdot)$ and $\Phi(\cdot)$ are the probability density and cumulative distributive functions and the quantity in brackets is the Inverse Mill's Ratio

(IMR). The IMR can be estimated given our distributional assumptions and consistent estimates of the participation equation coefficients. Therefore, the two-step procedure consists in estimating first Γ_j=($\mu_j, \theta_j, \gamma_j, \delta_j$) for *j*={*b,s*} over the full sample (participants and non-participants) by probit and then construct an estimate of the IMR. In the second step the parameters of the quantities equation can be consistently estimated by OLS over the participants' sample by including the estimated IMR as an extra regressor to avoid the omitted variable bias. Therefore, the second stage in each system of equations is:

$$m^s = V'\Psi_s + \lambda_s \sigma_{\varepsilon_s \upsilon_s} + \eta_s \quad (11a)$$

$$m^b = V'\Psi_b + \lambda_b \sigma_{\varepsilon_b \upsilon_b} + \eta_b \quad (15a)$$

where $\lambda_s$is the IMR for sellers and $\lambda_b$is defined similarly for buyers. The new residuals η_s and $\eta_b$have now mean zero but are heteroschedastic. The t-test on the coefficients of the IMR is a test of whether or not the errors are correlated and sample selection correction is needed. Standard errors in the second step are inflated to account for the extra uncertainty deriving from estimation of Γ_j=($\mu_j, \theta_j, \gamma_j, \delta_j$) for *j*={*b,s*} in the first step.

Identification of the systems of equations is based on two more assumptions, in addition to the distributional one. First, that the errors are conditionally mean independent on *W*, i.e. $E\left[\varepsilon_j \middle| W\right] = 0$ for *j*={*s,b*}. The analysis of the impacts of the CGP program was based on a Randomized Control Trial which insures the strongest form of statistical independence of treatment status, namely that potential outcomes are independent of treatment status. This implies the much weaker assumption of conditional independence needed for identification in (11)-(18). The second assumption, although not formally necessary, requires that $V \subset W$, i.e., that there are variables in *W* that determine market participation but do not influence decisions on quantities, so can be excluded from *V* (*exclusion restrictions*). In fact, the IMR is a non-linear function of the index $W'\Gamma_j$ for *j*={*s,b*} but in practice behaves linearly over the central range of values of the index. This makes the extra regressor λ collinear with the rest of the regressors in the quantity equation casing "weak identification" problems that lead to high standard errors in the second stage (Vella, 1998). We use economic theory to derive our exclusion restrictions. In particular, we use fixed transaction costs proxies which we established to determine the farm-household's decision to participate in the market but not the decision on how much to trade. We follow the literature on this and use dummies for the ownership of communication facilities, namely a dummy for owning a TV, one for owning a radio and one for owning a cell phone. Access to these facilities mitigates the fixed costs of obtaining market and other information and should, therefore, narrow the autarchic price band and increase the likelihood of participation. The rest of the exogenous variables, common to *X* and *Z*, include the set of standard variables theoretically expected to affect marketing decisions. These consist of a rich set of household and community characteristics measured at baseline and proxies for proportional transactions costs. We include household size which determines labour supply for production and demand for consumption. We also include a measure for the degree of labour constraints in the household as given by the dependency ratio, which we measure here as the number of dependants over the number of working age household members[2]. We include a dummy for whether the household is female headed which negatively influences the household's ability to access information. The age and education of the household head are proxies for the household's

[2] In the current context, we consider as dependents those under the age of 15 and over the age of 64. The productive part of the household is composed of the members aged between 15 and 64 years.

ability to obtain and properly process market information. Education level is captured by the number of years of completed education by the head. We control also for the fixed assets that contribute to the production of goods. In particular, we control for the total area of operated land at baseline and the number of tropical livestock units owned by the household at baseline. We include the community level prices of the major crops, namely, maize, cassava, rice, sweet potatoes, beans and those of seeds. Finally, the proxies of PTCs include variables related to transportation costs. These are variables that either directly explain transportation costs, such as the time to get to the output market and to the input market, or that mitigate them, such as the ownership of means of transportation, in particular, a dummy for owning a motorcycle. Ownership of means of transportation influences both the decision to participate in the market and how much to trade. This is because of their double nature as both FTC- and PTC-mitigating facilities. They may be used to gather market information by physically going to the input or output market but at the same time households may use them to transport goods to and from the market thus mitigating variable transportations costs (Alene et al., 2008). All regressions include two district dummies, as a third dummy is omitted and serves as a reference category.

There are several types of responses to a given change in covariates in the Heckman selection model. The coefficient vectors Ψ_j=$(\alpha_j, \tau_j, \beta_j, \pi_j)$ and Γ_j=$(\mu_j, \theta_j, \gamma_j, \delta_j)$ are purged of selection bias but they refer to unobservable variables. In fact, they measure the change in the desired marketed quantity (m^{j*}) and the latent propensity to engage in market transactions (I^{j*}), respectively, caused by a unitary change in one of the exogenous variables. Our interest lies instead in the change in the observed probability of market participation and in the change in actual quantities exchanged conditional on participation. These marginal effects are derived from the model coefficients. The change in the probability of market participation per unit change in the i-th explanatory variable is given by $\frac{\partial P(I^j=1|W)}{\partial W_i} = \Gamma_{ji}\, \phi\big(W'\Gamma_j\big)$. These are the effects on the *extensive margin*, i.e. changes in the value of sales or expenditures due to the entry or exit of new farmers in the market and to the resulting changes in the rate of market participation. Furthermore, for the i-th explanatory variable that is included both in the quantities and in the participation equations, the marginal effect on the expected value of actual marketed quantities conditional on participation is given by $\frac{\partial E(m^j|I^j=1,V)}{\partial V_i} = \Psi_{ji} - \sigma_{\varepsilon_j \upsilon_j}\Gamma_{ji}[\lambda_j(W'\Gamma_j)^2 - \lambda_j(W'\Gamma_j)W'\Gamma_j]$ (Greene, 2008). The latter formula represents the effects on the *intensive margin*, i.e. changes in the value of sales or expenditures due to changes in the marketed quantities of current market participants.

4.1 Heterogeneity of impacts

To this point we have focused on the overall impact of the programme in the whole population implicitly assuming in equations (11)-(18) that the causal effect of the programme is constant and common to all individual households, which seems untenable. It is more natural, especially in social contexts, for responses to a certain policy to vary in the population. Therefore, it seems reasonable to assume that the effect of cash transfers may be different for different subgroups in the population defined by certain characteristics. Here we focus on two types of heterogeneity analysis.

First, we are interested in whether there are groups of household definable by their observed characteristics that are affected more by cash transfers, in terms of commercialization, compared to otherwise observationally equivalent households. The usual way to estimate effects for specific subgroups is by including interactions of the treatment indicator with one or more regressors. Therefore, we estimate equations (11)-(18) by including interactions of the treatment dummy *D*, the time dummy *T* and of the term *D*T* with a subset of covariates included in *X* and *Z*. In this case the average effect differs across observable subsamples defined by different elements of *X* (e.g. education of household head, dependency ratio etc.) but is otherwise constant within those groups. This has important policy implications since knowing, for example, that the programme benefits more those with a larger endowment of agricultural tools or those who make a more intense use of fertilizers may hint at the need of agricultural policies complementary to cash transfers capable of putting those less endowed with certain inputs, to benefit more from cash transfers as far as commercialization is concerned. Exploring heterogeneity is important also because it may help policy makers improve the targeting of certain features of the programme to the appropriate population group that is more likely to respond to the programme (Bitler et al., 2006).

Second, estimating mean impacts may miss a lot, even across subgroups. Bitler et al., (2006) show that treatment effects may vary across quantiles of the outcome distribution not only in the full sample but also within well-defined demographic subgroups. The least commercialized households at the bottom of the marketed surplus distribution may benefit more than those at the top, causing the market surplus distribution to become more uniform and compressed. It could also happen that the programme benefits more those at the top of the marketed surplus distribution leaving unaffected those more in need and widening the commercialization gap between those who already buy and sell large quantities and those who are near the autarchic threshold. In order to capture this extra layer of impacts' heterogeneity we use quantile regression to estimate the effects of the programme *on* different quantiles of the marketed surplus distribution. Quantile treatment effects (QTEs) can be interpreted as treatment effects for households *at* particular quantiles of the control group outcome distribution if the *rank preservation* assumption is satisfied. Rank preservation is a strong assumption that means that a household rank in terms of marketed surplus would be the same regardless of being assigned to the treated or control group. In other terms, exposure to treatment leaves the rank of the household unchanged. In this case the QTEs may be attributed to the particular households that lie *at* the q-th quantile of the distribution. We do not gauge the validity of rank preservation here. However, even without this assumption QTEs remain a valid tool to investigate distributional impacts as they represent how various quantiles of the outcome distribution are affected differently in the treatment and quantile groups, but we cannot make inference on the impact on any particular household (Dammert, 2008).

More in general QTEs allow the analyst to overcome the inherent limitations of the conditional-mean framework whose assumptions are not always met in the real world. In particular, the homoscedasticity assumption frequently fails, which leads to the shape and spread of the outcome distribution varying with regressors. If the heteroscedasticity depends on the regressors, the estimated slope parameters differ in different quantiles of the outcome distribution. Since our regressor of interest is a binary treatment, a test of the equality of variance of the outcome distribution in the treated and control groups is usually used to detect heteroschedasticity and the possible presence of heterogeneous effects along the outcome distribution. To justify the use of quantile regression we test the hypothesis of the equality of variance across treatment arms by using a Levene's test. Rejection of the null implies treatment effect heterogeneity that a single mean treatment effect cannot fully explain (Ding et al., 2014; Mishra et al., 2015). The quantile regression framework is the usual approach to capture effect heterogeneity at different points of the outcome distribution in this case. Moreover, heavy-tailed distributions commonly occur in social phenomena, leading to a preponderance of outliers. The conditional mean can then become an inappropriate and misleading measure of central location because it is heavily influenced by outliers (Hao and Naiman, 2007). The QTE parameter estimates are relatively robust to outliers because, in contrast to the OLS, the magnitude of the dependent variable does not matter (Hao and Naiman, 2007). Buchinsky (1998) also notes that, when the error terms are not normally distributed, the QR estimator may be even more efficient than the OLS estimator.

To accommodate for the possibility of sample selection in the context of quantile regression we follow the approach proposed by Buchinsky (1998). We rewrite the quantities equation for sellers and buyers in quantile regression form, while the rest of the equations in both systems are the same as before.

$$m^{s*} = V'\Psi_s^q + \varepsilon_s \quad (11b)$$
$$m^{b*} = V'\Psi_b^q + \varepsilon_b \quad (15b)$$

where the vector of coefficients Ψ_s^q=($\alpha_s^q, \tau_s^q, \beta_s^q, \pi_s^q$) is indexed by q to highlight the fact that now they represent effects on the q-th quantile, q $\in$(0,1) of the outcome distribution. Here we maintain the assumption of the existence of *exclusion restrictions* $V \subset W$, but impose a stronger *exogeneity assumption*. In fact, for quantile regression we require full independence of the error terms $\varepsilon_j \perp (V, W)$ for *j*={*s,b*}. This implies that conditional quantiles of the errors are zero, $Q^q(\varepsilon_j|V) = 0$, and that the conditional quantile of the dependent variable may be expressed as $Q^q(m^{j*}|V) = V'\Psi_j^q$ for *j*={*s,b*}. Conditioning on participation in a given market regime we obtain the q-th conditional quantile of the observed marketed quantities:

$$Q^q(m^s|V) = V'\Psi_s^q + Q^q(\varepsilon_s|V, I^s = 1) \quad (11c)$$
$$Q^q(m^b|V) = V'\Psi_b^q + Q^q(\varepsilon_b|V, I^b = 1) \quad (15c)$$

The last term will, in general, be different from zero, thus generating selection bias $Q^q(\varepsilon_j|V, I^s = 1) = h_j^q(W, \mu_j, \theta_j, \gamma_j, \delta_j) \neq 0$ for *j*={*s,b*}. To correct for this possible bias we follow a two-step approach similar to the one applied for mean regression (Buchinsky, 1998). In the first step we estimate the bias term which has an unknown functional form. Therefore, we assume that $h_j^q(\cdot)$ is a function of an index $g_j = G(W, \Gamma_j)$ assumed linear in the parameters, so that $g_j = W'\Gamma_j$. This allows us to write the participation indicator as before, $I^j = [g_j > v_j]$ for *j*={*s,b*} (*index sufficiency assumption*). Therefore, we can construct the index by first estimating its parameters. We do so by using a semiparametric estimator proposed by Ichimura (1993). The coefficients Γ_j=($\mu_j, \theta_j, \gamma_j, \delta_j$) are found as the solution to the following optimization problem Γ_j=$\underset{\Gamma_j}{argmin}[I^j - \hat{E}(I^j|W)]^2$ where $\hat{E}(\cdot|\cdot)$ is a nonparametric estimate of the probabilities of selection into market regime *j*, for *j*={*s,b*}. In the second step we estimate the marketed quantities equations (11c) and (15c) on the sample of sellers and buyers, respectively, by including $h_j^q(\hat{g}_j)$ to correct for sample selection bias. We assume that h_j^q can be approximated by a series of orthogonal polynomials of maximum order k in $\hat{g}_j$, i.e. $P_k(\hat{g}_j)'\omega_j^q$, where ω_j is the coefficients' vector of the polynomial basis (Buchinsky, 2001; O'Martins, 2001). The quantile regression in the second step for sellers and buyers can be cast as:

$$m^s = V'\Psi_s^q + P_k(\hat{g}_s)'\omega_s^q + \zeta_s \qquad (11d)$$
$$m^b = V'\Psi_b^q + P_k(\hat{g}_b)'\omega_b^q + \zeta_b \qquad (15d)$$

where $Q^q(\zeta_j | V, I^s = 1) = 0$ by construction. For given k, both quantile regressions are estimated by use of linear programming algorithms on market participants only ($I^j = 1$, j={s,b}). One drawback of approximating the bias term through a power series is that the constant term of the polynomial and the intercept of the quantile regression cannot be separately identified. Therefore, we remove the $l = 1$ term from the series expansion and estimate the resulting quantile model (Segarra and Teruel, 2011). Finally, although the asymptotic covariance matrix of the second step coefficients has been derived in Buchinsky (1998), we follow previous studies and bootstrap standard errors in the second step for ease of implementation (Attanasio et. al., 2008).

The coefficients Ψ_j^q=($\alpha_j^q, \tau_j^q, \beta_j^q, \pi_j^q$) are purged of selection bias but refer to desired quantities or potential marketed surplus. The marginal effects on the conditional quantiles of the quantities actually exchanged in the market are obtained from the coefficients by taking the derivative with respect to i-th regressor in equations (11d) and (15d) i.e. $\frac{\partial Q^q(m^j | I^j=1, V)}{\partial V_i} = \Psi_{ji}^q + \omega_j^q \frac{\partial P_k(\hat{g}_j)}{\partial V_i}$

5. Results

Results for the estimation of equations (13) and (11a) for crops sales are shown in Table 1. The first two columns report the results for the participation equation while the last two refer to the market surplus equation given the choice of the household between participating as a seller and staying autarchic. The marginal effects associated with the variables in the first stage probit equation represent changes in the probability of participation, while the marginal effects in the quantities equation measure changes in the actual amount of sales for market participants for a unitary change in the regressor. Our main interest lies in the coefficient of the interaction term between the program dummy (*D*) and the follow-up dummy (*T*). This measures the extra change in the outcome experienced on average by the treated group relative to the change in outcome that occurs in the control group. From the estimate of the interaction coefficient in columns 1-2, it is clear that cash transfers beneficiaries experienced a statistically significant increase of around 12.7 percentage points in the likelihood of participating as sellers instead of staying autarchic. The program also induced non-autarchic farmers that were already taking part in market transactions to increase marketed quantities by 202k Kwacha (columns 3-4). In relative terms, this extra increase in sales for program beneficiaries, amounts to 67.3% of the average volume of sales in the whole sample at baseline. Therefore, increased commercialization from cash transfers resulted from an increase in both the share of farmers induced to switch from a status of self-sufficiency to participating as sellers (*extensive margin*) and in the amount sold by farmers who were already engaged in crop sales in the market (*intensive margin*).

The coefficient on the Inverse Mill's Ratio (lambda) is statistically significant which confirms the need to correct for sample selection bias in the quantities equation. Identification of the Heckman system of equations (13) and (11a) relies both on the nonlinearity of the functional form of the Inverse Mills Ratio and on the presence of exclusion restrictions. The contribution of the latter to overall identification is modest in our case since only one of the variables, namely the cellphone ownership dummy, is statistically significant in the participation equation. Ownership of this communication device is associated with a 12 percentage points increase in the probability of market participation.

Table 1: Mean effects for sellers (Heckman model)

	Participation		Quantity	
	Coefficient	t-statistics	Coefficient	t-statistics
T	0.496	(2.063)**	-1.80E+06	(-2.236)**
D	-0.069	(-3.448)***	-4.62E+04	(-0.584)
D*T	0.127	(4.749)***	202000	(1.693)*
HH size	0.001	(0.136)	41297.151	(1.611)
Fem-headed HH	0.076	(0.376)	-319720.696	(-0.498)
Edu. Of HH head	0.021	(3.962)***	13270.271	(0.580)
Age head of HH	0.004	(2.264)**	3288.230	(0.506)
Dependency ratio	-0.040	(-2.482)***	-65056.128	(-1.058)
Operated land (ha)	0.131	(5.908)***	169047.688	(1.896)*
TLU owned	0.003	(0.346)	252303.627	(13.447)***
Time to main mkt.	0.074	(4.733)***	-22860.348	(-0.318)
Time to inp. mkt.	0.057	(1.827)*	-103963.481	(-0.903)
HH own motorcyc.	0.679	(2.381)**	1590179.471	(1.978)**
Price of maize	-0.000	(-1.080)	-0.139	(-0.134)
Price of casava	0.000	(0.015)	9.495	(1.189)
Price of rice	-0.000	(-1.238)	-1.960	(-0.118)
Price of potatoes	-0.000	(-1.172)	-0.736	(-0.048)
Price of beans	0.000	(0.245)	25.135	(1.281)
Price of maize seed	-0.000	(-0.554)	-0.112	(-0.353)
Lambda			-193236.072	(-0.738)
HH owns TV	-0.130	(-1.123)		
HH owns stereo	0.058	(1.064)		
HH owns cellphone	0.120	(1.872)*		

Note: significance levels: * p < .1, ** p < .05, *** p < .01. t-statistics in brackets.

Household demographic characteristics have a strong influence on the participation decision but almost no influence on the quantities decisions. In particular, the age and education of the household head are both associated with a higher likelihood of participating in the market as a seller. The greater access to information that older heads have dominates other characteristics that are usually associated with older age, such as higher risk aversion and reluctance to adopt new production technologies. The latter may be attenuated by a better ability to process this information from a higher number of years of completed education. Dependency ratio, which is a direct determinant of the household's ability to supply labor and increase farm production, strongly reduces the household's chances of participating in the market. Turning to the endowments of land

and capital, an increase in the area of operated land of 1 ha is associated with a significant 13.1 percentage points increase in the likelihood to become a seller and with an increase of 169k Kwacha in the volume of sales of market participants. The number of tropical live units (TLU) is another proxy for farm size and it too is positively associated with the value of sales. It is evident that farmers who are well endowed with agricultural capital and land tend to be more commercialized. The price of some of the main crops and of the maize seeds have no effects whatsoever on output marketing decisions.

Variable transaction costs are captured here by three covariates, namely, travel time to the main market, travel time to the input market and a dummy for motorcycle ownership. The first two variable have a small but positive impact on the participation decision which is counterintuitive since we would expect farmers who leave further away from the markets to be relatively less likely to engage in trade, all other things being equal. One possible reason for this pattern may be that since these two covariates measure time of travel instead of distance, they may reflect differences in other factors which we do not control for, such as quality of roads or of public transport and ownership of means of transportation other than those included in the regression. The ownership of a motorcycle, which allows the farmer to mitigate transportation costs, has a strong positive influence on both the decision to participate and on the volume of sales. However, causality may run in both directions since higher sales may be used to finance the purchase of a motorcycle or other means of transportation.

Results for the estimation of equations (17) and (15a) for seeds purchases are shown in Table 2. The first two columns report coefficient estimates of the equation that models the choice between being self-sufficient and buying seeds on the market, while the last couple of columns report coefficient estimates of the quantities equation for the subsample of buyers of seeds. We note that cash transfers cause a statistically significant increase in the likelihood of market participation of 8.3 percentage points. The impact on the expenditure for seeds purchases is positive and sizable but is imprecisely estimated. We conclude that in the case of input markets commercialization, cash transfers act mainly on the extensive margin by lowering the threshold quantity above which it is convenient to buy products in the market instead of producing them in-house, thus inducing more farmers to participate. Our evidence shows that the marketing decisions regarding the quantities of seeds bought in the market by those who already participate as buyers are left unaffected by the program.

The coefficient of the Inverse Mills Ratio is strongly significant suggesting that OLS estimates of the quantities equation would be biased and confirming the adequacy of our choice to use a Heckman selection model instead. Of the three proxies of fixed transactions costs that we include in the participation equation to identify the Heckman model only the dummy for ownership of a TV set is significant, making overall identification less than optimal. This shows up in the low precision of the estimates in the quantities equation which should, therefore, be interpreted with some caution.

Table 2: Mean effects for buyers (Heckman model)

	Participation		Quantity	
	Coefficient	t-statistics	Coefficient	t-statistics
T	-0.088	(-0.397)	-5.16e+04	(-0.317)
D	0.006	(0.347)	-158.107	(-0.011)

D*T	0.083	(3.407)***	25472.913	(1.084)
HH size	0.002	(0.234)	1995.051	(0.341)
Fem-headed HH	0.126	(0.676)	326.865	(0.002)
Edu. Of HH head	0.014	(2.905)***	1922.060	(0.399)
Age head of HH	0.003	(1.894)*	862.969	(0.616)
Dependency ratio	-0.028	(-1.917)*	1049.057	(0.087)
Operated land (ha)	0.071	(3.795)***	9189.432	(0.476)
TLU owned	-0.014	(-1.526)	-2618.796	(-0.373)
Time to main mkt.	0.048	(3.245)***	9176.942	(0.651)
Time to inp. mkt.	-0.064	(-2.246)**	11012.742	(0.435)
HH own motorcyc.	0.338	(1.322)	130641.981	(0.677)
Price of maize	-0.000	(-0.106)	-0.067	(-0.280)
Price of casava	-0.000	(-1.198)	0.963	(0.628)
Price of rice	0.000	(0.945)	-0.502	(-0.122)
Price of potatoes	-0.000	(-1.602)*	0.558	(0.180)
Price of beans	0.000	(2.120)**	1.134	(0.222)
Price of maize seed	-0.000	(-0.332)	0.093	(1.627)*
Lambda			-134866.266	(-2.323)**
HH owns TV	0.165	(1.641)*		
HH owns stereo	0.042	(0.855)		
HH owns cellphone	0.046	(0.790)		

Note: significance levels: * p < .1, ** p < .05, *** p < .01. t-statistics in brackets.

The impacts of the household's demographic characteristics are similar to those observed for crop sales. Age and education of the household have both a positive impact on the probability of moving from a status of autarky to buying seeds in the market. Dependency ratio again hinders farm-households' commercialization as it limits the household's productive potential, its ability to supply labour in the farm and, as a result, the demand for seeds. As to land endowment, an increase of 1 ha in the area of operated is associated with an increased probability of buying seeds of 7.1 percentage points. Variable transaction costs as measured by the travel time to the input market have the expected sign in this case. An increase by one hour in travel time to the input market reduces the probability of buying seeds in the market by a significant 6.4 percentage points. Finally, price responsiveness is higher for input markets compared to output markets judging by the number of variables with a significant coefficient.

5.1 Heterogeneity of impacts

Given these headline results for the whole sample, we now focus on the observed heterogeneity in the effect of the CGP, i.e. how the impacts vary with households' observed characteristics. In particular, we are interested in whether there are groups of household definable by their observed characteristics that are affected more by cash transfers, in terms of commercialization, compared to otherwise observationally equivalent households. Moreover, we use this part of the study to investigate the interplay of cash transfers with transaction costs. As to extensive margin, cash transfers may be used by farmers to directly cover part of the fixed transactions costs thus lowering the threshold quantity above which it becomes convenient to sell crops in the market, or to invest in means that mitigate the costs of gathering information such as a cellphone. The impact on the intensive margin may work in a similar fashion, allowing framers either to directly cover part of the costs for transporting products to and from the market, or by allowing investments in transportation means.

The usual way to estimate effects for specific subgroups is by including interactions of the treatment indicator with one or more regressors. Therefore, we estimate equations (13), (17), (11a) and (15a) after including interactions of the *D*T* term with the dependency ratio, the area of operated land and, most importantly, the indicators of variable and fixed transaction costs. The estimated coefficients of the interaction terms for the participation and quantities equations of crop sales are shown in Table 3 below.

Table 3: Mean subgroup effects for sellers (Heckman model)

	Participation		Quantity	
	Coefficient	t-statistics	Coefficient	t-statistics
D*T*Dep. Ratio	0.006	(0.194)	-191000	(-1.417)
D*T*Operated land	-0.003	(-0.067)	-64900	(-0.394)
D*T*Dist. main mkt.	0.003	(0.099)	50071	(0.409)
D*T*Dist. inp. mkt.	0.008	(0.227)	-15100	(-0.105)
D*T*HH owns motorcycle	-0.176	(-65.407)***	502000	(0.245)
D*T*HH owns TV	0.006	(0.050)		
D*T*HH owns stereo	-0.044	(-0.764)		
D*T*HH owns cellphone	-0.121	(-1.728)*		

Note: significance levels: * p < .1, ** p < .05, *** p < .01. t-statistics in brackets.

On the extensive margin, the cash transfers program increased the likelihood of households without a motorcycle to participate in the market as sellers more than it did for household that own such means of transportation. The reason for this may be that transportation costs are more binding on poorer households and the extra liquidity provided by the program is more effective at the margin for this subgroup of households. An analogous argument may be applied to the cellphone ownership. The program was more beneficial to households without a cellphone which face relatively higher costs to gather information. On the intensive margin, we find no evidence of differentiated impact along the dimensions of the observed characteristics included as interactions.

Table 4: Mean subgroup effects for buyers (Heckman model)

	Participation		Quantity	
	Coefficient	t-statistics	Coefficient	t-statistics
D*T*Dep. Ratio	-0.017	(-0.611)	9094	(0.597)
D*T*Operated land	0.074	(1.986)**	-26000	(-1.173)
D*T*Dist. main mkt.	-0.043	(-1.569)	4365	(0.278)
D*T*Dist. inp. mkt.	0.066	(2.118)**	-14300	(-0.783)
D*T*HH owns motorcycle	-2.917	(-50.100)***	-1130000	(-4.449)***
D*T*HH owns TV	0.025	(0.249)		
D*T*HH owns stereo	-0.02	(-0.399)		
D*T*HH owns cellphone	0.053	(0.860)		

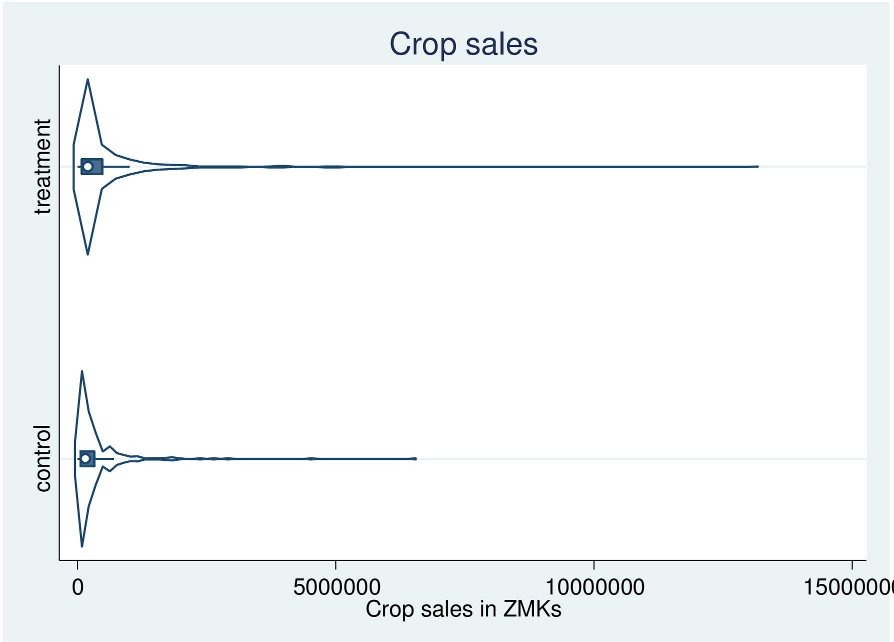
Note: significance levels: * p < .1, ** p < .05, *** p < .01. t-statistics in brackets.

The estimated coefficients of the interaction terms for the participation and quantities equations of seeds purchases are shown in Table 4. The program benefited bigger farmers, as proxied by the area of operated land, to a greater extent compared to smaller farmers. For the former group the likelihood of participating as a buyer was 7.4 percentage points higher than the latter group. This seems reasonable since bigger farms are better equipped to take advantage of the extra liquidity provided by the program while farms that are too small may lay deep in the autarchic price band. The programme increased the likelihood of participation more for households that report longer travel time to the input market and that do not own a motorcycle. These are the households for which transportation costs are more binding and for which one extra kwacha has the highest return at the margin in terms of market participation. Finally, in term of intensity of participation, farmers that do not own a motorcycle increase the purchases of seeds by 1130k more relative to those who do.

Overall, the interaction coefficients that relate to fixed and variable transaction costs show that cash transfers produce higher impacts, both in terms of participation and volume of revenues and expenditure for households that face more binding costs. CTs act as a mitigating factor and help program beneficiaries overcome this particular trade barriers by allowing them to either cover part of the transaction costs or to invest in technologies that reduce these costs.

Before commenting estimation results from the quantile regression approach we motivate its use to capture treatment effect heterogeneity along the outcome distribution in the current context. When the conditional distribution of the outcome changes both its location and its shape as a result of a change in the conditioning variable, a hypothetical mean regression line that goes through the conditional means is no longer parallel to the quantile regression lines the pass through the conditional quantiles of the outcome distribution. The conditioning variable has heterogeneous effects at different quantiles of the outcome distribution. Moreover, the conditional mean regression fails to correctly model central location shifts if the response distribution is asymmetric in which case the mean and median do not coincide. When this happens the median may be more appropriate to capture the central tendency of the distribution. To model both location shifts and shape shifts, Koenker and Bassett (1978) proposed the quantile-regression model. The QR estimates the differential effect of a covariate on various quantiles in the conditional distribution, with the median and the off-median quantiles. The fitted regression lines capture the location shift (the line for the median), as well as scale and more complex shape shifts (the lines for off-median quantiles) (Hao and Naiman, 2007).

Figure 2: Conditional density of the outcome variables by treatment status



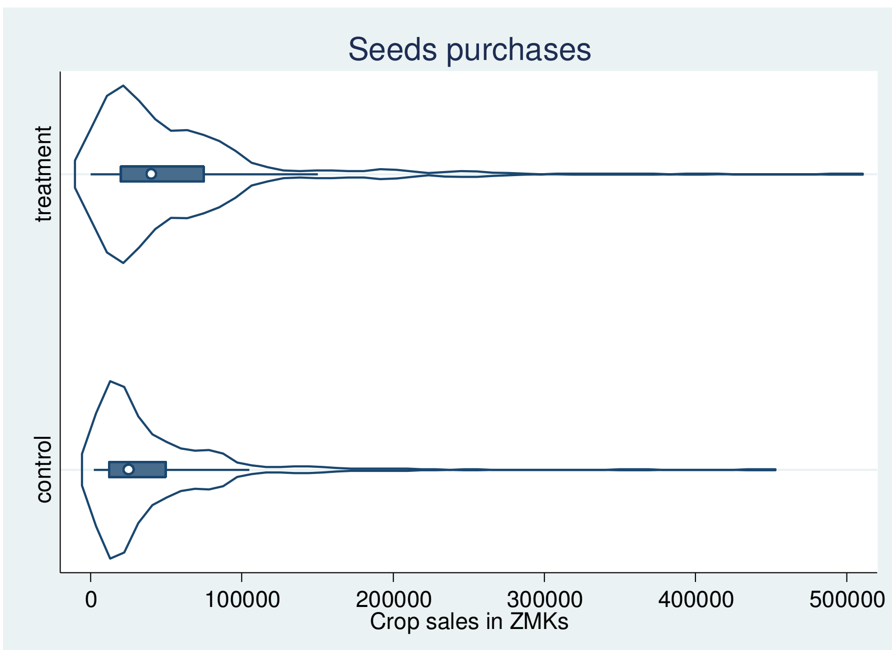


Figure 2 shows violin plots of the distribution of crop sales (upper panel) and seeds purchases (lower panel) by treatment status. Violin plots are usually used to illustrate how the central tendency and the shape of the conditional distribution of the outcome change as a result of treatment (Mishra et al., 2015). These graphs combine box plots and density traces in one diagram. The box plot identifies the center, the spread, asymmetry and outliers in the data, while the density shows the actual shape of the distribution. The conditional distributions of our outcome variables are highly skewed and asymmetrical which motivates the use of median regression to capture the effects of treatment on the central tendency of the distribution. The program induces an increase in the standard deviation of both distributions causing them to change shape and stretch out, although this pattern is more pronounced for crop sales. In fact, a Levene's test used to assess the null hypothesis of equal variances of our outcome variables in the two treatment arms returned p values close to 0. Against this background we resort to quantile regression to capture the heterogeneous effect of the treatment variable on different points of the outcome distribution.

Table 5 shows the estimates of the coefficient on the interaction term (*DT*) from equations (11d) and (15d) for the nine deciles of the outcome distribution. The aim here is to describe the effect of the program across the entire conditional distribution of crop sales and seeds expenditure. Estimation is restricted to the sample of market participants, namely, sellers and buyers, respectively. Both equations incorporate semiparametric correction for sample selection by including the first two terms of an orthogonal polynomial in the linear index $g_j = W'\Gamma_j$, *j*={*s*,*b*}.[3] These extra polynomial terms have a significant impact in both equations, hence confirming the importance of controlling for the selection of farmers into a market regime. The rest of the covariates in equations (11d) and (15d) are the same as those included in the corresponding mean-regression equations (11a) and (15a).[4]

Table 5: Quantile treatment effects for sellers and buyers

	Sellers		Buyers	
	Coefficient (β_s^q)	t-statistics	Coefficient(β_b^q)	t-statistics
$\beta_j^{0.1}$	25766	(1.981)**	2795	(0.945)
$\beta_j^{0.2}$	42874	(2.293)**	4660	(1.213)
$\beta_j^{0.3}$	37173	(1.550)	9377	(2.597)***
$\beta_j^{0.4}$	54940	(1.932)*	11650	(2.748)***
$\beta_j^{0.5}$	68498	(1.819)*	10418	(1.820)*
$\beta_j^{0.6}$	91556	(1.918)*	21636	(2.776)***
$\beta_j^{0.7}$	154000	(2.634)***	19692	(1.971)**
$\beta_j^{0.8}$	141000	(1.712)*	25231	(1.741)*
$\beta_j^{0.9}$	258000	(1.693)*	32160	(1.216)

Note: significance levels: * p < .1, ** p < .05, *** p < .01. Bootstrap t-statistics from 350 replications in brackets. *j*={*s*,*b*} and *q*={0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9}.

First of all we highlight the differences between the mean-regression approach and the quantile regression approach. The median treatment effect for sellers given by $\beta_s^{0.5}$ is considerably lower than the average treatment effect from the corresponding mean regression model. The reason for this finding is that the mean suffers from the undue influence of very high values from the right tail of the crop sales distribution. It is, indeed, clear that the average treatment impact is driven by the upper quantiles effect. In relative terms though, if we compare median treatment effect to

[3] To save on space we do not show estimates from the first step estimation in which the semiparametric estimator of Ichimaura (1993) is applied to recover the coefficients of the index $g_j = W'\Gamma_j$. The dependent variable, the independent variables and the exclusion restrictions are the same as those in probit estimation of the first step of the Heckman selection model, but estimation is semiparametric instead. Therefore, results are analogous to those of the participation equation of the standard Heckman model presented in the previous section.

[4] To save on space we only present coefficient estimates for the interaction term. The quantile effects for the rest of the covariates are available from the authors upon request.

the median of the crop sales distribution at baseline, the impact of the program amounts to a 52% increase in crop sales at the center of the distribution. Secondly, our results show that quantile treatment effects present an increasing pattern. The marginal effects on different quantiles are represented graphically in Figure 3 (left graph). QTEs at top quantiles are as large as ten times the QTEs at the bottom quantiles, although statistical precision of the estimates is low at top quantiles. An increasing trend in QTEs implies that the program benefitted more big farmers who were already selling large quantities of crop in the market with considerable distributional impacts. This is reflected in the strong stretching out of the crop sales distribution as we have previously illustrated in Figure 2.

The QTEs for seeds purchases are shown in the last couple of columns in Table 5. The median treatment impact ($\beta_b^{0.5}$=10418) is almost half the average treatment impact. In relative terms the program impact amounts to a 34.7% increase in seeds purchases at the center of the distribution. Similarly to the mean treatment impact, which was not statistically different from zero, the median impact is near the edge of statistical insignificance. The QTEs at the two tails of the seeds purchases distribution are not statistically different from zero. The bulk of the program impacts are concentrated at the off-median QTEs near the center of the seeds purchases distribution, in particular, at the 3rd and 4th deciles and at the 6th and 7th deciles. This results in limited distributional impacts of the program and in a much smaller alteration in the shape of the outcome distribution. This is clear from Figure 2 where the seeds purchases distribution for the treated has a slightly stretched out right tail.

Figure 3: Quantile treatment effects for sellers and buyers

6. Conclusions

To cash in on the potential benefits of commercialization, smallholder farmers need to engage in increased farm production and market exchanges. However, the barriers to market participation are often high, making it a huge challenge to participate in commercial agriculture. The most significant of these barriers are argued to be transaction costs. This paper focuses on the role of Unconditional Cash Transfer in helping smallholder overcome barriers to trade by mitigating transaction costs. We use data from a Randomized Controlled Trial collected for the evaluation of the Child Grant Program (CGP) - Zambia's flagship social protection cash transfer program. We employ a Heckman correction model that allows us to estimate the effects of the program on the propensity to engage in trade and on the traded quantities while correcting for the selectivity bias that may result from farmers' self-selection into a certain market regime.

We find that the program significantly contributes to pushing farmers out of autarky and to increase their market participation both as buyers in input markets and as sellers in output markets. Another interesting finding is that the program produced greater benefits for those household that leave further away from markets or that lack telecommunication technology, or in other terms for those that face more binding transaction costs from transportation of information gathering. This highlights the need for policy makers to combine social protection interventions with measures aimed at improving market infrastructure by designing markets that meet a community's needs, choosing a suitable site for a new market, guaranteeing adequate connections and the rapid dissemination of information on prices and other market factors. Finally, the quantile regression analysis indicates that while the effects for buyers are more uniformly spread along the expenditure distribution, the impacts for sellers are higher at top quantiles, causing a further widening apart of the revenues distribution.

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Appendix

Table A1: Characteristics of the sample at baseline by treatment status

	Controls	Treated	Diff
HH size	5.690	5.746	-0.124
	(2.087)	(2.100)	
Female headed HH	0.996	0.994	0.005
	(0.062)	(0.078)	
Age of HH head	-29.54	29.57	-0.349
	(9.081)	(9.128)	
Education of HH head	3.99	4.341	-0.318*
	(3.284)	(3.403)	
Dependency ratio	2.39	2.385	0.038
	(1.545)	(1.513)	
Number of TLU	0.363	0.593	-0.148
	(1.631)	(6.279)	
Operated land (ha)	0.479	0.522	-0.03
	(0.634)	(0.962)	
Time to main mkt.	4.266	3.954	-0.312***
	(149.19)	(129.75)	
Time to inp. mkt.	4.330	4.416	0.0862**
	(191.50)	(193.39)	
HH own motorcyc.	0.000873	0.00520	0.00433**
	(1.41)	(3.48)	
Price of maize	36799.1	25890.3	-10908.8***
	(24.31)	(95.77)	
Price of casava	10554.1	8558.9	-1995.2***
	(36.09)	(84.50)	
Price of rice	4097.2	3683.2	-414.1***
	(52.60)	(62.83)	
Price of beans	4740.6	4523.9	-216.7*
	(109.02)	(56.53)	
Price of maize seed	57956.9	23386.6	-34570.4***
	(8.71)	(25.32)	
HH owns TV	0.0166	0.0225	0.00596
	(4.39)	(5.16)	
HH owns radio	0.108	0.114	0.00619
	(11.79)	(12.20)	
HH owns cellphone	0.0865	0.0919	0.00547
		(10.80)	
Dist. of Kaputa	0.294	0.297	0.00316
	(21.84)	(22.09)	
Dist. of Kalabo	0.352	0.351	-0.000707
	(24.93)	(24.97)	
Dist. of Shangombo	0.354	0.351	-0.00245
	(25.02)	(24.97)	

Note: *** significant at 1%; ** significant a 5%, *significant at 10%.

Table A2: Descriptive statistics of the outcome variables at baseline by treatment status

	Controls	Treated	Diff
Crop sales	270961.7	334245.6	63284.0
	(11.21)	(5.16)	(0.98)
Share of sellers	0.239	0.198	-0.0416*
	(18.97)	(16.85)	(-2.41)
Seed purchases	40622.4	44103.7	3481.2
	(11.58)	(11.64)	(0.67)
Share of buyers	0.128	0.134	0.00605
	(12.98)	(13.38)	(0.43)

Note: *** significant at 1%; ** significant a 5%, *significant at 10%.