Agricultural Intensification and Market Participation under Learning Externality: Impact Evaluation on Small-scale Agriculture

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Abstract

This paper provides empirical evidence regarding the impact of agricultural technologies on smallholders' output market participation. The analysis is based on Farmer Innovation Fund impact evaluation survey collected by the World Bank in 2010-2012 covering 2,675 households in Ethiopia. Endogenous treatment effect and sample selection models are employed to account for the self-selection bias in technology adoption and market participation. Regressions based on matching techniques are employed for robustness check. The estimation results show that the use of improved agricultural inputs significantly affects farm households marketable surplus production. We found evidence that application of high-yielding varieties increases surplus crop production by 7.39 percent per year, whereas chemical fertilizer use increases surplus by 2.32 percent. When farmers apply the two inputs jointly, marketed surplus increases by 6 percent which establish the complementarity of the two technologies. Marketable surplus crop production and market participation of farmers are determined by access to modern inputs, crop price, farm size, availability of labor, and infrastructure. Access to credit and training fosters technology adoption, however, we are unable to witness learning externality from neighbors on smallholders marketed surplus. Therefore, agriculture and rural development policy need to focus on supporting agricultural technology adoption.

JEL Codes: D04, O12, Q13

Keywords: Surplus production, technologies, social network, endogenous treatment effect model, Ethiopia

1 Introduction

One importance of studying development economics is to understand how individuals are able to make transition out of poverty. Adoption of improved technologies may be viewed as a means of this transition since improved agricultural technologies is central to transformation of farming systems and a path out of poverty in developing countries (Besley and Case, 1993). It is considered that modern agricultural inputs enable resource poor smallholder farmers to produce marketable surplus and quality products. In developing countries, promoting farmers market participation is an important effort necessary to bring agricultural transformation (Braun et al., 1994). Improving the productivity, profitability, and sustainability of agriculture is the main pathway out of poverty for the rural farm households using agriculture for development (World Bank, 2008).

Producer's production technology choice might affect the productivity. Increased productivity gain is not an end by itself and the production should be linked to the market for driving profits. Increasing farmers' potential in productivity and marketable surplus requires substantial diffusion of modern agricultural technologies. Braun et al. (1994) argue that commercialization is the result of a simultaneous decision making behavior of farm households in production and marketing. Thus, commercializing subsistence agriculture is an essential pathway towards economic growth and development for developing countries (Pingali and Rosegrant, 1995). On the one hand, commercial transformation of subsistence agriculture is expected to result in positive impact on household food security and welfare (Pingali, 1997). On the other hand, improving rural farmers' access to improved technologies and productive assets might stimulate smallholders' market participation (Barrett, 2008).

Sub-Saharan African countries where agriculture is the predominant sector that supports the livelihood of the majority of the poor, increasing technology adoption such as new agricultural practices, high-yielding varieties, and the associated products such as crop insurance have the potential to contribute to economic growth and poverty reduction among the poor (Kelsey, 2011). According to Ravallion et al. (2007), many of the poor in SSA and South Asia are living in rural areas and they are farmers. Nearly 75 percent of those living in less than one dollar a day will remain rural until 2040. Thus, there is a direct link between poverty reduction and increasing the productivity of agriculture.

The pathway out of poverty trap of many SSA countries depends on growth and development of the agricultural sector. A more dynamic and inclusive agriculture is required to accomplish the Sustainable Development Goals (SDGs). Among others, one of the main objectives of the sustainable development goals is eradicating extreme poverty, hunger and investing in rural areas for inclusive and sustainable rural transformation. This is possible by increasing the productivity of agriculture through yield increasing technologies in order to sustain the food security of rural smallholder farmers. The Economic Commission for

Africa also reported that around 46 percent of the population in SSA lived in less than 1 dollar a day in 2003 which is slightly more than in 1980 and in 1990, the hunger and poverty reduction requires that the income of the poor people and source from which they derive their livelihoods should be enhanced (ECA, 2005). Thus, pro-poor income growth originating in agriculture development could reduce poverty (FAO, 2002).

The growth of the agricultural sector in SSA determines the economic growth by creating market opportunities for other sectors directly or indirectly (Asfaw et al., 2010). Since long time ago, agricultural economics studies indicated, development in agriculture is the most effective way out of poverty that agriculture is at the heart of the livelihoods of the poor, while constraints operating on agriculture especially in rural areas are challenging. In response to this, institutional and infrastructure development is necessary to ensure broad-based, low cost market access, and well-functioning input and output marketing. Farmers must have access to productive technologies and adequate private and public goods to participate in input and output marketing (Barrett, 2008). The key to expand marketing opportunities of developing countries is increasing agricultural production in international, regional, and domestic markets (World Bank, 2007). Agricultural production is closely related to marketing, market access, and market development, whereas poorly functioning markets, weak domestic demand, and lack of export possibilities are the major constraints for agricultural growth (Diao and Hazell, 2004).

A large body of literature indicates that agriculture in most SSA is subsistence and farmers face challenges to gain income from marketed surplus. One of the major challenges is the use of local varieties for crop production. For instance, for many decades, the export of agricultural product in Ethiopia has been dominated by a few commodities like coffee, oil-seeds, pulses, Khat, and livestock products (leather, live animals and meat). Largely, coffee accounts for about 65 percent of the foreign exchange earning (Rashid et al., 2011). However, the export from cereal crops is negligible. Exceptionally, *Tef*[1] production by most smallholder farmers' is for market and the country exports to other foreign countries. However, the weak agricultural commodity market stagnates the sector (World Bank, 2005). Diao and Hazell (2004) argue that due to the downward trends in world prices, the increased production of traditional export crops has not been translated into much growth in farm income. This is because many exporters from Asia and Latin American countries who have improved the quality of products met the increased demand of importing countries. Thus, Sub-Saharan Africa is the developing world region with the highest dependence on exports of traditional primary agricultural products (ECA, 2007). The low productive local varieties limit farmers market competitiveness (Asfaw et al., 2010).

Although in some African countries the potential gain from traditional crop

[1] *Tef* is a nutritious small-grained cereal.

exports are high, for instance, the export of cocoa from Cote d'Ivoire and Ghana, tobacco from Zimbabwe and Malawi, the region wide gains are small. According to Diao and Hazell (2004), even though African traditional export crops regained their ground and returned to their historic highs in terms of world market shares equivalent to annual growth rate of 6 percent, the per capita real agricultural income for all of Africa would grow only by 0.3 to 0.4 percent. The small income of traditional export crops might result in small share of the total agricultural GDP; hence it may have weak linkage to the rest of the domestic economy. Production side investment and increasing market development is the way to improve productivity and product quality that increases farmers' competitiveness in the domestic and international market.

Developing countries have started to promote the diversification of production and exports through improved technologies away from traditional commodities in order to accelerate economic growth, to create employment opportunities, and reduce poverty. For instance, in Ethiopia since the market oriented policy reform in 1990s, the government opened up for FDI into the agricultural sector. For example, the export from flower farm industry experienced a boom growing from 0.3 million US dollar in 2001 to 113 million US dollars in 2007 (Joosten, 2007). Gebreeyesus and Iizuka (2012) argue that the flower farm industry in Ethiopia is an extraordinarily fast and successful diversification into a non-traditional export product. Within less than a decade, the country ranks second in Africa for flower exports next to Kenya, and fifth in non-EU exporters to the EU market. The same experience of Zambia; the export of fresh vegetable and cut flowers grown on smallholder farm rose from 6 million US dollar in 1994 to more than 33 million US dollar in 2001 (Diao and Hazell, 2004). This accounts for around 40 percent of total agricultural export. Thus, market oriented agricultural production coupled with technological progress and improvements in institutional and infrastructure development results in great impact on economic development (Minten and Barrett, 2005).

Since the export gains from horticultural crops discussed above signify a progressive and remarkable result, replication to other commodities such as cereal crops requires appropriate technological investment. This is because those staple food crops are important for the growing population's food security and are the major source of income for smallholders. Besides, more than 70 percent of the rural population in Ethiopia produce cereal crops, however, lack of technological change and market imperfection have often locked smallholder farmers into subsistence production and contributed to stagnation of the sector (Shiferaw and Teklewold, 2007).

For instance, in the 2014 cropping season, from the total cropped area and production of grain crops, the share of cereal crops is around 78 percent and 86 percent, respectively (CSA, 2014). Statistical figures show that more than 96 percent of the total grain production is produced by peasant farmers, while commercial grain production takes only around 4 percent. However, even though the share of grain cropped area is less for cereals in commercial farms, the highest proportion of total grain production comes from cereals. The differences in improved input usage and farm management during the survey year between smallholder and commercial farmers shows some differences in crop yield level (CSA, 2014). The lack of knowledge and continuous use of low-yielding varieties coupled with agro-ecological condition of the areas could be the major cause for lower smallholders productivity. Thus, the low-yielding local varieties could limit farmers from market supply and stagnate the sector into subsistence that farmers may not even yield a ton per hectare.

For many years, the government of Ethiopia working with extension program diffuses agricultural technologies to improve smallholders' crop productivity and farmers income from surplus crop production. Paradoxically, recent study indicates that farmers' use of main agricultural inputs such as HYVs is less than 5 percent (Taffes et al., 2013; CSA, 2013). The low adoption rate and use can be partly explained by limited access to input credit (ATA, 2014). Thus, there are initiatives by governmental and non-governmental organizations among the rural households to participate in different associations such as agricultural cooperatives, farmer's group, savings and microcredit cooperative, other local groups. It is expected that farmers share and/or access information about new agricultural practices, and inputs and output price information. This suggests that learning from neighbor can play an important role in the adoption of new agricultural technologies. Either in a social or economic network, learning from others through rural social networks system increase adoption of new technologies and encourage farmers' participation in input and output marketing.

Studies also indicates that farmers can adopt new agricultural inputs from their neighborhoods (Conley and Udry, 2010; Bandiera and Rasul, 2006). Individuals may act like their neighbors in the adoption of new technologies, hence friends and neighbors are important sources of information for fertilizer adoption in rural India (Foster and Rosenzweig, 1995). This is because, new users of technology may learn its characteristics from each other. Such learning can influence farmers' decision in input choices and method of application. Conley and Udry (2010) also claim that farmers increase or decrease fertilize use when their neighbors, using more or less fertilizer than them make unexpectedly high profits from surplus crop production. Due to sequential information flow from one neighborhood to the next, social learning provides a natural explanation for the gradual diffusion of new technologies even in homogenous populations (Munshi, 2007). This learning can explain the wide variation in the response to external interventions across and otherwise within identical communities simply as a consequence of the randomness in information signals that the society received. Thus, learning does not takes place in isolation, rather it involves a range of actors and networks; both in the formal and informal ways (Gebreeyesus and Iizuka, 2012).

With this background, this paper provides empirical evidence on the implication of smallholder farmers improved agricultural technology adoption which in turn affects marketable surplus production in the presence of rural social networks. As many countries secure high prices by raising the quality of products, establishing grading system, and segregating different qualities for export, improvements in input usage, market access, and credit enable farmers to compete in the domestic and international markets. Therefore, analyzing the impact of HYVs and inorganic fertilizer on farmers' market participation is needed to guide the type of intervention needed to facilitate the commercial transformation of subsistence agriculture.

Using household level data from Farmer Innovation Fund (FIF) impact evaluation survey collected by the World Bank in Ethiopia in 2010-2012, the study evaluates the impact of improved technology adoption on smallholders' output market participation. The study also analyzes the effect of neighborhood in the adoption of agricultural technologies among rural farm households. Since technologies may not be randomly assigned, households endogenously self-select by themselves. The self-selection bias in technology adoption and market participation are captured by applying endogenous treatment effect model. Farmers use of high-yielding varieties and inorganic fertilizer is found to have a positive and significant effect on market surplus production. Potential factors that affect smallholders' technology adoption and market participation are access to modern inputs, cereal crops price, farm size, availability of labor and infrastructure. Access to credit and training fosters agricultural technology adoption.

The rest of the paper is organized as follows. Section 2 gives an overview of the cereal crop marketing system in Ethiopia. The relationship between technology adoption and market participate is discussed in section 3. Section 4 presents the theoretical framework and the empirical model. Section 5 describes the data source, and descriptive analysis of the data. The econometric results are discussed in section 6. Section 7 concludes with policy implications drawn from the results.

2 Overview of Cereal Crop Marketing in Ethiopia

Although agricultural production system in Ethiopia is small-scale, cereal crops are the most important food crops that the majority of the rural households produce for consumption and receive income by selling the produce. Usually, commercialization is discussed with respect to large scale farming systems and ignoring smallholders and poor farm households' participation. Pingali (1997) argued that markets allow households to increase their income by producing the highest returns to land and labor. This cash can be used to buy necessary household goods rather than be constrained to produce everything that the household needs. Considering the fact that small farmers produce only a little surplus, the earned income may not help them to overcome the poverty trap.

Since subsistence agriculture is not a viable option to ensure food security and household welfare, commercializing subsistence agriculture is one of the development strategies that Ethiopian government has adopted through Agricultural

Development-Led Industrialization (ADLI) policy. After the economic reform of the country in 1991, grain marketing has been liberalized, and restrictions on grain trade have been lifted. As a result, official pricing on grain trade have been eliminated in Ethiopia. However, according to Gebremedhin and Hoekstra (2007), smallholders are unable to benefit from the commercialization process due to low yielding crop varieties, poor rural infrastructure, high transaction cost, and inadequate services. Spielman (2008) also reported that it is an unfortunate fact that the poor and those in remote areas have so far gained little from commercializing subsistence agriculture. To ensure the benefit of rural smallholders from commercializing subsistence agriculture, government and other development agencies are confronted with the challenges of increasing participation in input and output markets or providing exit options for employment in other sectors (Gebremedhin et al., 2009).

Although public agricultural extension programs in terms of new technology awareness creation resulted in positive impact on rural farm households, output side investment is poorly functioning. Spielman (2008) also reported that education and training of producers and traders is sadly neglected in Ethiopia, and hence detailed studies of the training needs of various sectors of the grain marketing system are required. The marketing routes of cereal crops in Ethiopia range from local assemblers and traders to inter-regional grain traders and brokers. Due to free marketing system, traders are more or less setting the price when transactions are made. Besides, the high transaction costs force rural farm households to sell farm output in the village market at a lower price relative to price in the urban markets. Hence, farmers are unable to take advantage of a potentially high crop output price. To support rural farm households, central and local government authorities could help farmers to sell either to cooperative unions or other organization.

The increased demand for staple food crops is linked to investments in productivity enhancing technologies and measures to reduce marketing costs that have significant impact on poverty reduction and economic growth (Diao and Hazell, 2004). The operation of grain marketing system in Ethiopia needs investments on both production and marketing fronts. According to Gebremedhin and Hoekstra (2007), creating good marketing institutions is necessary to support sellers and buyers interactions. The functioning and structure of marketing system specially for staple food crops is mainly constrained by factors such as lack of grading and quality control system, inefficient market information delivery, lack of well coordinated supply chain, under developed infrastructure and high transaction costs (Shiferaw et al., 2008).

Production side investment such as agricultural input credit, rural education, training and improving storage facilities prolonging the credit repayment period until the seasonal crop prices rise might increase the benefit of smallholders from marketed surplus. Kelly et al. (2003) claim that most agricultural input credits are expected to be paid back at the time when farmers collect farm output. However, the bulk ration of cereals especially during harvesting time will make farmers lose from their marketed surplus. Besides, the high transaction costs may not offset the credit accessed. To this end, providing agricultural inputs credit and other support services will result in improved well-being of rural smallholders.

3 Interdependence Between Market and Technologies

Analyzing the relationship between market and technology is complex. Thus, this study looked at the relationship between market and technologies from farm households' perspective. It is assumed that a market is equally important as technology adoption, implying that farmers' market participation decision and technology adoption decision are mutually interdependent. It is expected that farm household input technology choices might affect their market participation. On the other hand, the returns from adoption of improved agricultural production technology choice can be influenced by the nature of the market. This implies that the increased productivity in the use of yield increasing technologies may imply facing significant price risk.

Markets also create networks between farmers, public, and private agencies in buying superior technologies and selling the produced farm outputs to expand their earning potential. Such market networks set a legal and institutional context for economic transactions, and provide a physical place for transactions. Farmers input choice may be linked to the physical and spatial dimensions of local markets, especially the extent to which households in rural areas have access to markets and a range of service providers. Hence, markets open the opportunity to farm households and other rural enterprises to trade or sell farm output. They can also buy improved inputs or tap into a range of public and private services such as extension and credit access. The more accessible the markets are, the greater the rural populations capability to remain economically self-sufficient and maintain food security. Similarly, greater are the options for diversifying production and marketing that results in improving the livelihood of the rural population.

4 Theoretical Framework

There is a large body of empirical literature that documented that agricultural technology adoption reduces poverty (Evenson and Westphal, 1995; De Janvry and Sadoulet, 2002; Trigo and Cap, 2004; Yu et al., 2011). Other studies indicate the benefit in terms of market surplus crop production (Pingali and Rosegrant, 1995; Pingali, 1997; Timmer, 1997; Diao and Hazell, 2004; Barrett, 2008). Since an investment in new technology is also an investment in learning about improved technologies, the introduction of such technologies are either by farmers own experimentation or through government intervention. It is also argued that the social networks facilitate the diffusion of new technologies (Evenson and Westphal, 1995). However, analyzing the impact of technology adoption on smallholders' market participation linking with rural social network system is challenging. This is because defining the set of neighbors from whom an individual can learn and the interdependence of technology preference to the neighbor may be subject to unrelated risk. Conley and Udry (2010) explained that distinguishing technology learning from other phenomena that may give rise to similar observed outcomes is problematic. This is because in the absence of learning farmers may act like their neighbors as a result of interdependence.

Empirical estimation of the impact of agricultural technology adoption on smallholders market participation linked to the rural social networks is rare due to limitation of data about information on interconnectedness (Conley and Udry, 2010). However, there is an enormous theoretical literature on social learning. Indeed, Bandiera and Rasul (2006) report social learning as a nonlinear process demonstrated in the adoption of sunflower in northern Mozambique. Munshi (2004) shows information flows related to new technology are weaker in a heterogeneous population. Using micro-level data, this study evaluates farmers' market participation and intensity of market participation in the technology adoption process to contribute to the empirical literature that links technology adoption and rural social networks. Bandiera and Rasul (2006) indicate that given the possible unavailability of direct data on information interconnectedness, assuming the observed relationship between households' like geographical proximity to the unobserved flow of information about new technologies is critical. Since our dataset is at villages level survey containing more information about rural farm households technology adoption behavior, it allows us to assess the neighborhood effect in the analysis. Bandiera and Rasul (2006) argue that farm households' are operating agricultural activities in a competitive inputs and output market, and it is reasonable to assume that there may have no social restrictions to access information from their neighbors.

Suppose a farmer's expected profit from adopting a new set of technologies is $\gamma x_{it} + \psi_{it}$, where $\psi_{it} = g(\psi_{it-1}, I_{t-1}, x_{it}) + \epsilon_{it}$. Where I_{t-1} is farmers' previous year experience about new agricultural technologies up to $t-1$ year. ψ_{it} is either farmers' perception about new technologies or their adoption behavior which may vary depending on household wealth, access to information from neighborhood, credit availability, training, rural education, and so on. Because of farmers' characteristics, x_{it} may vary at a time t , ψ_{it} may bias the parameter estimates of γ, but it gives us insights about farmers characteristics which are associated with ultimately accepting the new technologies. Although the dataset used for analysis is cross-sectional in nature (pooled data), the information on the adoption process allows us to look at the dynamic structure of farmers technology adoption by creating a discrete choice model of the sample households. Let $d_{it=1}$, if farmer i was adopting a new technology at time t, $t \in [1, ..., \tau]$ and zero otherwise.

Thus, a probit model can be

$prob\{d_{it=1}\} = \phi((\gamma_{xi} + \rho_T + \sigma[TXx_i])/\sigma_u)$

where T is a set of $\tau - 1$ year indicators and TXx_i are the interaction terms that allows the effect of farmers characteristics to change over the adoption process, and u_i is independently and normally distributed. From this, in terms of new agricultural input use and access to information from neighbors, it is expected that farmers adoption behavior could increase. Thus, due to knowledge externality, farmers' use of new inputs can be as a result of other farmers behavior or practices and these externalities affect others' decision with respect to farmers agricultural practices or adoption choices. Earlier the model of agricultural technology adoption and information externality using improved cotton cultivars was described by Besley and Case (1994). This model is redefined later by Foster and Rosenzweig (1995) on wheat and rice varieties adoption study in India. The model indicates that farmers increasing marketed surplus crop production depends on the application of improved agricultural inputs, and rural social networks increases farmers adoption behavior.

4.1 Empirical model

When evaluating the impact of agricultural technology adoption on farmers output market participation, taking into account the endogeneity of adoption and market participation decision is crucial. Technologies are not randomly assigned into households, farmers decide whether to adopt or not and the decision to participate or not to participate into output marketing may lead to the self-selection bias. The heterogenenity of households in terms of household wealth, institutional service, access to information and other related factors, both the observed and unobserved factors affects adoption and market participation decision, hence both adoption and market participation are potentially endogenous. The failure to account for this potential selection bias may result in inconsistent estimates of the impact of technology adoption (high-yielding varieties and inorganic fertilizer) on market participation.

Most empirical studies have used different econometric techniques to correct for the selection bias. The most commonly used analytical approaches in the literature include the sample selection model (Winter-Nelson and Temu, 2005; Balagtas et al., 2007; Alene et al., 2008) and switching regression model (Vance and Geoghegan, 2004; Bwalya et al., 2013). Moreover, households participation into output market which is the intensity of market participation may give rise to too many zeros. The traditional approach to evaluate data that yields a censored dependent variable has been to apply a Tobit model. In the Tobit model, all households including those censored zero values are included without considering the source of the zeros.

It can be assumed that all zeros that arise by non-participation decision of households could be due to socioeconomic, demographic, institutional, information access, and other related factors (Newman et al., 2003). The two level decision of households in technology adoption and how much is supplied to the market are taken to be the same in the Tobit model; however, the explaining variables may not be the same. To address the problem associated with the censored observations generated by households non-participation decision (Heckman, 1979), sample selection model is more appropriate than the Tobit model. Unlike the Tobit model, the sample selection model considers that the censored observations arise mainly from the respondents self-selection. This is because, the model assumes that the evaluation on the selected sub-sample which is the censored observation results in the sample selection bias. By undertaking a two-step estimation procedure, the sample selection model overcomes the censored regression problem.

Recently, Guo and Fraser (2014) indicated that since the development of the sample selection model econometricians have formulated many new models and estimators. One of the important developments in this direction is applying the sample selection model to estimation of treatment effects in non-experimental data. Exceptionally, in the case of treatment effect model, the selection equation of the dummy variable indicates the treatment condition that directly enters into the outcome regression. Thus, the outcome variable is observed in both cases of treated and untreated households. Following the recent empirical literature, endogenous treatment-effect model is employed to account for the self-selection bias of adoption and market participation decision. Regression based on sample selection model is measured to understand the factors that determine households which do not participate in the output market (zero values). Both endogenous treatment effect model and the sample selection model allow variables to vary more freely in the second stage than variables in the first stage. Assuming that market participation measured in volume of crop sold is a linear function of a vector of explanatory variables and a dummy adoption variable, a linear outcome regression equation can be specified as

$$Y_i = x_i\beta + t_i\delta + \epsilon_i \tag{1}$$

Selection equation

$$t_i^* = z_i\gamma + u_i \tag{2}$$

$$t_i = \begin{cases} 1 & \text{if } t_i^* > 0 \\ 0 & , otherwise \end{cases} \tag{3}$$

$$prob(t_i = 1|z_i) = \Phi(z_i\gamma) \tag{4}$$

And

$$prob(t_i = 0|z_i) = 1 - \Phi(z_i\gamma) \tag{5}$$

Where ϵ_i and u_i are bi-variate normal distribution with mean zero and co-variance matrix:

$$\begin{bmatrix} \sigma^2 & \rho\sigma \\ \\ \rho\sigma & 1 \end{bmatrix} \tag{6}$$

where, Y is the outcome variable (households participation into output market), x_i represent a vector of exogenous factors affecting market participation and intensity of participation, β, δ and γ are the parameters to be estimated, t_i^* is the latent technology adoption which is not observed, z_i is the observed factors that affect households high-yielding varieties and inorganic fertilizer adoption, t_i is the dummy variable that shows whether households adopt or not adopt high-yielding varieties and inorganic fertilizer, and ϵ_i and u_i are the random disturbance terms associated with technology adoption and market participation in the market that have mean zero and constant variance.

As the sample selection model, the treatment effect model is estimated in a two-step procedure using maximum likelihood estimator. Let $f(\epsilon, u)$ be the joint function of ϵ_i and u_i shown in equation (1) and (2). Thus, according to Maddala (1983), the joint density of Y and t is specified as

$$(y, t = 1) = \int_{-\infty}^{z\gamma} f(y - \delta - x\beta, u)du,$$

$$(y, t = 0) = \int_{z\gamma}^{\infty} f(y - x\beta, u)du$$

The likelihood function that maximizes the probability of the parameter estimate for household i is specified as

$$l_i = ln\Phi\left\{\frac{-z_i\gamma + (y_i - x_i\beta - \delta)\rho/\sigma}{\sqrt{1-\rho^2}}\right\} - \frac{1}{2}\left(\frac{y_i - x_i\beta - \delta}{\sigma}\right)^2 - ln(\sqrt{2\pi\sigma}) \tag{9}$$

$fort_i = 1, \; foradopters$

$$l_i = ln\Phi\left\{\frac{-z_i\gamma(y_i - x_i\beta)\rho/\sigma}{\sqrt{1-\rho^2}}\right\} - \frac{1}{2}\left(\frac{y_i - x_i\beta - \delta}{\sigma}\right)^2 - ln(\sqrt{2\pi\sigma}) \tag{10}$$

$fort_i = 0, \; fornon - adopters$

To understand whether farm households do not participate in output market (censored dependent) because of other factors that prohibit from market participation, sample selection model is applied by first estimating a probit in the first stage on whether they supplied the produce to the market or not. The inverse Mills' ratio was then generated and used in the second-stage to explain the volume of sale by crop sellers. The probit model is specified as

$$Prob(M_p = 1) = Prob(Q_s > 0) \tag{11}$$

$$= F(Z_m \alpha_m) + u_1, u_1 \sim N(0, 1) \tag{12}$$

where M_p takes the value of one if farmers supplied the produce crop during the survey year (2010 and 2012), Q_s is the total quantity supplied to the market measured in volume of output sold in the previous years, Z_m is the potential variables that are expected to affect market participation, α_m is the parameter to be estimated, u_1 is a random error term with zero mean and constant variance. Thus, a regression model of the intensity of participation is specified as

$$Q_s = X_m \beta_m + \gamma_m \lambda_m + u_2, u_2 \sim N(0, \sigma^2) \tag{13}$$

Where X_m is a vector of explanatory variables, β_m is the parameter to be estimated, and λ_m is the inverse Mills' ratio which is calculated as $\lambda_m = \phi(Z_m \alpha_m)/\Phi(Z_m \alpha_m)$ in order to account for the sample selection in the intensity of participation (of marketed surplus), ϕ and Φ are the probability density function and the cumulative distribution functions, respectively; γ_m is the associated parameter to be estimated, and u_2 is a random disturbance term with mean zero and constant variance, σ^2.

4.2 Robustness

Since Heckman (1976) brought the sample selection model into modern economics literature, empirical studies have used this method to address the selection bias that arises due to self-selection. Our result also shows that the correlation between the error terms in the main regression and selection equations is greater than zero (Table 3 and 4), indicating that the unobservables that improve the surplus crop production tend to occur with the unobservables that affect farmers technology adoption. Both the endogenous treatment effect and sample selection model address the endogenity of adoption and market participation. However, due to a liner functional form assumptions, the coefficients on the control variables are similar for adopters and non-adopters of technologies. Since the coefficients may vary, this assumption may not hold (Becerril and Abdulai, 2010). There is also a normally distributed error terms assumption between the outcome equation and adoption equation. To assess the consistence of the result against different assumptions and complement the above two models, regression based on matching techniques such as propensity score matching is implemented.

In impact evaluation like the impact of HYVs and inorganic fertilizer adoption on market surplus production, the important issue is the specification of the average treatment effect in a counterfactual framework (Rosenbaum and Rubin, 1983). The average treatment effect can be computed as

$$ATE = E(Y_1|D = 1) - E(Y_0|D = 1) \tag{14}$$

Equation (14) is based on the assumption that the marketed surplus that households produced before technology adoption $E(Y_0|D = 1)$ can reasonably be approximated by the market surplus that is produced by non-adopters $E(Y_0|D = 0)$. This is because we do not observe $E(Y_0|D = 1)$, we only observe $E(Y_1|D = 1)$ and $E(Y_0|D = 0)$. According to Rosenbaum and Rubin (1983), the propensity score, conditional probability of receiving treatment given the pre-treatment characteristics is specified as

$$P(X) \equiv Pr\{D = 1|X\} = E\{D|X\} \tag{15}$$

where $D = \{0, 1\}$ is indicator of households exposure into treatment and X is a vector of households characteristics before treatment. Estimating the treatment effect based on the propensity score needs two assumptions: The Conditional Independence Assumption (CIA) and Commune Support Condition (Becker and Ichino, 2002). The Propensity Score Matching (PSM) systematically estimates the counterfactuals for the unobserved values $E(Y_1|D = 0)$ and $E(Y_0|D = 1)$ to estimate impacts with the underlying assumption of ignorability treatment (Rosenbaum and Rubin, 1983). Due to the conditional independence assumption, once controlling for the observed characteristic, the treatment assignment is as good as randomization. In the case of common support condition, the average treatment effect for the treated is only defined within the region of common support. From this assumption, households having the same characteristics have a probability of being both treated and untreated (Heckman et al., 1998).

To match similar technology adopters and non-adopters group, the commonly used matching methods that are extensively used in the literature are: Nearest Neighbor Matching (NNM) and Kernel-Based Matching KBM). The NNM method matches each treated household with are non-treated households that have the closest propensity score. The NNM is usually applied with or without replacement. Kernel-based matching (KBM) uses a weighted average of all households in the non-treated group in order to construct a counterfactual. One of the main advantage of KBM is that it produces ATT estimates with lower variance due to utilizing more information.

Above all, the three models, endogenous treatment effect, sample selection and matching methods solve the selection bias of adoption and market participation decision. The sample selection model assumes selection is affected by unobservable, whereas both the selection model and matching technique assume selection is affected by observables. Hence, the matching methods address the selection on unobservables by imposing the distributional and a linear functional form assumptions and extrapolating over regions having no common support (see Table 6). This suggests that the selection bias may be reduced by avoiding the functional form assumptions and imposing a common support condition (Heckman et al., 1998; Smith and Todd, 2005).

5 Data and Descriptive Statistics

5.1 Data source

The analysis is based on household level data from Ethiopian Farmer Innovation Fund (FIF) impact evaluation survey conducted in 2010-2012 by the World Bank.[2] The survey covers 2,675 households drawn from two regions and fifty-one rural villages. The survey is a rich dataset which contains valuable information on several factors determining technology adoption including household specific characteristic, asset holding (farm and non-farm asset), institutional factors, indicators of infrastructure facility, and households participation into output market.

The survey also includes information on the rural social network system and membership of households in several rural associations. Including access to information, farmers have interviewed the kind of information they access and who are the source of information either extension agents or neighborhood farmers.[3] It is expected that farmers share information with other neighbor farmers on their farm practices. Farmers also interviewed the usefulness of the information they accessed and the number of persons they contacted. They also interviewed whether they participate in labor sharing activities with the neighbor farmers. Our dataset also includes information on farm households' participation in both formal and informal rural associations including farmers' organization and participation into a group meeting and/or training activities. Based on this data, we evaluate the impact of HYVs and inorganic fertilizer adoption on smallholder farmers' output market participation.[4]

[2]The Farmer Innovation Fund (FIF) is a component of the rural capacity building project conducted in two regions (Amhara and Tigray), Ethiopia. The main objective of FIF is improving rural households agricultural production system, marketing, and empowering women participation in extension services. The three rounds survey collect a Baseline data in 2010, Midline survey in 2012, and Endline survey in 2013. For this study, we used the Baseline and Midline data as the Endline survey is unavailable.

[3]Neighbors are farmers who practice agricultural activities in the nearby areas.

[4]Mainly the analysis focuses on major grain crops such as Wheat, Maize, Sorghum, Barley, and Tef. This is because the majority of farm households produce cereal crops in the study areas.

Table 1: Summary statistics of the full sample

Variables definition	Mean	Std.dev	Min	Max
Market participation (yes=1 if participate in output market)	0.33	0.47	0	1
Participation intensity (Quantity sold in kg)	342.4	957.8	0	30,000
Improved seed (yes=1 if farmers used)	0.46	0.49	0	1
Inorganic fertilizer (yes=1 if used)	0.80	0.39	0	1
HYVs and inorganic fertilizer (yes=1 if used both)	0.41	0.44	0	1
Age of household head (years)	44.2	12.2	18	107
Gender (yes=1 if the head is male)	0.82	0.38	0	1
Educational level of head1 (illiterate (0 yrs- reference))	76.8	0.42	0	0
Educational level of head2 (read and write (1-3))	9.8	0.29	0	1
Educational level of head3 (primary schooling (4-8))	10.0	0.30	0	1
Educational level of head4 (high school and above)	2.5	0.15	0	1
Household size (household members)	5.8	2.1	1	14
Farm size (in hectare)	1.3	4.2	0	90.45
Irrigation use (yes=1 if farmer use irrigation)	0.39	0.48	0	1
Labor use (number of working days per year)	332.6	213.9	21	1630
Credit access (yes=1 if access to credit)	0.70	0.45	0	1
Non-farm income (yes=1 if access to off-farm income)	0.51	0.49	0	1
Expenditure for inputs (amount of money spent for new inputs)	867.4	1007.4	0	11808
Farmers training (yes=1 if farmers participate)	0.63	0.48	0	1
Neighborhood information (yes=1 if farmers access information)	0.97	0.15	0	1
Number of persons contacted (average number of persons)	3.5	11.3	0	500
Membership of rural associations (yes=1 if member)	0.88	0.31	0	1
Market distance (distance to nearest market center (hours))	2.7	4.5	0	18
Mode of transport1 (animals- reference)	74.9	0.43	0	1
Mode of transport2 (walk)	0.16	0.37	0	1
Mode of transport3 (car)	0.084	0.27	0	1
Selling price (average selling price per unite (kg) sold in Birr)	821.1	1162.8	5.5	12.49
Regional dummy (yes=1 if Amhara region, 0 otherwise)	0.46	0.49	0	1

5.2 Descriptive statistics

Tables 1 and 2 present the summary and descriptive statistics of the sample households. The study sample households are 82 percent male and 77 percent are illiterate. Households using at least one improved HYVs among the five cereal crops are 46 percent, whereas inorganic fertilizer users are higher, 80 percent. When we look at farm households using the two technologies simultaneously, we found 41 percent of them. The percentage of our sample households' who participate in at least one crop output marketing is 33 percent. On average, smallholders who participate in the market sold 324 kg of crop output per year.

The mean age of household head is 44 years, indicating that farm households can therefore be describes as young and belong to economically active groups. This gives the opportunity that younger household heads are more dynamic with regard to adoption of agricultural innovations. The average size of the cultivated land is about 1.3 hectare. The households size is nearly 6 persons per household. This may ensure adequate supply of family labor for crop production and adoption of improved agricultural technologies.

With regard to adoption of HYVs and inorganic fertilizer, Table 2 provides some descriptive information on the key variables that determine rural households' agricultural technologies adoption and market participation. Adopters category in HYVs do not seem to significantly differ from non-adopters in terms of age (around 44 years), educational status, cultivated land (nearly 1.4 hectare), non-farm income activity, and use of irrigation technologies (39 percent). However, they are different on the rest of the variables in both HYVs and inorganic fertilizer adoption.

The descriptive statistics also indicate that the two group of households who adopted HYVs and inorganic fertilizer are different regarding access to credit, participation in farmers' training program, membership in rural associations, and spending for improved inputs (HYVs and inorganic fertilizer). The differences also appeared in information access from neighborhood and the average number of persons contacted in order to get information on modern agricultural input and output marketing. These differences are likely to cause differences in the adoption of the two technologies that can affect their market participation. Farmers are members in various rural associations,[5] it is expected that, they may share information about new agricultural inputs and output marketing.

By comparison, technology adopters earned higher from crop sale, 991 *Birr* compared to non-adopters (528 *Birr*). This indicates that HYVs and inorganic fertilizer use increase the crop quality which enable farmers benefit in terms of selling price. Adopters of HYVs and inorganic fertilizer spend around 1,335 *Birr* to purchase the two important inputs. The average market distance households travel to the nearest market place is around 3 hours. This may be a challenge for technology adopters to travel for long distance in order to sell farm output, hence farmers may be forced to sell in the near-by market at lower price. Market distance imposes a transaction cost to farm households and determines the volume of crops sold. This suggests that access to market is the key component in the adoption of yield increasing agricultural technologies. About 81.3 percent are using animal transport to carry farm output to the nearest market place, whereas vehicle users are only 6.7 percent, and the remaining 11.9 percent carry themselves (see Table 2). This indicates that poor infrastructure facility and limited access to vehicle may hinder farm households to invest marketable agricultural production. It is also a challenge to promote new agricultural technologies.

[5] Rural associations which the village farmers participate in are farmer's group, agricultural cooperative, savings and microcredit cooperative, and various informal local groups. Our data indicate that the group members have regular meeting in a weekly bases, in every two weeks, monthly, and some groups also meet once in every three months.

Table 2: Descriptive statistics

	HYV			Fertilizer			Multiple		
	Treated	Control		Treated	Control		Treated	Control	
	Mean (SD)	Mean (SD)	t/χ^2	Mean (SD)	Mean (SD)	t/χ^2	Mean (SD)	Mean (SD)	t/χ^2
Market participation	40.1	28.3	-7.5***	35.2	27.4	-4.0***	39.8	23.1	-7.1***
Participation intensity	154.3	78.0	-3.9***	117.1	97.1	-0.8	160.8	97.4	-1.7*
	(372.0)	(704.2)		(322.0)	(1121.4)		(386.7)	(1274.7)	
Improved seed	46.11								
Inorganic fertilizer				80.1					
Multiple adoption							41.0		
Age of head	44.4	44.8	0.9	45.0	43.0	-4.1***	44.4	42.6	-3.1***
	(12.0)	(12.3)		(11.8)	(13.1)		(11.7)	(12.7)	
Male	86.6	81.1	-4.4***	85.3	77.0	-5.4***	86.8	74.7	-6.6***
Female	13.4	18.8		14.7	22.9		13.1	25.2	
Educational level- illiterate	76.4	77.3		74.0	89.9		75.2	90.7	
Read and write (1-3)	11.0	8.9		11.1	4.7		11.3	3.4	
Primary school (4-8)	10.1	11.2	0.1	12.0	4.6	-7.6***	10.8	5.1	-6.0***
High school and above	2.5	2.5		2.9	0.7		2.6	0.7	
Household size	5.9	5.7	-2.2***	5.9	5.5	-5.2***	5.9	5.4	-5.3***
	(2.1)	(2.0)		(2.0)	(2.1)		(2.0)	(2.1)	
Farm size cultivated	1.4	1.3	-0.1	1.2	1.7	3.1	1.3***	1.8	2.1**
	(4.1)	(4.5)		(3.6)	(6.2)		(4.1)	(6.9)	
Irrigation use	38.8	39.6	0.5	41.4	30.6	-5.3***	38.7	27.9	-4.5***

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Table 2 – continued

Labor use	377.5	302.5	-10.3***	355.6	265.1	-9.9***	374.4	220.9	-14.5***
	(221.1)	(196.7)		(207.4)	(214.6)		(212.6)	(163.7)	
Credit access	79.5	60.2	-12.9***	84.1	8.7	-52.3***	86.9	7.5	-50.5***
Non-farm income access	52.2	50.9	-0.7	52.6	46.7	-2.6***	53.3	48.2	-1.9*
Expenditure for inputs	1210.3	574.1	-20.1***	1078.7	19.6	-28.1***	1334.9	0	-26.9***
	(1183.2)	(706.7)		(1020.9)	(86.8)		(1181.6)	(0)	
Farmers training	72.6	55.7	-10.1***	66.6	51.5	-6.9***	73.5	47.1	-10.5***
Neighborhood information	98.9	96.3	-4.6***	97.2	99.2	2.6***	98.8	98.9	0.1
Number of persons contact	4.2	3.1	-2.6***	3.7	3.2	-0.8	4.1	2.7	-1.8*
	(16.1)	(4.3)		(12.4)	(6.4)		(16.5)	(2.5)	
Membership of association	91.6	86.5	-4.5***	90.1	83.6	-4.4***	93.0	85.3	-4.8***
Market distance	3.0	2.5	-1.9*	3.1	1.2	-5.5***	3.2	1.1	-4.5***
	(5.1)	(3.9)		(4.8)	(2.5)		(5.2)	(2.1)	
Selling price	965.1	657.1	-4.6***	868.2	613.3	-2.8***	990.9	528.1	-4.1***
	(1253.8)	(1032.3)		(1182.3)	(1074.7)		(1229.7)	(797.8)	
Mode of transport1 (animal)	78.4	70.5		79.9	48.2		81.3	45.3	
Mode of transport2 (walk)	13.2	20.8		14.2	29.4		11.9	32.0	
Mode of transport3 (car)	8.3	8.6	-3.5***	5.8	22.3	-8.1***	6.7	22.6	-8.1***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Standard deviations in parentheses

Source: Author calculation using FIF data 2010 and 2012.

From the descriptive analysis above comparing the mean differences in terms of farmers market participation rate, the quantity supplied, human capita such as educational level, access to institutional service, and participation in rural association between HYVs and inorganic fertilizer adopters and non-adopters shows that adopters are better off than non-adopters in output market participation. However, comparing the mean differences between the two groups of households may not account for the effect of households specific characteristics, socioeconomic factors and other observed and unobserved factors. If not taken into account these factors may confound the impact of technology adoption on market surplus production with the influence of other characteristics. Hence, to evaluate the true impact of HYVs and inorganic fertilizer on households' quantity supplied of crop output to the market, endogenous treatment effect model is employed by accounting for the selection bias that arise from the fact that the two groups of households (adopter and non-adopter of improved technologies) may be systematically different. Regression based on sample selection model is also applied to understand the factors that determine farm households' decision not to participate in the markets by taking into account the endogenity of households decision into market participation.

6 Econometric Result

The estimation results presented in this section show the two main objectives of the paper. First, the analysis evaluates the impact of agricultural technology adoption on smallholders market surplus crop production and emphasizes the relationship between technology adoption and market participation. Second, the analysis identifies the main factors that determine market participation and sales volume. Goetz (1992) indicated that separating the decision of farmers whether or not to participate in the market from the decision of how much is supplied to the market is appropriate. We first estimate the endogenous treatment effect model specifically to assess the impact of HYVs and inorganic fertilizer on farmers' market surplus crop production. Then, sample selection model is applied to understand whether the decision of farmers not to participate in output market is because of other factors.

By taking into account the endognity of market participation decision, the sample selection model result shows that factors such as farm size, crop prices, labor use, mode of transport, livestock ownership, location and year dummy positively and significantly affect smallholders' market participation decision. The coefficient of credit is negative and significant in the case of multiple adoption. This may be because of the credit repayment period which is not to be immediately at the time when farmers collect their farm output which could enhance farmers' technology adoption and market participation. The transaction cost argument we discussed earlier also indicates smallholders' incurring high cost due to inappropriate services accessed.

6.1 Estimation of the treatment effects

The estimation result shows that improved agricultural technology adoption is positively and significantly correlated with smallholders' market surplus production. This is an encouraging result given the fact that farmers in Ethiopia are small-scale and they produce cereal crops on small land holdings. Hence, sustainable intensification of modern inputs is a good option to increase food production and smallholders' participation in output markets. As many empirical studies indicated, the effect of improved agricultural technologies such as HYVs and inorganic fertilizer are positively correlated with poverty reduction through marketable surplus production for the households income. Bezu et al. (2014) found that adoption of improved maize positively correlated with the per capita income for the poorer households in Malawi. The income from surplus crop sale enables the rural poor to spend on other consumption goods besides their own consumption. Other study by Becerril and Abdulai (2010) found in terms of per capita expenditure and poverty rate, adopters of HYVs are better off than non-adopters.

The empirical estimation result of the treatment effect model shows that use of high-yielding varieties increases marketable surplus production by 7.4 percent per year, whereas inorganic fertilizer use increases it by 2.3 percent. The multiple adoption of the two technologies jointly increase the surplus by 6 percent. This indicates that high-yielding varieties and inorganic fertilizer are complementary inputs that smallholders use to produce marketable surplus. The finding of Asfaw et al. (2011) also shows that the average treatment of improved chickpea adoption contributed to farmers' chickpea sold ranges from 16 to 20 percent. Similarly, Martey et al. (2012) in Ghana reported the extent of maize and Cassava sold by smallholders are 53 and 72 percent, respectively, whereas the total agricultural commercialization with respect to these two crops is 66 percent.

The endogenous treatment effect estimates of HYVs and inorganic fertilizer adoption are presented in Table 3. The estimates of the coefficients of correlation between the random errors in the adoption equation and outcome regression of surplus production is significant. This implies that the first-stage of the adoption regression model result and the second-stage outcome regression model results together show that both observed and unobserved factors influence the adoption decision and the performance of technologies given households technology adoption decision. The significance of the coefficient of correlation between the adoption equation and surplus production from technology adoption indicates self-selection occurred in HYVs and inorganic fertilizer adoption.

The result indicates that commercializing subsistence agriculture is based on supporting the intensification of marketable agricultural production in general, and cereal crop production in particular for both domestic and export market. This is evidenced by smallholders *Tef* production in Ethiopia. Because of high demand in the market, smallholders produce this crop almost for market and the production system is through intensification of purchased inputs such as improved seed and inorganic fertilizer. Besides, the increasing reputation of *Tef* as a "super grain" being gluten-free and other micronutrients such as calcium, iron, vitamin B and high in protein, a promising niche market is now developing the foreign countries such as in Europe and America. Currently, a Dutch website is also marketing *Tef* under a profit sharing contract with Ethiopian governmental authorities as "The grain that makes you stronger". This indicates that the development of agricultural market has contributed to the adoption of improved technologies such as new varieties (Keleman et al., 2009).

The development of infrastructure is also a major factor in explaining improved agricultural technology adoption and farm households market participation. Given the correlation and arbitrariness in the choice between different types of infrastructure, various studies have used different measures. Depending on the information we have in the data, we use how much hours rural farm households travel to the nearest market place to purchase improved inputs and to sell farm output, and how farmers transport farm output to the market. The result shows that the associated infrastructure facility such as access to vehicle positively contributed to farmers market participation and new agricultural input use. Access to credit and training resulted in positive impact for agricultural technology adoption. The positive effect of credit access and training programs indicates that farmers' accessing financial assistance enables them to invest in appropriate agricultural production technologies. Rural education and finance are the most important components for agricultural production and marketing in the rural farm family (Spielman, 2008).

Table 3: Endogenous treatment effect estimation result

	HYV		Fertilizer		Multiple	
Quantity sold	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Treatment indicators	7.392***	0.978	2.324*	1.217	6.013***	1.009
Age of head	0.007	0.024	-0.009	0.023	0.002	0.024
Gender of head	1.037	2.077	1.027	2.104	1.136	2.083
Household size	-0.124	0.140	-0.088	0.133	-0.094	0.135
Read and write (1-3)	-0.607	0.887	-0.413	0.841	-0.514	0.858
Primary schooling (4-8)	1.219	0.905	0.202	0.854	0.731	0.874
High school and above	0.668	1.577	0.408	1.496	0.536	1.526
Farm size	0.082	0.059	0.119**	0.056	0.085	0.058
Irrigation use	-0.054	0.895	-0.181	0.907	-0.131	0.894
Credit access	0.038	0.665	-0.078	0.825	-0.720	0.696
Non-farm income	-0.070	0.601	-0.374	0.606	-0.020	0.601
Labor use	0.232*	0.128	0.313***	0.129	0.251**	0.128
Farmers training	-1.553***	0.611	0.089	0.542	-1.056*	0.587
Neighborhood information	0.831	1.836	0.803	1.850	0.818	1.828
Number of persons contact	-0.022	0.015	-0.016	0.015	-0.016	0.015
Membership of associations	0.020	1.067	0.562	1.084	-0.064	1.076
Selling price	0.179***	0.023	0.200***	0.022	0.184***	0.023
Market distance	0.074	0.063	0.061	0.061	0.071	0.061

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Table 3 – continued

Mode of transport-walking	-0.882	0.799	-1.171	0.771	-0.793	0.778
Mode of transport-car	1.548	0.984	2.618***	0.956	2.360***	0.949
Livestock owned	0.415***	0.105	0.438***	0.106	0.409***	0.105
Region	1.348**	0.591	1.639***	0.607	1.374**	0.592
Year	2.262**	1.005	2.077**	1.025	2.177**	1.003
Constant	-4.682	3.326	-3.940	3.395	-3.454	3.296
Treatment indicators						
Expenditure for inputs	0.000***	0.000	0.003***	0.000	0.000***	0.000
Age of head	-0.007*	0.003	-0.000	0.009	-0.007*	0.004
Household size	0.022	0.022	-0.061	0.060	0.018	0.023
Read and write (1-3)	0.111	0.144	-0.004	0.359	0.103	0.150
Primary schooling (4-8)	-0.499***	0.140	0.133	0.420	-0.399***	0.144
High school and above	-0.122	0.250	1.006	0.798	-0.071	0.254
Farm size	0.009	0.014	-0.053	0.148	0.006	0.012
Credit access	0.074	0.097	1.983***	0.237	0.570***	0.105
Farmers training	0.595***	0.091	0.057	0.240	0.565***	0.096
Number of persons contact	0.009	0.007	-0.001	0.005	0.001	0.002
Selling price	0.006 *	0.003	-0.007	0.010	0.005	0.003
Market distance	-0.000	0.010	0.053	0.048	0.001	0.010
Mode of transport-walking	0.055	0.131	0.10564	0.284	0.062	0.139
Mode of transport-Car	0.523***	0.166	0.114	0.329	0.322*	0.172
Constant	-0.815 ***	0.232	-1.415***	0.530	-1.448***	0.253
athrho	-0.519	0.079	-0.090	0.200	-0.377	0.086

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lnsigma	2.104	0.029	2.049	0.022	2.071	0.026
rho	-0.477	0.061	-0.100	0.199	-0.360	0.075
sigma	8.202	0.240	7.766	0.174	7.933	0.209
lambda	-3.916	0.584	-0.699	1.548	-2.859	0.638
LR with endogenous treatment						
Log likelihood =	-3999.0155					
Number of obs	992		992		992	
Wald chi^2(23)	255.12		218.54		204.59	
Prob > chi^2	0.000		0.000		0.000	
LR test (rho=0):chi^2(1) =	21.35		0.16		12.31	

6.2 Determinants of market participation and sales volume

Farm households market participation and volume of crop sale are determined by access to improved inputs, farm size, output price, labor use, infrastructure facility, and livestock ownership. The land holding per household and availability of labor are the main factors of production that enable farm households to produce a surplus crop for market. Land holding measured in hectare is found to positively and significantly affect smallholders market participation. This suggests that in a scarce land access areas and high population pressure the hypothesis of induced innovation such as land use intensification policy of yield increasing agricultural inputs per unit of land enables farmers to produce marketable surplus. As an important input for agricultural activities, labor supply is positively correlated with adoption of improved technologies and market participation. This indicates that the competitive advantages of small farms have over large commercial farms would be using family labor to reduce the cost of production.

The price of agricultural product is expected to be positively related with adoption of yield increasing technologies. We found that adoption of HYVs and inorganic fertilizer are positively correlated with output price. The finding of Alene et al. (2008) also shows a one percent increase in maize prices increases the maize supply by 1.67 percent among maize sellers. Although prices for similar crops vary across villages and time, the output price we controlled is a farm-level price that farm households self reported. We found evidence that crop price significantly affects adoption of yield-increasing technology for market surplus production, indicating that marketable surplus increases with crop price. This suggests that a price elasticity of supply change with the adoption of modern agricultural technologies is of basic importance to income of smallholder. The benefit of farmers is that they sell farm output at a higher price than the cost of production given that farm income remains a major source of income for the rural households in Ethiopia. Higher market price or lower transaction cost encourage farmers participation into output market and create market linkage between different agents. Cadot et al. (2005) estimate the cost of entry into agricultural markets and found evidence that for farmers who sell farm output average agricultural profits are 30 percent higher than subsistence farmers in Madagascar.

Livestock is an asset and most researchers found it to be an economic variable that is highly correlated with adoption of agricultural technologies. Farmers use livestock for both crop production and transporting supply of farm output to the market. Due to the poor infrastructure facility such as road, accessibility of vehicles is lower. This is a challenge for rural farm households facing imperfect or incomplete markets for surplus production and market supply. Sadoulet and De Janvry (1995) argue that the main source of imperfect market that agrarian households face includes, costs incurring from poor infrastructure, long market distance, high marketing margin, and imperfect information. To this effect, their production and consumption decisions are no longer separable. Due to poor market coordination across time and space, farm households in rural areas are unable to take advantage of the spatial or temporal price arbitrage. Similarly, Gabre-Madhin (2001) reported that market infrastructure is severely limited in Ethiopia where, nearly half of the rural population does not have access to all-weather roads. Thus, around 72 percent of the grain production is retained for on-farm use and weak storage infrastructure results in larger storage loses and vulnerability of the grain to moisture and pests. This suggests that access to market plays an important role in intensifying crop production. Farmers with poor access to market have little or no incentive to adopt improved varieties (Alene and Manyong, 2007).

In order to account for the differences in crop production and market supply potential between the two study regions (Amhara and Tigray regions), regional dummy is included in our regression. The location dummy captures many area specific characteristics like population density, fertility and/or type of soil, rainfall availability and so on (Asfaw et al., 2011). Location dummy is positively and statistically significant, implying that the surplus production is higher in Amhara region than in Tigray region. This may be because of area under improved HYVs and inorganic fertilizer coupled with favorable weather conditions that facilitates positive growth rate of crop production in Amhara region than in Tigray region.

Table 4: Sample selection model estimation result

	HYV		Fertilizer		Multiple	
Market participation	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Age of household head	0.002	0.036	-0.019	0.028	-0.031	0.040
Gender of household head	0.931	2.721	1.222	2.399	1.453	2.962
Household size	-0.094	0.209	-0.078	0.154	0.005	0.220
Read and write (1-3)	-0.225	1.275	-0.594	0.924	-0.390	1.315
Primary schooling (4-8)	1.349	1.453	-0.088	0.946	0.827	1.471
High school and above	1.526	2.281	0.486	1.639	1.608	2.357
Farm size	0.065	0.073	0.121**	0.059	0.076	0.071
Irrigation use	0.620	1.263	0.218	1.005	1.381	1.353
Credit access	-0.265	1.082	-0.351	0.887	-2.358*	1.364
Non-farm income	-0.352	0.921	-0.389	0.710	-0.318	1.014
Labor use	0.219	0.180	0.376***	0.152	0.284	0.203
Farmers training	-1.661	1.056	0.127	0.628	-1.105	1.062
Neighborhood information access	2.215	3.007	0.465	2.019	1.798	3.077
Number of persons contact	-0.026	0.019	-0.019	0.016	-0.022	0.019
Membership of associations	-0.374	1.929	0.835	1.362	0.248	2.544
Selling price	0.160***	0.034	0.223***	0.025	0.207***	0.036
Market distance	0.087	0.088	0.056	0.065	0.061	0.090
Mode of transport- walking	-1.456	1.286	-1.409	0.942	-1.250	1.435

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Table 4 – continued

Mode of transport- Car	1.467	1.401	4.552***	1.231	4.633***	1.629
Livestock owned	0.471***	0.158	0.489***	0.123	0.465***	0.171
Region	1.195	0.907	1.630***	0.656	1.442	0.971
Year	3.212**	1.518	2.911***	1.177	5.109***	1.725
Constants	2.900	5.181	-2.518	3.801	1.315	5.590
Treatment indicators						
Expenditure for inputs	0.000***	0.000	0.003***	0.000	0.000***	0.000
Age of household head	-0.006*	0.003	-0.001	0.009	-0.007*	0.004
Household size	0.032	0.022	-0.068	0.059	0.021	0.023
Read and write (1-3)	0.135	0.144	0.019	0.359	0.133	0.149
Primary schooling (4-8)	-0.461***	0.140	0.147	0.420	-0.356***	0.144
High school and above	-0.114	0.252	0.951	0.778	-0.069	0.256
Farm size	0.009	0.013	-0.083	0.069	0.006	0.012
Credit access	0.104	0.097	1.983***	0.236	0.587***	0.104
Farmers training	0.588***	0.091	0.084	0.235	0.559***	0.095
Number of persons contact	0.013	0.008	-0.001	0.005	0.002	0.003
Selling price	0.008**	0.004	-0.006	0.010	0.007*	0.004
Market distance	-0.003	0.010	0.058	0.047	-0.000	0.010
Mode of transport- walking	0.066	0.131	0.121	0.285	0.096	0.138
Mode of transport- car	0.480***	0.162	0.123	0.319	0.305*	0.171
Constants	-1.000***	0.233	-1.375***	0.516	-1.571***	0.252
mills						
lambda	-6.10222	1.570	-0.727	1.802	-4.798	1.347

Continued on next page...

Table 4 – continued

rho	-0.638	-0.110	-0.514
sigma	9.551	8.177	9.334
Selection model- two-step			
Number of obs.	1015	1001	1018
Censored obs.	456	156	513
Uncensored obs.	559	845	505
Wald $chi^2(22)$	69.48	201.36	89.89
Prob > chi^2	0.000	0.000	0.000

The result of matching techniques shown in Table 5 below is consistent with the results found in the previous two methods. It shows that technology adoption positively affects the surplus crop production. The result of the Nearest Neighbor Matching (NNM) indicates that the average difference in the volume of crop output sold between similar pairs of farm households that belong to different technological status. With similar estimation technique as NNM, the Kernal Based Matching (KBM) shows the causal effects of the two technologies estimates appear to be similar to those of the NNM. This indicates that the matching methods estimation result supports the endogenous treatment effect and the sample selection model results. Thus, the causal effect of improved agricultural technology adoption on poverty reduction is greater by improving the rural households income through surplus crop sale. The result is consistent with previous poverty analysis measuring the differential impact of agricultural technology adoption on poverty reduction among rural households. Becerril and Abdulai (2010) found that adoption of improved maize reduces the probability of falling below poverty line roughly by between 19 to 31 percent in Mexico. Similarly, Mendola (2007) shows that adoption of HYVs has a positive and robust effect on household income and the way out of poverty in rural Bangladesh.

Table 5: Matching methods

Matching techniques	Outcome	ATET	ATEU	Difference	S.E.	T-stat
PSM	Quantity sold					
	HYV adoption	7.68	6.02	1.65	0.82	2.00
	Inorganic fertilizer	6.76	5.82	0.94	1.14	0.83
	Multiple adoption	7.99	4.96	3.02	0.59	5.04
NNM	Quantity sold					
	HYV adoption	7.68	5.71	1.97	0.69	2.85
	Inorganic fertilizer adoption	6.76	6.42	0.34	1.02	0.34
	Multiple adoption	7.99	5.60	2.39	0.69	3.46
KBM	Quantity sold					
	HYV adoption	7.68	5.81	1.86	0.59	3.15
	Inorganic fertilizer	6.76	5.22	1.53	1.03	1.49
	Multiple adoption	7.99	5.63	2.35	0.59	3.96

Table 6: Common support

	Psmatch2: Treatment assignment	Psmatch2 Common support On suppor	Total
HYV	Treated	559	559
	Untreated	433	433
Total			992
Chemical fertilize	Treated	845	845
	Untreated	147	147
Total			992
Multiple adoption	Treated	505	505
	Untreated	487	487
Total			992

7 Conclusion

This study evaluates smallholder farmers improved agricultural technology adoption and its impact on market surplus crop production in Ethiopia. Given the self-selectivity bias in the adoption of technologies, endogenous treatment effect model is used to account for endogenity of adoption and market participation. The empirical estimation result indicates that adoption of improved cereal crop varieties help farmers to produce market surplus crop production. Specifically, HYVs adoption is found to increase surplus production by 7.4 percent , whereas inorganic fertilizer use contributed for marketed surplus of 2.3 percent. When farmers implement the two technologies jointly, they increase the volume of sale by 6 percent. This indicates targeting intensification towards new agricultural technologies can have far reaching poverty reduction implication especially in rural areas where farming is the major source of income and food production. Developing mechanisms to expand rural farmers' access to HYVs and inorganic fertilizer is, therefore, a reasonable policy instrument to raise income of smallholders through market surplus production.

The findings show that improved technologies are the priority requirement for changing rural households agricultural production and market participation system, while elements of institution service such as access to the market, infrastructure development, efficient input distribution system, and appropriate economic incentives such as farmers taking advantage of output price must be present. Farmers' participation in farmer training centers plays a center role in modern agricultural inputs use and share knowledge with other farmers, indicating that training fosters agricultural technology adoption. Moreover, farmers' exchanging experience and information in the training centers facilitate the diffusion of agricultural technologies both formal and informal way when farmers communicate with other neighbor farmers. This shows that learning from others determines technology adoption and increase the diffusion of modern inputs. The result also shows that availability of labor positively contributed to technology adoption and surplus crop production, suggesting that labor intensive technology is appropriate like countries Ethiopia where there is surplus labor force. The overall finding indicates that the development of a more dynamic and competitive agricultural sector in Ethiopia requires appropriate rural institutions that respond effectively to the changing agricultural technology adoption and market conditions.

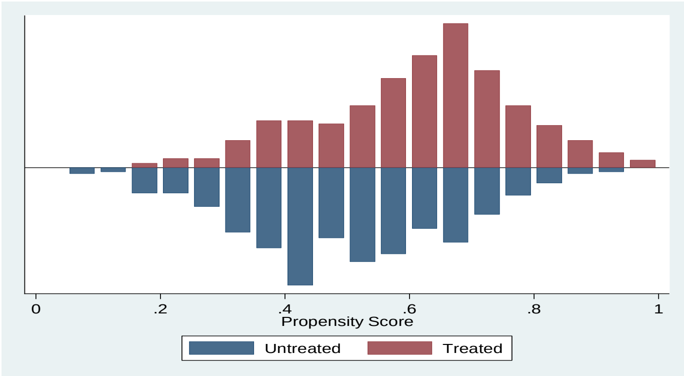
Policy interventions to improve smallholders' agricultural technology adoption and market participation include improving infrastructure, access to credit, rural education and training. Surplus crop production with the use of new agricultural technologies may also face price risk. Reducing the adverse effect of sunk cost and price risk through risk management schemes like support price, searching price through negotiation with private companies and farmers organization such as cooperative unions should be the government's strategy to encourage farmers' agricultural technology adoption and market participation. Farmers' organizations also allow producers to access market (input, output and capital markets), suggesting that farmers' organizations play an important role in helping rural smallholder farmers by providing the necessary services, that is where farmer organization comes in. Therefore, farmers' access to appropriate information on improved agricultural inputs and output marketing system play a crucial role in farm households technology adoption and market participation.

Appendix

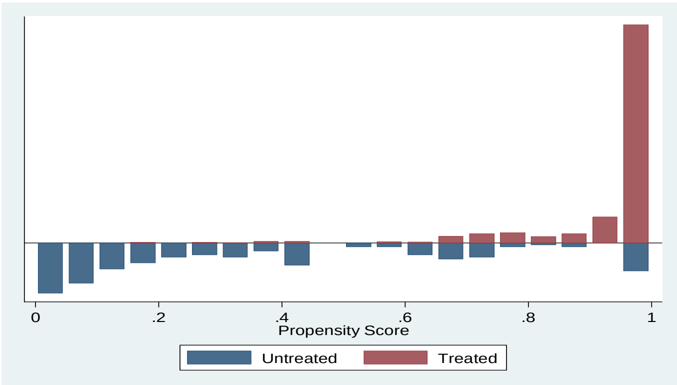
Table 7: Farmers adoption rate of the two technologies

HYV	Chemical fertilizer		
	Adopt	Not-adopt	Total
Adopt	1,536	170	1,706
Not-adopt	1,426	568	1,994
Total	2,962	738	3,700

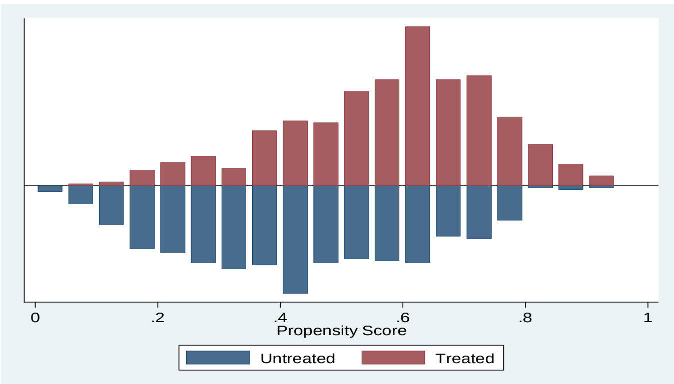
Figure 1: Distribution of propensity score



(a) HYV



(b) Chemical fertilizer



(c) Combined use

Source: Farmer Innovation Fund (FIF) impact evaluation survey 2010 and 2012

References

Alene, A. D. and V. Manyong (2007). The effects of education on agricultural productivity under traditional and improved technology in northern nigeria: an endogenous switching regression analysis. *Empirical economics 32*(1), 141–159.

Alene, A. D., V. Manyong, G. Omanya, H. Mignouna, M. Bokanga, and G. Odhiambo (2008). Smallholder market participation under transactions costs: Maize supply and fertilizer demand in kenya. *Food Policy 33*(4), 318–328.

Asfaw, S., B. Shiferaw, and F. Simtowe (2010). Does technology adoption promote commercialization? evidence from chickpea technologies in ethiopia. In *CSAE 2010 Conference on Economic Development in Africa, University of Oxford, UK*, pp. 21–23.

Asfaw, S., B. Shiferaw, F. Simtowe, and M. G. Haile (2011). Agricultural technology adoption, seed access constraints and commercialization in ethiopia. *Journal of Development and Agricultural Economics 3*(9), 436–477.

ATA (2014). The new agricultural input sales system. Technical report.

Balagtas, V., J. Y. Coulibaly, M. Jabbar, and A. Negassa (2007). Dairy market participation with endogenous livestock ownership: Evidence from côte d'ivoire. In *AAEC annual meeting, Portland, Oregon TN.*

Bandiera, O. and I. Rasul (2006). Social networks and technology adoption in northern mozambique*. *The Economic Journal 116*(514), 869–902.

Barrett, C. B. (2008). Smallholder market participation: Concepts and evidence from eastern and southern africa. *Food Policy 33*(4), 299–317.

Becerril, J. and A. Abdulai (2010). The impact of improved maize varieties on poverty in mexico: a propensity score-matching approach. *World Development 38*(7), 1024–1035.

Becker, S. O. and A. Ichino (2002). Estimation of average treatment effects based on propensity scores. *The stata journal 2*(4), 358–377.

Besley, T. and A. Case (1993). Modeling technology adoption in developing countries. *The American Economic Review*, 396–402.

Besley, T. and A. Case (1994). Diffusion as a learning process: Evidence from hyv cotton. Technical report.

Bezu, S., G. T. Kassie, B. Shiferaw, and J. Ricker-Gilbert (2014). Impact of improved maize adoption on welfare of farm households in malawi: a panel data analysis. *World Development 59*, 120–131.

Braun, J. v., E. Kennedy, et al. (1994). *Agricultural commercialization, economic development, and nutrition.* Johns Hopkins University Press.

Bwalya, R., J. Mugisha, and T. Hyuha (2013). Transaction costs and smallholder household access to maize markets in zambia. *Journal of Development and Agricultural Economics 5*(9), 328–336.

Cadot, O., L. Dutoit, and M. Olarreaga (2005). How costly is it for poor farmers to lift themselves out of subsistence?

Conley, T. G. and C. R. Udry (2010). Learning about a new technology: Pineapple in ghana. *The American Economic Review*, 35–69.

CSA (2013). Annual agricultural sample survey (online). Technical report.

CSA (2014). Annual agricultural sample survey (online). Technical report.

De Janvry, A. and E. Sadoulet (2002). World poverty and the role of agricultural technology: direct and indirect effects. *Journal of Development Studies 38*(4), 1–26.

Diao, X. and P. Hazell (2004). Exploring market opportunities for african smallholders. Technical report, International Food Policy Research Institute (IFPRI).

ECA (2005). *The poverty challenge in Africa: placing decent employment at the heart of the battle.* United Nation Economic Commission for Africa.

ECA (2007). Accelerating africa's development through diversification.

Evenson, R. E. and L. Westphal (1995). Technological change and technological strategy. *Handbook of development economics 3*(1), 2209–99.

FAO (2002). Reducing poverty and hunger: The critical role of financing for food, agriculture and rural development. In *International Conference on Financing for Development Monterrey, Mexico*, pp. 18–22.

Foster, A. D. and M. R. Rosenzweig (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of political Economy*, 1176–1209.

Gabre-Madhin, E. Z. (2001). *Market institutions, transaction costs, and social capital in the Ethiopian grain market*, Volume 124. Intl Food Policy Res Inst.

Gebreeyesus, M. and M. Iizuka (2012). Discovery of flower industry in ethiopia: Experimentation and coordination. *Journal of Globalization and Development 2*(2).

Gebremedhin, B. and D. Hoekstra (2007). Cereal marketing and household market participation in ethiopia: the case of teff, wheat and rice. In *AAAE Conference Proceedings (2007)*, pp. 243–252.

Gebremedhin, B., M. Jaleta, and D. Hoekstra (2009). Smallholders, institutional services, and commercial transformation in ethiopia. *Agricultural Economics 40*(s1), 773–787.

Goetz, S. J. (1992). A selectivity model of household food marketing behavior in sub-saharan africa. *American Journal of Agricultural Economics 74*(2), 444–452.

Guo, S. and M. W. Fraser (2014). *Propensity score analysis: Statistical methods and applications*, Volume 11. Sage Publications.

Heckman, J. J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. In *Annals of Economic and Social Measurement, Volume 5, number 4*, pp. 475–492. NBER.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, 153–161.

Heckman, J. J., H. Ichimura, and P. Todd (1998). Matching as an econometric evaluation estimator. *The Review of Economic Studies 65*(2), 261–294.

Joosten, F. (2007). Development strategy for the export-oriented horticulture in ethiopia. *Wageningen, Netherlands*, 52.

Keleman, A., J. Hellin, and M. Bellon (2009). Maize diversity, rural development policy, and farmers' practices: lessons from chiapas, mexico. *The Geographical Journal 175*(1), 52–70.

Kelly, V., A. A. Adesina, and A. Gordon (2003). Expanding access to agricultural inputs in africa: a review of recent market development experience. *Food Policy 28*(4), 379–404.

Kelsey, J. (2011). Market inefficiencies and the adoption of agricultural technologies in developing countries.

Maddala, G. S. (1983). *Limited-dependent and qualitative variables in econometrics.* Number 3. Cambridge university press.

Martey, E., R. M. Al-Hassan, and J. Kuwornu (2012). Commercialization of smallholder agriculture in ghana: A tobit regression analysis. *African Journal of Agricultural Research 7*(14), 2131–2141.

Mendola, M. (2007). Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural bangladesh. *Food policy 32*(3), 372–393.

Minten, B. and C. B. Barrett (2005). Agricultural technology, productivity, poverty and food security in madagascar. *Productivity, Poverty and Food Security in Madagascar (January 2005).*

Munshi, K. (2004). Social learning in a heterogeneous population: technology diffusion in the indian green revolution. *Journal of Development Economics 73*(1), 185–213.

Munshi, K. (2007). Information networks in dynamic agrarian economies. *Handbook of development economics 4*, 3085–3113.

Newman, C., M. Henchion, and A. Matthews (2003). A double-hurdle model of irish household expenditure on prepared meals. *Applied Economics 35*(9), 1053–1061.

Pingali, P. L. (1997). From subsistence to commercial production systems: The transformation of asian agriculture. *American Journal of Agricultural Economics*, 628–634.

Pingali, P. L. and M. W. Rosegrant (1995). Agricultural commercialization and diversification: processes and policies. *Food policy 20*(3), 171–185.

Rashid, S., A. Negassa, et al. (2011). Policies and performance of ethiopian cereal markets. *Ethiopia Strategy Support Program 2*.

Ravallion, M., S. Chen, and P. Sangraula (2007). New evidence on the urbanization of global poverty. *Population and Development Review 33*(4), 667–701.

Rosenbaum, P. R. and D. B. Rubin (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika 70*(1), 41–55.

Sadoulet, E. and A. De Janvry (1995). *Quantitative development policy analysis*. Johns Hopkins University Press Baltimore.

Shiferaw, B. and H. Teklewold (2007). Structure functioning of chickpea markets: evidence based on analysis of value chains linking smallholders and markets. Technical report, Working Paper 6, International Livestock Research Institute (ILRI), Nairobi, Kenya.

Shiferaw, B. A., T. A. Kebede, and L. You (2008). Technology adoption under seed access constraints and the economic impacts of improved pigeonpea varieties in tanzania. *Agricultural Economics 39*(3), 309–323.

Smith, J. A. and P. E. Todd (2005). Does matching overcome lalonde's critique of nonexperimental estimators? *Journal of econometrics 125*(1), 305–353.

Spielman, D. (2008). Encouraging economic growth in ethiopia: Perspectives on agricultural input markets, agricultural extension and advisory services, and agricultural education and training. *Briefing note. Washington, DC: International Food Policy Research Institute*.

Taffes, A. S., P. Dorosh, and S. A. GEMESSA (2013). 3 crop production in ethiopia: Regional patterns and trends. *Food and agriculture in Ethiopia: Progress and policy challenges 74*, 53.

Timmer, C. P. (1997). Farmers and markets: The political economy of new paradigms. *American Journal of Agricultural Economics*, 621–627.

Trigo, E. J. and E. J. Cap (2004). The impact of the introduction of transgenic crops in argentinean agriculture.

Vance, C. and J. Geoghegan (2004). Modeling the determinants of semi-subsistent and commercial land uses in an agricultural frontier of southern mexico: a switching regression approach. *International Regional Science Review 27*(3), 326–347.

Winter-Nelson, A. and A. Temu (2005). Impacts of prices and transactions costs on input usage in a liberalizing economy: evidence from tanzanian coffee growers. *Agricultural Economics 33*(3), 243–253.

World Bank (2005). *Well-being and poverty in Ethiopia: The role of agriculture and agency.* World Bank.

World Bank (2007). *World development report 2008: Agriculture for development.* WorldBank.

World Bank (2008). World development report 2008: Agriculture for development. Technical report, WorldBank.

Yu, B., A. Nin-Pratt, J. Funes, and S. A. Gemessa (2011). Cereal production and technology adoption in ethiopia. *Ethiopia Strategy Support Program II (ESSP II), ESSP II Working Paper 31.*