

SUBMITTED ARTICLE

Complementary technology adoption and smallholder commercialization: Panel data evidence from Ethiopia

Martin Paul Tabe-Ojong Jr.^{1,2} | Abebayehu Girma Geffersa³

¹World Bank Group, Washington, DC, USA

²Disaster Management Training and Education Centre (DiMTEC), University of the Free State, Bloemfontein, South Africa

³CSIRO Agriculture and Food, Canberra, Australian Capital Territory, Australia

Correspondence

Martin Paul Tabe-Ojong Jr., Disaster Management Training and Education Centre (DiMTEC), University of the Free State, Bloemfontein, South Africa.

Email: tabeojongmartinpaul@gmail.com

Editor in charge: Alessandro Bonanno

Abstract

Agricultural transformation involves the transition from subsistence agriculture marked by cultivating crops for auto-consumption to cultivating crops for output markets. This transition from subsistence agriculture to market-oriented agriculture can be a key policy boost to economic development, but evidence on the key entry points to increasing smallholder commercialization remains scarce. We examine the relationship between the adoption of improved maize varieties (IMVs), inorganic fertilizers, and smallholder commercialization. We model commercialization as a two-step decision process involving market participation and the extent of participation (sales quantity) conditional on participation. Given these two related steps, we estimate a double-hurdle model in both linear and non-linear forms. Employing a three-wave panel dataset from Ethiopia, we use the household fixed effects and correlated random effects model with the control function approach. We find the adoption of IMVs to be significantly associated with both market participation

This is an open access article under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2024 The Authors. *Applied Economic Perspectives and Policy* published by Wiley Periodicals LLC on behalf of Agricultural & Applied Economics Association.

and the extent of participation. This relationship is also true for fertilizers, where we show a positive association between fertilizer use and commercialization. Given the seeming complementarity in the use of both IMVs and fertilizers, we further estimate their joint adoption. We use the multinomial endogenous switching regression model where we show greater commercialization gains under joint adoption. These findings are in line with a growing literature supporting the bundling of agricultural technologies. Given these insights, we provide empirical and policy support to the scaling of agricultural technologies as they have the potential to induce agricultural transformation by unlocking market opportunities.

KEYWORDS

adoption, inorganic fertilizers; commercialization; Ethiopia; improved maize varieties; market participation

JEL CLASSIFICATION

O12, Q13, Q16

In the face of global development challenges such as poverty, food insecurity, and growing inequality especially in lower and middle-income countries, agricultural transformation can be a key policy instrument to boost economic development (Carletto et al., 2017; Fan, 2020). Agricultural transformation occurs following the transition and evolution of subsistence farming marked by the cultivation of crops (cereals) for auto-consumption to cultivating crops for sale. At the early stages of agricultural transformation, increasing productivity and production of marketable surplus of staple food crops is instrumental for agricultural commercialization as it links farmers with output markets (Pingali & Rosegrant, 1995). Recognizing this, promoting the intensive production of staple crops, and improving smallholders' access to markets have been leveraged as rural development strategies in many developing countries over the past three decades (Ariga et al., 2019). However, smallholders in Africa are often unable to exploit the potential gains from commercialization mainly due to a lack of enabling institutional environment and supply-side constraints such as high transaction costs limiting access to productivity-enhancing modern farm inputs needed to generate a marketable surplus (Barrett, 2008; Akter et al., 2021; Chavas & Nauges, 2020; de Oca et al., 2020; Norton & Alwang, 2020; Tabe-Ojong, Hauser, & Mausch, 2022).

Thus far, commercialization has been shown to improve smallholder welfare (Gefferesa & Tabe-Ojong, 2024; Muriithi & Matz, 2015; Ochieng et al., 2020; von Braun, 1995) and reduce income and multidimensional poverty (Ogotu & Qaim, 2019). Relatedly, commercialization has also been shown to address issues of rural wealth and prosperity by increasing asset ownership and livestock accumulation (Cazzuffi et al., 2020; Tabe-Ojong, Hauser, & Mausch, 2022).



Besides these livelihood and welfare implications of smallholder commercialization, contrasting food security, dietary quality, and nutritional benefits have been established. While Ogutu et al. (2020) found commercialization¹ to increase food security and dietary quality, specifically calorie and micronutrient consumption, van Asselt and Useche (2022) rather found commercialization to lead to overweight and obesity with decreasing autonomy over female plot management. Earlier insights from some cross-country analysis found little or no relationship between commercialization and nutrition (Carletto et al., 2017). Overall, the relationship between commercialization and nutrition seems inconclusive, heterogeneous and driven by many contextual realities (Haji, 2022). However, more evidence points to its immense nutritional gains for farm families.

Given these large welfare and livelihood gains, smallholder commercialization could be a crucial entry and leveraging point for development and agricultural policy to tackle aspects of poverty, food security and rural inequality. However, it is not completely clear what could significantly drive commercialization. With insights from the non-separable agricultural household model where the production and consumption decisions of households are assumed to be non-separable, the use of targeted yield-enhancing agricultural inputs such as improved seeds and fertilizers that increase production could be one way of increasing smallholder commercialization. In this regard, we examine the relationship between the adoption of improved maize varieties (IMVs), fertilizers and commercialization among smallholder farmers. We begin by estimating the relationship between the adoption of the two inputs (IMVs and fertilizers) and commercialization independently. We then consider the complementary use of both inputs and estimate its relationship with commercialization. Our analysis relies on a three-wave panel dataset from maize farmers in three major maize-producing regions in Ethiopia. We exploit the panel nature of the dataset to estimate the Mundlak Chamberlain device (correlated random effect model) to control for unobserved heterogeneity. We also use the control function approach to account for some potential endogeneity concerns. We use the average adoption rates of IMVs and fertilizers at the community level as instrumental variables in the control function.

We conceptualize and examine smallholder commercialization as a two-step process where we estimate (1) the decision to participate in the market, and (2) the quantity of output that is sold to the market conditional on participating. We thus use the Cragg's double-hurdle model to jointly estimate these relationships exploring both non-linear and linear specifications to reduce identification by functional form. We find the adoption of IMVs to be positively associated with both the decision to participate in markets and the quantity of output sold conditional on participation. This is also the case for the use of fertilizers where we obtain a positive association with commercialization. Considering the complementary use of both IMVs and fertilizers, we estimate the relationship between the joint adoption of both technologies and commercialization. Here, we estimate a multinomial endogenous switching regression model to capture this potential interdependency. We again find a positive relationship although with larger magnitudes, suggesting that the bundled use of both IMVs and fertilizers could offer higher commercialization gains.

Our analysis adds to the body of existing literature on agricultural transformation in a couple of ways. First, we offer supporting and novel insights to the use of improved seeds and fertilizers in driving commercialization. While the extant literature on the link between the adoption of improved seeds and commercialization is growing, the relationship between the adoption of fertilizers and commercialization is not well established though it is intuitive to assume a positive relationship. This may however not be direct as increasing farm production cost may hurt commercialization. Existing literature has mostly established a positive association between the

adoption of improved agricultural technologies and smallholder commercialization (Aker et al., 2021; Awotide et al., 2016; Singbo et al., 2021; Smale et al., 2018; Tabe-Ojong, Mausch, et al., 2022; Tabe-Ojong, Smale, et al., 2022). To our knowledge, only Tesfay (2020) has examined the relationship between the adoption of fertilizers and commercialization despite the high returns from fertilizer adoption (Duflo et al., 2008).

Our second contribution comes from examining the complementary relationship between the use of IMVs and fertilizers and how this relates to commercialization. The use of improved crop varieties and fertilizers can increase commercialization either independently or jointly, in which case the latter may be more impactful. The bundled use of agricultural inputs has been argued to lead to greater yields and welfare improvements (Khonje et al., 2018). This is even more the case for IMVs and fertilizers as maize is one crop that requires the use of fertilizers for both vegetative and crop maturation and growth. The complementary use of maize seeds and fertilizers have been particularly shown to increase yields and consumption expenditure in Ethiopia (Ahmed, 2022). Our analysis supports and corroborates the joint use of IMVs and fertilizers since it offers greater commercialization gains for farm households.

The third contribution is using panel data to improve learning on the relationship between IMVs, fertilizers and commercialization. Most of the existing analyses with the exception of Tabe-Ojong, Mausch, et al., 2022 have mostly relied on one-period cross-sectional datasets. While this is not much of a problem given that multi-period data are not easy to obtain, it potentially limits learning about the relationship between technology adoption and commercialization which is a dynamic process that may at best be understood under different periods. Further exacerbating the constraining issue of single-period data may be the aspect of context as the learning so far is limited to production systems in different contexts. While it is in principle possible to generalize based on the similarity in production systems in many developing countries, it may be more beneficial to have new evidence from different production environments to improve on the external validity of previous studies. This has the potential to improve learning on the relationship between technology adoption and smallholder commercialization. Finally, our focus on maize is unique as it is a staple which is heavily consumed in many countries and relevant for food security. Given that we observe that maize farmers are commercializing beyond just consuming, we offer some insights on agricultural transformation which seems to be inclusive.

The rest of this article is structured as follows: the [Overview of Maize Production and Input Use in Ethiopia](#) section offers a brief background of maize production in Ethiopia and the role of IMVs and fertilizers. The [Conceptualization and Analytical Approach](#) section dives into the analytical technique where we first establish a conceptual link between technology adoption and commercialization and later describe the empirical model and strategy that we use to establish the relationship between IMVs, fertilizers and commercialization. While the [Data and Variables](#) section describes the farm household survey and data as well as some descriptive statistics, the [Results and Discussion](#) section presents and discusses the empirical results. The article ends with the [Conclusion and Policy Implications](#) section.

OVERVIEW OF MAIZE PRODUCTION AND INPUT USE IN ETHIOPIA

Ethiopia is the second most populous nation in Africa with about 117 million people (World Bank, 2021). Agriculture is the dominant sector and mainstay of Ethiopia's economy,



contributing about 35% of the country's GDP and over 70% of employment opportunities (World Bank, 2021). Maize is predominately a subsistence food crop in Ethiopia, and household food security is mainly defined in terms of access to maize and other important staples, as in most SSA countries. The country's maize production includes subsistence farmers, smallholder commercial farmers, large-scale commercial farmers, and a few state-owned and private commercial farms. Subsistence farmers are the major maize producers in the country with landholding considerably varying from less than 0.5 ha to over 10 ha (CSA, 2019). According to the CSA estimates, there were 15.6 million agricultural households with an average farm size of 0.95 ha in 2015 (CSA, 2016).

Despite the immense potential of the country's agricultural sector, the huge gap between food production and consumption continues to widen in Ethiopia. Although food production has increased over the years, it is not keeping pace with the country's burgeoning population, leading to its growing reliance on foreign food aid. In recent years, population pressure has also caused a rapid decline in farm sizes, exacerbating the food crisis in Ethiopia. In response, the Ethiopian government has embarked on an agricultural transformation policy since the mid-2000s, prioritizing intensive farming of major food crops, such as maize (Abate et al., 2015; Geffersa, 2023). In 2005, the Government set a 5-year Plan for Accelerated and Sustained Development to End Poverty (Ministry of Finance and Economic Development [MoFED], 2006). More recently, the government has implemented agricultural development policies consistent with the country's five-year Growth and Transformation Plans (GTP-I and GTP-II—implemented in 2011 and 2015, respectively). Such policy initiatives give importance to improving the productivity of major food crops, such as cereals, through the provision of extension services to boost the dissemination of fertilizer and improved seeds.

Given the growing importance of maize in household food consumption, and for achieving food security, the national policy initiatives so far emphasized enhancing maize productivity through improved access to modern inputs. To boost access to modern inputs to smallholder farmers, the government of Ethiopia has substantially increased the extension agent-to-farmer ratio (1:476), which is substantial compared to 1:1000, 1:1603 and 1:2500 for Kenya, Malawi, and Tanzania, respectively (Abate et al., 2015). As a result, over 60 IMVs have been released by the national system during the past two decades (Abate et al., 2015). Consequently, in recent years, maize has emerged as a leading crop in Ethiopia, in terms of the scale and volume of production (Figure 1), utilization of modern inputs and the number of farmers producing it (CSA, 2016, 2019). Compared to other major cereals produced in Ethiopia, maize has the largest share in the country's crop production (CSA, 2016, 2019, 2021). For example, in the 2020/2021 cropping-season, maize accounted for an estimated 45.65% of the total cropland area and 54.91% of the volume of crop production (CSA, 2021). Over the past two decades, the average area allocation for maize production is large, compared with the area allocation for all other major cereals (CSA, 2016, 2019). Further, maize has recently emerged as the single most important food crop in Ethiopia, in terms of the number of farmers engaged in cultivation. In the 2014/2015 cropping season, for example, about 10% of the country's population produced maize that accounted for 95% of the national maize production (World Bank, 2019).

Regarding input use, maize farmers receive higher modern agricultural inputs, such as fertilizers and improved seeds when compared to other cereals in Ethiopia. Recent estimates indicate that Ethiopia is among six SSA countries with fertilizer application rates higher than the SSA average (Ariga et al., 2019; Sheahan & Barrett, 2017). According to the recent national agricultural sample surveys (CSA, 2018, 2019, 2021), of the total area under fertilizer application,

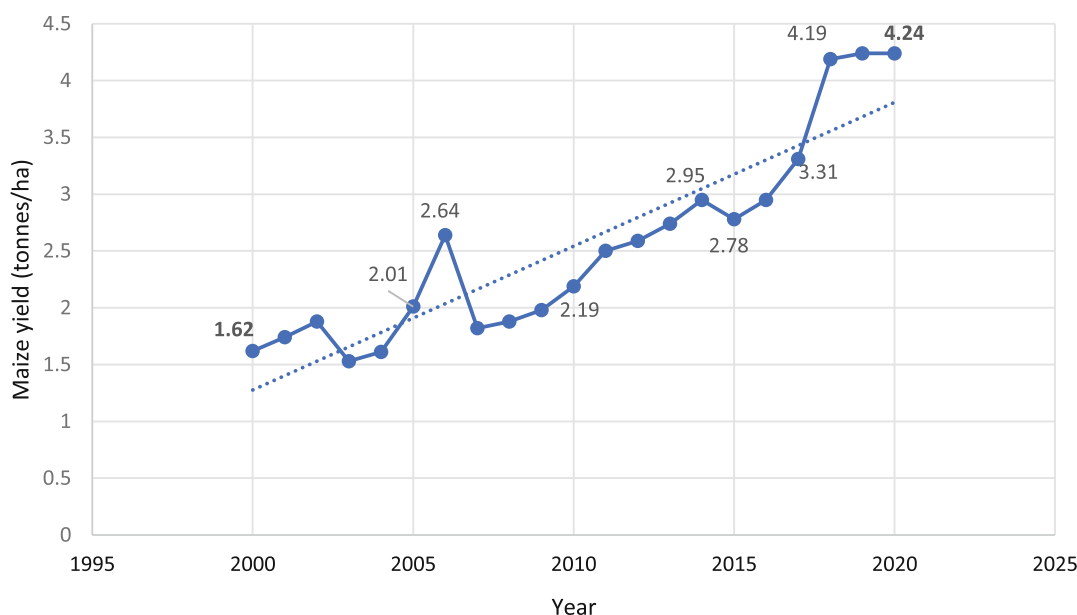


FIGURE 1 Annual maize yield in Ethiopia (2000–2020). The data in this figure represent the national maize yield based on FAOSTAT, encompassing maize harvests from all types of farms, including smallholder, large-scale commercial, and a few state-owned and private commercial farms. *Source:* Authors' construction based on FAOSTAT (2022).

the highest rates have been reported for maize production compared to other cereals (Figure 2). For example, in 2020/2021 cropping season, a total of 2,345,435 quintals of chemical fertilizer was applied on 1,195,442 hectares of crop production (CSA, 2021). Of this, the second highest crop area (412,146 hectares [22.19%]) was reported for maize next to potatoes (CSA, 2021).

The large proportion of maize area combined with its high per hectare yield resulting from increased use of modern inputs has made maize the major contributor to the country's food production. For example, the national maize yield increased from 1.62 tonnes/ha in 2000 to 4.24 tonnes/ha in 2020 (see Figure 1). In terms of the volume of production, the contribution of maize has been large compared to other cereals over the past two decades. Arguably, much of the increase in maize yield in recent years is attributed more to expanded use of modern inputs than to area expansion (Figure 2). Such achievements in transforming smallholder maize productivity through increased adoption of modern inputs has substantially contributed to the rapid agricultural output growth in Ethiopia and is widely perceived as a success story for possible broader implementation elsewhere in SSA (see Abate et al., 2015; Bachewe et al., 2018). Multiple factors including better research-extension linkages have contributed to the expansion and productivity changes in the maize sector (Abate et al., 2015).

This recent achievement in transforming smallholder maize productivity in Ethiopia has substantially contributed to rapid agricultural output growth in the country and played a significant role in household food consumption (see Abate et al., 2015; Bachewe et al., 2018). In addition to playing a key role in household consumption, the share of maize in the total marketed cereal has increased in Ethiopia over the past few decades (FAO, 2014; Rashid et al., 2010).

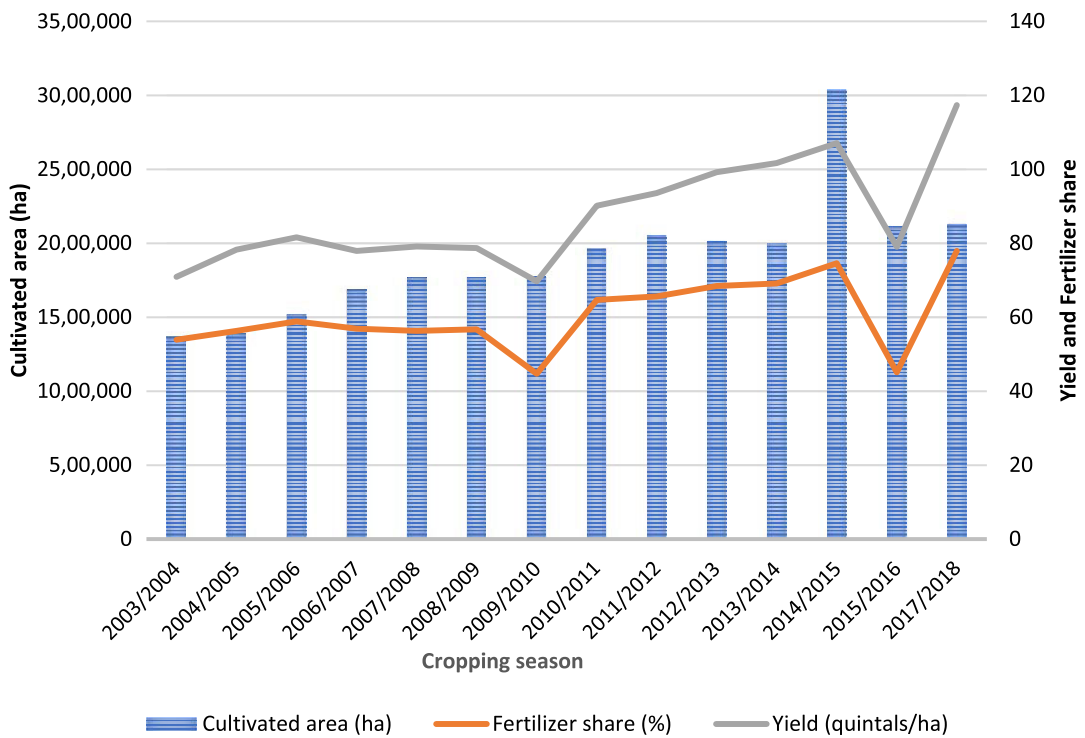


FIGURE 2 Trends in maize yield, fertilizer use and land allocations in Ethiopia (2003/2004–2017/2018). *Source:* Author's construction based on CSA Agricultural Sample Survey reports—for smallholders (CSA, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2014, 2015, 2016, 2018, 2019). To save space, these reports are listed as additional references in Appendix B.

CONCEPTUALIZATION AND ANALYTICAL APPROACH

Conceptual framework

Agricultural commercialization implies the transition from low-productivity semi-subsistence agriculture to high-productivity market-oriented agriculture (Barrett 2008). This transition has been referred to as agricultural transformation which comes with increased productivity and commercialization and could lead to economic diversification and accelerate economic growth (Timmer 2008). The importance of commercialization dates to early economists such as Adam Smith and David Ricardo with the idea that households do produce either for auto-consumption or for trading the surplus after satisfying home consumption. Clearly, the concepts of specialization and comparative advantage stand out strongly as households will specialize, produce, and trade the goods it has some comparative advantage on while sourcing the goods it has little or no comparative advantage in its production.

Given the associated welfare implications of agricultural commercialization, the question then is how to drive commercialization and ensure that farmers escape semi-subsistence poverty traps. While the answer may lie in getting prices right based on various trade and price policies,² this may not be sufficient in pushing households to markets (Barrett 2008). To sufficiently drive households to markets, access to improved crop technologies, especially those

technologies which can increase yields under various biotic and abiotic stresses seem crucial as this may be necessary to generate marketable surplus even under extreme weather events and environmental conditions. Complementing this with institutional, rural, and public infrastructure may induce broad-based market development.

To understand and frame the discussion on the relationship between the adoption of IMVs, fertilizers, and commercialization, we employ insights from the non-separable agricultural household model with missing markets (Janvry et al. 1991). Given that these models have been well developed and adapted with many tweaks on transaction cost and technology adoption (Key & Sadoulet, 2000; Renkow et al. 2004; Tabe-Ojong, Hauser, & Mausch, 2022), we prefer to not repeat this but explore and more fully conceptualize this for the case of IMVs and fertilizers in Ethiopia. The key insight from these theorizations is that market access is not uniform and different variants of transaction costs deter households from participating in markets. Transaction costs may make households either participate in markets or remain autarkic. Also, it may induce heterogeneous commercialization wherein some households sell different portions of their harvest, with others not participating in markets. Heterogeneous commercialization could also be due to limited production owing to the use of inefficient methods of production, climate change, and the non-use of novel farm technologies. Moreover, the use of some of these improved farm technologies may reduce some aspects of transaction cost faced by households in efficiently participating in markets (Tabé-Ojong, Hauser, & Mausch, 2022).

The adoption of improved crop varieties and fertilizers can reduce fixed transaction costs associated with participating in markets (Key & Sadoulet, 2000; Renkow et al. 2004; Tabé-Ojong et al. 2021). Fixed transaction costs refer to the three main cost distinctions: (1) search costs associated with searching for the market or customer with best prices, (2) negotiation and bargaining costs which is related to search cost but common in situations of information asymmetry about prices, especially where households have to effectively bargain to get the best prices for the outputs and (3) sorting and time implication cost which refers to the time spent in making the output acceptable for market conditions. Improved varieties are usually of a higher standard with better market features that may make them easily sellable on the market. Given that the quality is standard, and the product is more uniform, households can comfortably bargain and obtain higher prices for their products. Relatedly, the time spent on sorting and pre-screening is reduced for these improved seeds. Thus, the transaction cost involved with the use of an improved variety may be lesser than that of a landrace or local variety.

Beyond reducing fixed transaction cost and ensuring smallholder commercialization, the adoption of improved seeds may lead to farm production and productivity increases (Vaiknoras & Larochelle, 2021). This is even more the case for the drought resistant maize varieties that can build resilience to climate change by reducing yield losses from the effects of extreme weather events (Tabé-Ojong, Molua, et al., 2023). This is where the complementary role of fertilizers comes in to increase yields associated with the use of IMVs. Fertilization can be argued to increase the productivity and commercialization response in the use of IMVs. In the face of declining soil returns and degradation, the use of fertilizers offers the opportunity to enhance soil fertility, leading to greater yields and consequently increasing the marketable surplus. From the above conceptualization, it appears that adoption of modern inputs and commercialization decisions are sequential. However, farmers could also make these decisions jointly. For instance, an ambitious farmer may desire to have a marketable surplus and commercialize more which may trigger investments in farm inputs.

Empirical strategy

Empirical model for commercialization effect of technology adoption

Consistent with the literature on technology adoption and in line with theoretical predictions of market surplus, smallholder commercialization follows a two-staged process (Key & Sadoulet, 2000; Tabe-Ojong, Mausch, et al., 2022). Maize farmers first choose whether to sell or not before they make decisions on how much quantity of maize to be sold. To accommodate this, we use Cragg (1971)'s flexible double-hurdle model which allows for the possibility that factors determining market participation and those influencing the intensity of sale may be different (Burke, 2009; Ricker-Gilbert et al., 2011; Verkaart et al., 2017). Our empirical double-hurdle model for farmers' marketing decision involves two steps. In the first step (*Hurdle 1*), farmers decide whether to participate in markets. We estimated *Hurdle 1* using the probit model. Once *Hurdle 1* is crossed, farmers choose how much quantity of maize to sell (*Hurdle 2*), which is the second step representing the extent or the intensity of sale. We estimate the second hurdle using a truncated normal regression (Tobit model).

In estimating our double-hurdle model, the choice of the empirical panel data model is influenced by the assumptions we make about the error term. Typically, a potential econometric issue that would affect the estimation is a possible endogeneity problem which could arise from reverse causality, measurement error and unobserved heterogeneity. Unobserved heterogeneity could stem from the fact that the decision making of households are likely influenced by unmeasurable farm household characteristics such as skills, risk behavior, or individual perceptions, which could potentially correlate with the idiosyncratic error term. Applying a household fixed-effects estimator can help control unobservable heterogeneity in linear models. However, applying fixed-effects to a nonlinear model (e.g., double-hurdle model) could lead to biased and inconsistent estimates due to the potential incidental parameters problem which often arises when the length of the panel is small compared with the number of observations (Greene, 2004). Consequently, we employed the correlated random effects (CRE) approach to control for unobservable heterogeneity. The CRE framework, first proposed by Mundlak (1978) and relaxed by Chamberlain (1982), is a parametric approach that addresses the incidental parameter problem of a fixed-effects estimator by allowing dependence between exogenous variables and time-invariant unobserved factors (Wooldridge, 2013). Following Wooldridge (2013), we implement the CRE strategy by adding the time-average values of the time-varying explanatory variables ($\bar{x}_{ji}$) as additional controls in the double-hurdle model.

More formally, the two step decisions process in our CRE double-hurdle model can be specified as:

Hurdle 1: Decision to participate in maize market (a binary choice):

$$M_{it1}^* = \gamma + \Phi_1 A'_{it} + \beta_1 Z'_{it} + \rho_1 \bar{x}_{ji} + u_{it} \quad \text{for} \quad M_{it1} = \begin{cases} 1 & \text{if } M_{it1}^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Hurdle 2: Decision on the quantity of maize to sell conditional on market participation.

$$M_{it2} = \alpha + \Phi_2 A'_{it} + \beta_2 Z'_{it} + \rho_2 \bar{x}_{ji} + \epsilon_{it} \quad (2)$$

where M_{it1}^* is a latent variable denoting the probability of the household's decision to sell maize output. The observed quantity of sale is represented as M_{it2} ; A'_{it} denotes a vector of technology

adoption proxies captured by IMVs and fertilizer adoption; Z'_{it} is a vector of variables explaining the market participation decisions; β_1 and β_2 are the associated parameters for the factors determining the market participation decision and intensity of sale, respectively. u_{it} and ϵ_{it} are the respective error terms. The term $\bar{x}_{ji}$ denotes the time averages of the time-varying covariates for each j^{th} covariate for i^{th} farm household. Each hurdle defined above is conditioned by the household's socioeconomic characteristics including technology adoption status of the farm households. In addition to technology adoption variables, we included the same set of exogenous variables that may affect farmers' marketing decisions in both hurdles. All variables used in the analyses are defined in the [Definition of variables and descriptive statistics](#) section.

In addition to unobserved heterogeneity, we also control for possible reverse causality using the control function (CF) approach in two stages (Smith & Blundell, 1986; Wooldridge, 2015). In the first stage, we estimate a separate reduced-form CRE probit models for the adoptions of IMVs and fertilizer to obtain the generalized residuals for each equation. We estimate the reduced-form equations as a function of exogenous variables that include the control variables used in the double-hurdle marketing decision equation alongside the variable we used as an IV. A binary model is used to estimate IMVs adoption and inorganic fertilizer adoption decisions, which were estimated using a probit model. Therefore, as in the double-hurdle adoption model, we employed the CRE approach to control unobservable heterogeneity in estimating the two equations for adoption decisions.

Using a CF approach to estimate the reduced form equations for technology adoption requires at least one IV for each equation that is strongly partially correlated with the adoption indicator but is uncorrelated with the unobservables that affect commercialization. We use the average adoption rates of improved maize (IV1) and inorganic fertilizer (IV2) at the kebele level as instruments in the two separate adoption equations. IV1 was constructed by counting the number of households that grow IMV in a *kebele* (excluding the specific household) which was then divided by the total number of surveyed households in the *kebele*.³ Similarly, we generate IV2 by counting the number of households that applied inorganic fertilizer for maize production in a *kebele* (excluding the specific household) which was then divided by the total number of surveyed households in the *kebele*. We use this same procedure to generate an IV for the joint adoption of the two inputs.

The use of these instruments is motivated by the literature on social learning and neighborhood effect (Krishnan & Patnam, 2014; Tessema et al., 2016). As suggested by recent studies in SSA (Ogutu et al., 2020; Ogutu & Qaim, 2019; Tabe-Ojong, Mausch, et al., 2022), incorporating insights from social networks and peer effects provides strong IV in examining smallholder decision-making. It has been established that households in rural areas interact regularly and often make decisions based on the choices of their neighbors and peers especially in SSA countries where the public agricultural extension systems and formal institutions are still developing (Di Falco et al., 2020; Geffersa & Tabe-Ojong, 2024; Krishnan & Patnam, 2014). For example, previous studies in Ethiopia (see Krishnan & Patnam, 2014; Tessema et al., 2016) revealed that farmer-to-farmer interactions and peer effects enhanced technology diffusion among rural farming communities.

Thus, it may be the case that households that are surrounded by adopters of a specific agricultural technology also adopt the technology given significant social learning and neighborhood effect in Ethiopia. This implies that our IVs may be strongly correlated with adoption indicators, making it possibly relevant. For the case of exogeneity, it is not trivial to prove this condition from an empirical perspective. The lone way is to motivate why it may be exogenous



to error terms of the outcome equations. The IVs are constructed at a higher geographical scale and the reference household is excluded from the construction which may impose some form of exogeneity. However, we discuss some issues that may be associated with the IV. One may argue that the use of this IV only captures between and not within variation as well as there may be issues of omitted variable bias arising from the aggregation (Kubitza & Krishna, 2020; Tabe-Ojong, Lokossou, et al., 2023). That said, it is important to mention that getting strong and valid instruments is not trivial in most cross-sectional analysis but given that we have panel data, controlling for time invariant unobserved heterogeneity could significantly absorb most of the endogeneity concerns.

Given our interest in understanding the complementary relationship between joint adoption of IMVs and fertilizers, we create a separate adoption dummy to capture the joint use of both technologies. We use the same regression framework to estimate this relationship. Beyond this, we also use a multinomial endogenous switching regression model to estimate the average treatment effect of all technologies (IMVs, fertilizers and the joint use of both). MESR is a two-stage model where the factors driving the adoption of these technologies is modeled in the first stage while the second stage establishes the association between technology adoption and commercialization by exploiting the non-linearity of the first stage model for identification. Given that we already estimated the drivers of adoption of IMVs and fertilizer use, our interest lies in the second stage where the interdependencies in the use of these technologies are accounted for.

DATA AND VARIABLES

Farm household survey data

The paper relies on a comprehensive three-wave panel farm household survey data from three major maize producing regions of Ethiopia: Oromia, Benishangul-Gumuz and the Southern Nations, Nationalities and Peoples (SNNP). The surveys covering the 2009/2010, 2012/2013 and 2014/2015 cropping seasons were conducted by the Ethiopian Institute of Agricultural Research (EIAR) in collaboration with the International Maize and Wheat Improvement Centre (CIMMYT) using the multi-stage sampling technique. In the first stage, nine districts (five from Oromia, three from SNNP and one from Benshangul-Gumuz regions) were purposely selected based on the maize production potential and the agro-ecological suitability. In the second stage, a total sample of 69 *kebeles* were selected using the probability proportional to size sampling technique. Finally, in the selected *kebele*, the probability to proportional size sampling was also used to identify total sample households to increase the odds of households in high population *kebeles* being sampled.

The baseline survey covering the 2009/2010 production season consists of a total of 898 sample households while the second wave covering the 2012/2013 production season elicited information from 874 farm households. The third-round survey, which covered the 2014/2015 production season, interviewed 798 sample households. After checking for missing entries and further cleaning the data, we use a balanced panel of 680 households. To ensure that the results were not affected by households that left the panel between surveys (attriters) and those we dropped due to missing entries and incomplete data, we tested for a non-random attrition. The procedure involves first estimating a binary regression (attrition probit) model in which the dependent variable takes the value one for farm households which dropped out of the sample after the first wave and zero otherwise. We then regressed a binary model for attrition where

explanatory variables that are likely to affect farmers' marketing decision along with the lagged values of the outcome variable. In the attrition probit results, we found little evidence based on the statistical estimations that attrition could be a problem for the analysis.

Definition of variables and descriptive statistics

Table A1 provides a description of the key variables used in the regression analysis. As highlighted earlier, we conceptualize commercialization as a two-step process involving market participation and the extent of participation. Market participation is defined as a dummy taking the values of 1 and 0 for sellers and non-sellers, respectively. The extent of market participation refers to the quantity of maize that is sold in markets (kg).

Our main variables of interest; IMVs and fertilizer adoption are also dummy variables. We also have different household controls defined in detail in Table A1. We used initial values of assets (monetary values) and livestock ownership due to their endogenous nature in commercialization decisions. As such, we control for initial differences in capital stock among farm households. We also perform some basic summary statistics on the outcomes, variables of interest, and some control variables over the panel years. Prior to running our econometric models, we used natural logarithm to transform the quantity of maize sold, landholding and household asset variables because of the skewness of their distribution. We applied the inverse hyperbolic sine transformation when taking the logarithm to address the zero-observation problem. We also perform some basic summary statistics on the outcomes, variables of interest, and some control variables over the panel years. As shown in Table 1, market participation is quite high among smallholder farmers, and it is somewhat increasing over time (75%–82%). This is also the case with the quantity of maize that is sold, although there was a slight decrease in 2012 which eventually increased to about 1485 kg. The insights here corroborates high market participation rates in Malawi, Tanzania and Uganda (Carletto et al., 2017). IMVs and fertilizers are the main technologies adopted by farmers (approximately 86% vs. 75%). Households are middle-aged with about 3 years of primary education and have household sizes of about 5. Households have a high access to extension services and walk for about 80 min to the market.⁴ Households also have farm sizes of about 2 ha and participate in off-farm activities.

RESULTS AND DISCUSSION

First stage estimations and endogeneity test

We begin with a discussion of the relevance of the IVs. As highlighted earlier, we followed the control function approach in testing and controlling for endogeneity. In these regressions, we include all the control variables we use in the structural commercialization equation and include the IVs. Our IVs are relevant as they significantly determine the adoption of IMVs and fertilizers at the 1% level of probability. We then included the generalized residuals from that regression as additional controls in the structural commercialization equation. According to Wooldridge (2015), the significance of the generalized residual in the structural model suggests the presence of endogeneity. This approach to testing and controlling endogeneity in non-linear models is consistent with earlier empirical studies (see Geffersa et al., 2022; Ma & Abdulai, 2016; Ricker-Gilbert et al., 2011). The results presented in Table 2 indicate that the

**TABLE 1** Descriptive statistics of variables used in the analyses, by year.

Variables	2009/2010	2012/2013	2014/2015
Outcome variable	Mean	Mean	Mean
Market participation (yes = 1)	0.759 (0.428)	0.821 (0.384)	0.821 (0.384)
Quantity of maize sold (in kg) ^a	1183.24 (2022.31)	1157.73 (1575.45)	1484.60 (3166.45)
Independent variable of interest			
Improved maize adoption (yes = 1)	0.866 (0.341)	0.865 (0.342)	0.880 (0.300)
Fertilizer adoption (yes = 1)	0.751 (0.432)	0.749 (0.434)	0.819 (0.385)
Socioeconomic characteristics			
Age of the household-head (years)	41.25 (13.19)	43.87 (13.13)	46.71 (13.11)
Male-headed household (yes = 1)	0.91 (0.28)	0.92 (0.27)	0.92 (0.28)
Education level of the head (years)	3.26 (3.39)	3.16 (3.38)	3.04 (3.34)
Family size (AEU)	4.94 (2.25)	5.04 (2.22)	4.93 (2.01)
Landholding (ha) ^a	2.25 (1.95)	1.72 (1.46)	2.17 (1.77)
Initial level of livestock ownership (TLU)	4.16 (4.61)	4.16 (4.61)	4.16 (4.61)
Initial level of asset ownership (ETB) ^{a,b}	9380.47 (29558.53)	9380.47 (29558.53)	9380.47 (29558.53)
Off-farm employment (yes = 1)	0.62 (0.49)	0.57 (0.50)	0.52 (0.50)
Extension service (yes = 1)	0.96 (0.18)	0.97 (0.09)	0.66 (0.47)
Distance to main market (walking min.)	75.13 (108.03)	121.74 (103.52)	79.23 (96.68)
Land quality index (1 = best, ..., 9 = worst)	2.41 (1.46)	2.07 (1.41)	2.12 (1.16)
Rainfall shortage (yes = 1)	0.00 (0.00)	0.26 (0.44)	0.21 (0.41)
IV1: Kebele adoption rate of IMV	0.766 (0.233)	0.775 (0.216)	0.816 (0.204)
IV2: Kebele adoption rate of inorganic fertilizer	0.816 (0.174)	0.834 (0.174)	0.826 (0.159)

Note: Standard deviation in parentheses.

^aGiven the skewness of their distributions, we used natural logarithmic to transform the quantity of maize sold, landholding and household asset. The values reported here are the actual values before log transformation.

^bEthiopian-Birr (ETB) is a local currency, where 1 USD was equivalent to 17.01 ETB in 2009/2010, 20.50 ETB in 2012/2013 & 20.68 ETB in 2014/2015 cropping seasons.

TABLE 2 CRE double-hurdle model for IMV adoption effect on market participation and intensity of sale.

	Hurdle 1: Probability of market participation		Hurdle 2: Intensity of sale	
	Coeff.	APEs	Coeff.	APEs
IMV adoption (yes = 1)	0.620*** (0.045)	0.098*** (0.025)	0.465*** (0.101)	0.153*** (0.031)
<i>Generalized Residual</i>	0.156*** (0.027)	0.030*** (0.010)	0.025 (0.062)	0.026 (0.011)
Age of the head (years)	−0.003 (0.011)	−0.001 (0.002)	−0.001 (0.009)	−0.001 (0.002)
Gender of the head (male = 1)	−0.140* (0.079)	−0.064* (0.034)	0.071 (0.079)	−0.030 (0.033)
Education of the head (years)	0.022 (0.017)	0.004 (0.003)	0.031*** (0.010)	0.006*** (0.003)
Family size (AEU)	−0.017 (0.038)	−0.006 (0.007)	0.049*** (0.019)	−0.001*** (0.006)
Ln of landholding (ha)	0.194** (0.084)	0.027** (0.035)	0.720*** (0.124)	0.110*** (0.032)
Ln livestock ownership (TLU)	0.0004 (0.007)	−0.001 (0.003)	0.0001 (0.010)	0.0003 (0.003)
Ln initial asset ownership (ETB)	0.157*** (0.021)	0.037*** (0.008)	0.173*** (0.021)	0.050*** (0.010)
Extension service (yes = 1)	0.154*** (0.024)	0.029*** (0.027)	−0.041 (0.073)	0.016 (0.024)
Off-farm employment (yes = 1)	−0.103 (0.103)	−0.016 (0.021)	−0.017 (0.130)	−0.020 (0.018)
Market distance (in km)	0.0001 (0.0002)	0.0001 (0.0001)	0.0001 (0.0002)	0.000 (0.000)
Land quality (1 = best, ..., 9 = worst)	0.025* (0.014)	0.009* (0.006)	−0.055** (0.025)	−0.002** (0.006)
Rainfall shortage (yes = 1)	−0.070 (0.224)	−0.005 (0.028)	−0.231* (0.125)	−0.034* (0.026)
<i>Region dummies</i>	Yes		Yes	
<i>Year dummies</i>	Yes		Yes	
<i>Time averages (CRE)^a</i>	Yes		Yes	
Model summary				
Constant	−0.075 (0.065)		5.180*** (0.124)	
Number of observations	2040			
Number of households	680			
Log-likelihood	−2825.856			

Note: significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

^aAll results were estimated under a CRE framework where time averages of all time-varying explanatory variables were used as additional regressors, but the estimates for the time averages are not reported here to save space.



residual term is significant only in the first hurdle. This suggests that we reject the null hypothesis of IMV adoption being exogenous in market participation decision but not in the intensity of sale. Likewise, we did not detect endogeneity of joint adoption of the two technologies in the second hurdle (Table 3). Statistically significant coefficient for the generalized residual in both hurdles in Table 4 suggests a rejection of the null hypothesis that fertilizer adoption is exogenous in farmer's market participation decision and the sales intensity. To test how appropriate the IVs are, we perform some falsification test (see Di Falco et al., 2011) to verify whether the IVs under consideration are unrelated to commercialization except through their influence on the adoption outcomes (IMVs and fertilizers). We focus on a subset of farmers that do not use IMVs and fertilizers and include the IVs with other controls and check for statistical significance in both the selection and outcome equations. We do not find any statistical association between the IVs and commercialization for non-adopters (as shown in the appendix, Table A7), suggesting that the IVs may be appropriate.

IMVs and commercialization

Table 2 shows the relationship between adoption of IMVs and commercialization. We use the double-hurdle model to estimate both the decision to sell in markets and the quantity of maize sold conditional on participation. We report both the estimated coefficients from the double-hurdle model as well as the average partial effects (APEs). We show that households who grow IMVs are more likely to sell maize compared to non-adopters. We also show that households that participate in maize markets are more likely to increase their sales quantity by about 15%.

Our findings confirming the positive association between IMVs and commercialization are important given that maize is one of the important staple crops that are produced and consumed by rural farm households in Ethiopia. Given that we observe these positive implications of adoption, it could mean that IMVs offer some significant yield benefits to farmers such that they can cater for both their household food demands and sell some of their produce in markets to obtain income to relax their financial constraints in accessing other goods and services.

Our analysis is in line with the growing literature that has established a positive association between the adoption of improved crop varieties and commercialization (Akter et al., 2021; Awotide et al., 2016; Singbo et al., 2021; Smale et al., 2018; Tabe-Ojong, Mausch, et al., 2022). As we highlight in the conceptual linkage above, these studies have shown that improved crop varieties increase commercialization by increasing both yields and reducing transaction costs (Tabé-Ojong, Mausch, et al., 2022). Most of such varieties are drought resistant, heat tolerant making it possible to build climate resilience and reduce significant yield losses associated with extreme weather events especially in arid and semi-arid regions of Africa (Simtowe et al., 2019; Tabe-Ojong, Molua, et al., 2023). Beyond this productivity impacts, some of these improved varieties have market related traits which make them easily sellable in markets (Tabé-Ojong, Mausch, et al., 2022).

Fertilizer use and commercialization

After showing the positive association between IMVs and commercialization, we also estimate the relationship between fertilizer use and commercialization. Unlike the case of improved crop varieties, this has received little attention despite the important role of fertilizers in building

TABLE 3 CRE double-hurdle model for the commercialization effect of joint adoption of IMV and fertilizer.

	Hurdle 1: Probability of market participation		Hurdle 2: Intensity of sale	
	Coeff.	APEs	Coeff.	APEs
Joint adoption of IMV and Fertilizer (yes = 1)	0.807*** (0.0537)	0.130*** (0.023)	0.534*** (0.122)	0.217*** (0.031)
<i>Generalized Residual</i>	0.171*** (0.058)	0.031*** (0.009)	0.022 (0.038)	0.033 (0.009)
Age of the head (years)	−0.003 (0.011)	−0.001 (0.002)	−0.001 (0.009)	−0.001 (0.001)
Gender of the head (male = 1)	−0.159** (0.074)	−0.067** (0.033)	0.052 (0.088)	−0.038 (0.032)
Education of the head (years)	0.023 (0.016)	0.005 (0.003)	0.031*** (0.010)	0.006*** (0.003)
Family size (AEU)	−0.009 (0.038)	−0.004 (0.007)	0.049** (0.019)	0.001 (0.006)
Ln of landholding (ha)	0.252*** (0.063)	0.037*** (0.034)	0.735*** (0.105)	0.116*** (0.031)
Ln livestock ownership (TLU)	0.003 (0.005)	−0.001 (0.003)	0.001 (0.012)	0.001 (0.002)
Ln initial asset ownership (ETB)	0.141*** (0.018)	0.034*** (0.008)	0.175*** (0.023)	0.044*** (0.009)
Extension service (yes = 1)	−0.037 (0.076)	−0.007 (0.028)	−0.095 (0.066)	−0.030 (0.025)
Off-farm employment (yes = 1)	−0.069 (0.093)	−0.011 (0.021)	0.000 (0.117)	−0.012 (0.018)
Market distance (in km)	0.0001 (0.0004)	0.000 (0.000)	0.0002 (0.0001)	0.000 (0.000)
Land quality (1 = best, ..., 9 = worst)	0.015 (0.025)	0.007 (0.006)	−0.057** (0.024)	−0.004** (0.006)
Rainfall shortage (yes = 1)	−0.014 (0.216)	0.002 (0.028)	−0.225** (0.114)	−0.017 (0.025)
<i>Region dummies</i>	Yes		Yes	
<i>Year dummies</i>	Yes		Yes	
<i>Time averages (CRE)^a</i>	Yes		Yes	
Model summary				
Constant	0.080 (0.113)			
Number of observations	2040			
Number of households	680			
Log-likelihood	−2824.323			

Note: Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

^aAll results were estimated under a CRE framework where time averages of all time-varying explanatory variables were used as additional regressors, but the estimates for the time averages are not reported here to save space.

TABLE 4 CRE double-hurdle model for fertilizer adoption effect on maize market participation and intensity of sale.

	Hurdle 1: Probability of market participation		Hurdle 2: Intensity of sale	
	<i>Coeff.</i>	<i>APEs</i>	<i>Coeff.</i>	<i>APEs</i>
Fertilizer adoption (yes = 1)	0.874*** (0.110)	0.130*** (0.029)	0.657*** (0.143)	0.253*** (0.040)
<i>Generalized Residual</i>	0.167*** (0.039)	0.026*** (0.008)	0.058*** (0.014)	0.028*** (0.008)
Age of the head (years)	0.000 (0.013)	0.0004 (0.002)	0.001 (0.009)	−0.001 (0.002)
Gender of the head (male = 1)	−0.163** (0.067)	−0.060** (0.033)	0.074 (0.067)	−0.036 (0.033)
Education of the head (years)	0.019 (0.020)	0.004 (0.003)	0.028*** (0.010)	0.005* (0.003)
Family size (AEU)	−0.012 (0.041)	−0.005 (0.007)	0.053*** (0.019)	0.000 (0.006)
Ln of landholding (ha)	0.364*** (0.035)	0.054*** (0.034)	0.768*** (0.083)	0.144*** (0.032)
Ln livestock ownership (TLU)	0.006 (0.008)	0.0001 (0.003)	0.003 (0.012)	0.001 (0.003)
Ln initial asset ownership (ETB)	0.129*** (0.028)	0.033*** (0.009)	0.166*** (0.023)	0.045*** (0.009)
Extension service (yes = 1)	−0.312 (0.188)	−0.047 (0.031)	−0.241*** (0.062)	−0.083*** (0.031)
Off-farm employment (yes = 1)	−0.054 (0.097)	−0.006 (0.021)	−0.009 (0.121)	−0.012 (0.018)
Market distance (in km)	0.0001 (0.001)	0.000 (0.000)	0.0003*** (0.0001)	0.0001*** (0.000)
Land quality (1 = best,..., 9 = worst)	−0.020 (0.038)	0.001 (0.007)	−0.072*** (0.024)	−0.010*** (0.006)
Rainfall shortage (yes = 1)	−0.032 (0.221)	−0.003 (0.028)	−0.198** (0.099)	−0.025** (0.026)
<i>Region dummies</i>	Yes		Yes	
<i>Year dummies</i>	Yes		Yes	
<i>Time averages (CRE)^a</i>	Yes		Yes	
Model summary				
Constant	0.144 (0.123)		5.206*** (0.168)	
Number of observations	2040			
Number of households	680			
Log-likelihood	−2843.434			

Note: significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
^aAll results were estimated under a CRE framework where time averages of all time-varying explanatory variables were used as additional regressors, but the estimates for the time averages are not reported here to save space.

both soil organic matter and increasing soil fertility. Maize is one cereal that relies on fertilizer use for increased vegetation and fruit growth. Farmers who adopt IMVs have been shown to increase their fertilizer demand by about 12% as compared to local maize growers (Alene et al., 2008). In many smallholder settings, households have been shown to demand the less costly improved seeds before going in for the more costly fertilizers (Nkonya et al., 1997). Table 4 shows the relationship between fertilizer use and commercialization. The result indicates that fertilizer use is associated with a 13% increase in market participation and an associated 25% increase in the quantity of maize sold in markets. This increase is most likely due to the productivity impacts associated with the use of fertilizers (Tabe-Ojong, Ibarra, et al., 2023; Tesfay, 2020). Fertilizers add critical nutrients to the soil which may be important in increasing productivity. The use of fertilizers have been shown to exhibit high returns especially when used for cereals like maize (Duflo et al., 2008). Our results on the positive relationship between fertilizer and smallholder commercialization mirrors recent work of Tesfay (2020) who shows a positive association between fertilizer use and smallholder commercialization through productivity gains.

Complementary adoption and commercialization

Fertilizers and IMVs are two important technologies that can increase yields and commercialization. Typically, jointly using both technologies together provide synergistic benefits as IMVs could have larger yield responses to fertilization. The decision to use IMVs and fertilizers have been argued to be a joint process although the timing of purchase of these two may matter given that improved seeds are usually less costly than fertilizers (Nkonya et al., 1997). Fertilizer adoption have been highlighted as a usually reactive than proactive strategy as compared to the use of improved crop varieties. Most farmers would only apply fertilizers in their fields when they observe yellowing of their plants especially as they are costly. This makes the application of fertilizers to be an intermittent activity which also varies with time.

Given that the use of IMVs could have larger yield responses to the use of fertilizers, we consider the complementary use of both technologies and estimate its relationship with commercialization. We create a dummy variable capturing the joint use of both IMVs and fertilizers. We then use the Mundlak-chamberlain device to estimate both the decision to participate in markets and the quantity sold conditional on participation. We show in Table 3 that the joint adoption of both IMVs and fertilizers leads to a 13% increase in market participation and conditional on this, it further leads to a 21.7% increase in the quantity of maize sold in output markets. These results highlight that the joint use of IMVs and fertilizers offer greater commercialization gains than under the use of only IMVs.

Although we have established that the use of IMVs could have a larger commercialization response with the use of fertilizers, one may argue that we did not effectively capture the interdependency in the use of the various inputs. From an empirical viewpoint, it may be more intuitive to use the multinomial endogenous switching regression (MESR) as it efficiently captures these interdependencies (Khonje et al., 2018). Table 5 shows the average treatment effect of the different categories of technology adoption (IMVs, fertilizers and both IMVs and fertilizers) on commercialization. We show that the adoption of IMVs, fertilizers and the bundled use of both IMVs and fertilizers matter in increasing commercialization. However, the greatest commercialization gains are observed under the complementary use of both IMVs and fertilizers. This confirms our earlier results and supports the notion that adopting IMVs could lead to larger

TABLE 5 ATT estimates of the association between technology adoption and commercialization.^a

	Commercialization
Adoption of IMVs (1/0)	173.697* (102.786)
Adoption of fertilizers (1/0)	208.911** (104.817)
Joint adoption of IMVs and fertilizers (1/0)	446.502*** (37.835)
Additional controls (1/0)	Yes
Observations	2040

Note: Significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

^aAll results were estimated under a CRE framework where time averages of all time-varying explanatory variables were used as additional regressors, but the estimates for the time averages are not reported here to save space. Additional controls include age and gender of the household head, educational level, household size, farm size, livestock ownership, extension access, off-farm employment, distance to market, land quality, and rainfall shortage.

commercialization gains with the use of fertilizers. Previous analysis using switching regressions with multiple treatments found the complementary use of IMVs and fertilizers to increase yields and consumption expenditure (Ahmed, 2022). This is indicative of supportive of our claims that increase in commercialization as a response to the use of improved seeds and fertilizer occurs through increase in productivity.

Robustness check

So far, we have estimated the double-hurdle model to understand the relationship between IMVs, fertilizers and commercialization. In estimating the double-hurdle model, we relied on non-linear estimation strategies given the nature of our outcome variables, which can be argued to follow the form of non-linear corner solution models. In this regard, we utilized the probit model and the truncated regression model, which can both be argued to have limitations in terms of identification. Non-linear models are often very restrictive and typically rely on identification by functional form. Moreover, they are cumbersome to interpret. As a robustness check on the estimates, we also estimate standard linear models which are easy to interpret and usually avoid identification by functional form (Angrist & Pischke, 2008). We thus relaxed the dependency assumption in the double-hurdle model and estimate the first stage using the linear probability model and the second stage using ordinary least squares. The results which are presented in the appendix (Tables A4–A6) are similar in direction, magnitudes, and statistical significance with the original estimates given credence to estimation and the findings of the analyses.

CONCLUSION AND POLICY IMPLICATIONS

Using panel data from Ethiopia, we investigate the relationship between the adoption of IMVs, fertilizers, and smallholder commercialization. Exploiting the panel nature of the data and using various empirical strategies, alternative specifications, and robustness checks, we find three main results. Firstly, the adoption of IMVs is positively associated with smallholder

commercialization, leading to increased market participation and a greater extent of participation among those already involved. Secondly, we demonstrate that the use of fertilizers also contributes to the commercialization of smallholder agriculture. Thirdly, we find that the simultaneous adoption of IMVs and fertilizers results in greater commercialization gains for households. This result corroborates a growing literature highlighting that the complementary/bundled use of some interdependent agricultural technologies can offer immense gains for smallholder households.

Our findings support the notion that technology adoption can be a key entry point for boosting smallholder commercialization with implications for economic development. Given this, we offer some policy implications that can lead to increased adoption of agricultural technologies. First, our analysis lends support to various initiatives that target the development and dissemination of agricultural technologies such as improved crop varieties and fertilizers. Second and related to the first, our analysis also gives credence to upscaling plans and programs. Given that most adoption programs start as pilots, it would be important to scale this out to many more farmers as the commercialization gains are significant. As a third policy direction, it would be important to strengthen rural and market infrastructures as they may limit the potential gains of commercialization from technology adoption.

Although not directly implied by our results, the fourth policy implication would be to address some of the information constraints farmers are facing in accessing improved agricultural technologies. This is related to various aspects of both fixed and variable transaction costs which have been argued to deter market participation and make smallholder farmers autarkic. As implied by our conceptual framework, IMVs can drive smallholder commercialization by reducing various aspects of search, bargaining and negotiation costs. Given that we also obtain greater commercialization gains for the complementary use of both IMVs and fertilizers, it would be necessary to strengthen the knowledge systems of households. In many rural areas, different forms of farmer advisory and extension systems could be used to drive such knowledge system changes. Finally, it would be important to strengthen seed systems to ensure that improved seeds are consistently available for farmers to access and utilize.

We end with some limitations and caveats that should frame the interpretation of our work, as well as potential areas for future research. First, we guard against an absolute generalization of the analysis given that the situation in Ethiopia may be different from other nations. However, this difference may not be valid for other developing countries especially in Africa where maize farmers face similar production and institutional constraints. In these cases, generalizations could be made to the smallholder farm sector in Africa. That notwithstanding, it would be beneficial to see further research addressing these important aspects of agricultural transformation. Secondly, we have used panel data and other estimation strategies to establish robust associations between IMVs, fertilizers and commercialization. However, we refrain from claiming strict causality since we only used observational data. Studies with more rigorous designs, such as experimental studies, are encouraged to push more towards causality and internal validity.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ENDNOTES

¹ Relatedly, Mumin and Abdulai (2020) show that transitioning through different market orientations is associated with increases in household food and nutrient consumption.



- ² This may be largely insufficient based on the slow performance of the various market-oriented liberalization policies and various trade policies that have previously been implemented in many African countries. These trade and price policies have been insufficient in stimulating market-based development.
- ³ A *kebele* is the smallest administrative unit in Ethiopia that is smaller than a *woreda* (or district), but larger than a village.
- ⁴ It is important to highlight that the measurement of market distance was established through self-reported walking durations. While this approach to measure market distance can provide valuable insights into market accessibility, it is crucial to acknowledge that relying on respondents' self-reports could introduce variability in the reported time estimates. Given these potential sources of error, it is important to interpret walking time estimates with caution.

REFERENCES

- Abate, T., B. Shiferaw, A. Menkir, D. Wegary, Y. Kebede, K. Tesfaye, M. Kassie, G. Bogale, B. Tadesse, and T. Keno. 2015. "Factors that Transformed Maize Productivity in Ethiopia." *Food Security* 7(5): 965–981.
- Ahmed, Musa Hasen. 2022. "Impact of Improved Seed and Inorganic Fertilizer on Maize Yield and Welfare: Evidence from Eastern Ethiopia." *Journal of Agriculture and Food Research* 7: 100266. <https://doi.org/10.1016/j.jafr.2021.100266>.
- Akter, Sonia, Namrata Chindarkar, William Erskine, Luc Spyckerelle, Julie Imron, and Lucia Viana Branco. 2021. "Increasing Smallholder farmers' Market Participation through Technology Adoption in Rural Timor-Leste." *Asia & the Pacific Policy Studies* 8(2): 280–298. <https://doi.org/10.1002/app5.329>.
- Alene, Arega D., V. M. Manyong, G. Omany, H. D. 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. <https://doi.org/10.1016/j.foodpol.2007.12.001>.
- Angrist, J. D., and J. Pischke. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, New Jersey: Princeton University Press.
- Ariga, J., E. Mabaya, M. Waithaka, and M. Wanzala-Mlobela. 2019. "Can Improved Agricultural Technologies Spur a Green Revolution in Africa? A Multi-Country Analysis of Seed and Fertilizer Delivery Systems." *Agricultural Economics* 50: 63–74. <https://doi.org/10.1111/agec.12533>.
- Awotide, Bola Amoke, Aziz A. Karimov, and Aliou Diagne. 2016. "Agricultural Technology Adoption, Commercialization and Smallholder Rice farmers' Welfare in Rural Nigeria." *Agricultural Economics* 4(1): 1–24. <https://doi.org/10.1186/s40100-016-0047-8>.
- Bachewe, F. N., G. Berhane, B. Minten, and A. S. Taffesse. 2018. "Agricultural Transformation in Africa? Assessing the Evidence in Ethiopia." *World Development* 105: 286–298.
- Barrett, Christopher B. 2008. "Smallholder Market Participation: Concepts and Evidence from Eastern and Southern Africa." *Food Policy* 33(4): 299–317.
- Burke, W. J. 2009. "Fitting and Interpreting Cragg's Tobit Alternative Using Stata." *Stata Journal* 9(4): 584–592.
- Carletto, Calogero, Paul Corral, and Anita Guelfi. 2017. "Agricultural Commercialization and Nutrition Revisited: Empirical Evidence from Three African Countries." *Food Policy* 67: 106–118. <https://doi.org/10.1016/j.foodpol.2016.09.020>.
- Cazzuffi, Chiara, Andy McKay, and Emilie Perge. 2020. "The Impact of Agricultural Commercialisation on Household Welfare in Rural Vietnam." *Food Policy* 94: 101811. <https://doi.org/10.1016/j.foodpol.2019.101811>.
- Chamberlain, G. 1982. "Multivariate regression models for panel data." *Journal of Econometrics* 18(1): 5–46.
- Chavas, J.-P., and C. Nauges. 2020. "Uncertainty, Learning and Technology Adoption in Agriculture." *Applied Economic Perspectives and Policy* 42(1): 42–53.
- Cragg, J. G. 1971. "Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods." *Econometrica* 39(5): 829–844.
- CSA. 2016. *Agricultural Sample Survey (2015/16): Report on Area, Production and Farm Management Practice of Belg Season Crops for Private Peasant Holdings* Addis Ababa, Ethiopia: Central Statistical Agency (CSA) the Federal Democratic Republic of Ethiopia. Retrieved from http://www.gatefarms.com/assets/downloads/belg_report_2016_2008.pdf

- CSA. 2018. *Agricultural Sample Surveys (2017/2018): Report on Area and Production of Major Crops (Private Peasant Holdings, Meher Season)* Addis Ababa, Ethiopia: Central Statistical Agency (CSA), the Federal Democratic Republic of Ethiopia Retrieved from <http://www.csa.gov.et/survey-report>
- CSA. 2019. *Agricultural Sample Surveys (2018/19): Report on Area and Production of Major Crops (Private Peasant Holdings, Meher Season)* Addis Ababa, Ethiopia: Central Statistical Agency (CSA), the Federal Democratic Republic of Ethiopia Retrieved from <http://www.csa.gov.et/survey-report>
- CSA. 2021. *The Federal Democratic Republic of Ethiopia Central Statistical Agency (CSA) Agricultural Sample Survey 2020/21 (2013 E.C)* <http://www.statsethiopia.gov.et/wp-content/uploads/2022/02/Area-Production-and-Farm-Management-Practices-Private-Peasant-Holdings-Belg-Season-2020-21-2013-E.C.pdf>
- de Oca, Montes, O. Munguia, and R. Llewellyn. 2020. "The Adopters Versus the Technology: Which Matters More when Predicting or Explaining Adoption?" *Applied Economic Perspectives and Policy* 42(1): 80–91.
- Di Falco, S., A. Doku, and A. Mahajan. 2020. "Peer Effects and the Choice of Adaptation Strategies." *Agricultural Economics* 51(1): 17–30.
- Di Falco, S., M. Veronesi, and M. Yesuf. 2011. "Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia." *American Journal of Agricultural Economics* 93: 829–846.
- Duflo, Esther, Michael Kremer, and Jonathan Robinson. 2008. "How High Are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya." *American Economic Review* 98(2): 482–88. <https://doi.org/10.1257/aer.98.2.482>.
- Fan, Shenggen. 2020. "Reflections of Food Policy Evolution over the Last Three Decades." *Applied Economic Perspectives and Policy* 44(3): 380–394.
- FAO. 2014. Monitoring and analysing food and agricultural policies in Africa Synthesis report 2013. F. a. A. O. (FAO) <http://www.fao.org/3/a-i3513e.pdf>
- FAOSTAT. 2022. *Food and Agriculture Organization (FAO) Country Statistics* Food and Agriculture Organization (FAO). <http://www.fao.org/faostat/en/#data>
- Geffersa, A. G. 2023. "Agricultural Productivity, Land Use Intensification and Rural Household Welfare: Evidence from Ethiopia." *Agrekon* 62(3–4): 309–327.
- Geffersa, A. G., F. W. Agbola, and A. Mahmood. 2022. "Improved Maize Adoption and Impacts on Farm Household Welfare: Evidence from Rural Ethiopia." *Australian Journal of Agricultural and Resource Economics* 66(4): 860–886.
- Geffersa, A. G., and M. P. J. Tabe-Ojong. 2024. "Smallholder Commercialisation and Rural Household Welfare: Panel Data Evidence from Ethiopia." *European Review of Agricultural Economics* 51(1): 54–90.
- Greene, W. 2004. "Fixed Effects and Bias Due to the Incidental Parameters Problem in the Tobit Model." *Econometric Reviews* 23(2): 125–147.
- Haji, Jema. 2022. "Impact of Agricultural Commercialization on Child Nutrition in Ethiopia." *Food Policy* 113: 102287. <https://doi.org/10.1016/j.foodpol.2022.102287>.
- Janvry, Alain de, Marcel Fafchamps, and Elisabeth Sadoulet. 1991. "Peasant Household Behaviour with Missing Markets: Some Paradoxes Explained." *The economic journal* 101(409): 1400–1417.
- Key, Nigel, Elisabeth Sadoulet, and Alain de Janvry. 2000. "Transactions Costs and Agricultural Household Supply Response." *American Journal of Agricultural Economics* 82(2): 245–259. <https://doi.org/10.1111/0002-9092.00022>.
- Khonje, Makaiko G., Julius Manda, Petros Mkandawire, Adane Tufa, Alene Hirpa, and D. Arega. 2018. "Adoption and Welfare Impacts of Multiple Agricultural Technologies: Evidence from Eastern Zambia." *Agricultural Economics* 49(5): 599–609. <https://doi.org/10.1111/agec.12445>.
- Krishnan, P., and M. Patnam. 2014. "Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption?" *American Journal of Agricultural Economics* 96(1): 308–327.
- Kubitza, Christoph, and Vijesh V. Krishna. 2020. "Instrumental Variables and the Claim of Causality: Evidence from Impact Studies in Maize Systems." *Global Food Security* 26: 100383. <https://doi.org/10.1016/j.gfs.2020.100383>.
- Ma, W., and A. Abdulai. 2016. "Does Cooperative Membership Improve Household Welfare? Evidence from Apple Farmers in China." *Food Policy* 58: 94–102.
- MoFED. 2006. "A Plan for Accelerated and Sustained Development to End Poverty (PASDEP) (2005-2010)." In *The Federal Democratic Republic of Ethiopia, Ministry of Finance and Economic Development (MoFED)*. Addis



- Ababa, Ethiopia. https://planipolis.iiep.unesco.org/sites/default/files/ressources/ethiopia_pasdep_2005_2010.pdf.
- Mumin, Yazeed, Abdul, and Awudu Abdulai. 2020. "Informing Food Security and Nutrition Strategies in Sub-Saharan African Countries: An Overview and Empirical Analysis." *Applied Economic Perspectives and Policy* 44(1): 364–393.
- Mundlak, Y. 1978. "On the Pooling of Time Series and Cross Section Data." *Econometrica* 46(1): 69–85.
- Muriithi, Beatrice W., and Julia Anna Matz. 2015. "Welfare Effects of Vegetable Commercialization: Evidence from Smallholder Producers in Kenya." *Food Policy* 50: 80–91. <https://doi.org/10.1016/j.foodpol.2014.11.001>.
- Nkonya, Ephraim, Ted Schroeder, and David Norman. 1997. "Factors Affecting Adoption of Improved Maize Seed and Fertiliser in Northern Tanzania." *Journal of Agricultural Economics* 48(1–3): 1–12. <https://doi.org/10.1111/j.1477-9552.1997.tb01126.x>.
- Norton, G. W., and J. Alwang. 2020. "Changes in Agricultural Extension and Implications for Farmer Adoption of New Practices." *Applied Economic Perspectives and Policy* 42(1): 8–20.
- Ochieng, Justus, Beatrice Knerr, George Owuor, and Emily Ouma. 2020. "Food Crops Commercialization and Household Livelihoods: Evidence from Rural Regions in Central Africa." *Agribusiness* 36(2): 318–338. <https://doi.org/10.1002/agr.21619>.
- Ogutu, S. O., T. Gödecke, and M. Qaim. 2020. "Agricultural Commercialisation and Nutrition in Smallholder Farm Households." *Journal of Agricultural Economics* 71(2): 534–555.
- Ogutu, S. O., and M. Qaim. 2019. "Commercialization of the Small Farm Sector and Multidimensional Poverty." *World Development* 114: 281–293.
- Pingali, P. L., and M. W. Rosegrant. 1995. "Agricultural Commercialization and Diversification: Processes and Policies." *Food Policy* 20(3): 171–185.
- Rashid, S., K. Getnet, and S. Lemma. 2010. Maize Value Chain Potential in Ethiopia: Constraints and Opportunities for Enhancing the System G. O. Research. <https://gatesopenresearch.org/documents/3-354>
- Renkow, Mitch, Daniel G. Hallstrom, and Daniel D. Karanja. 2004. "Rural Infrastructure, Transactions Costs and Market Participation in Kenya." *Journal of development economics* 73(1): 349–367.
- Ricker-Gilbert, J., T. S. Jayne, and E. Chirwa. 2011. "Subsidies and Crowding out: A Double-Hurdle Model of Fertilizer Demand in Malawi." *American Journal of Agricultural Economics* 93(1): 26–42.
- Sheahan, M., and C. B. Barrett. 2017. "Ten Striking Facts about Agricultural Input Use in Sub-Saharan Africa." *Food Policy* 67: 12–25.
- Simtowe, Franklin, Emily Amondo, Paswel Marennya, Dil Rahut, Kai Sonder, and Olaf Erenstein. 2019. "Impacts of Drought-Tolerant Maize Varieties on Productivity, Risk, and Resource Use: Evidence from Uganda." *Land Use Policy* 88: 104091. <https://doi.org/10.1016/j.landusepol.2019.104091>.
- Singbo, Alphonse, Felix Badolo, Jourdain Lokossou, and Hippolyte Affognon. 2021. "Market Participation and Technology Adoption: An Application of a Triple-Hurdle Model Approach to Improved Sorghum Varieties in Mali." *Scientific African* 13: e00859. <https://doi.org/10.1016/j.sciaf.2021.e00859>.
- Smale, Melinda, Amidou Assima, Alpha Kergna, Véronique Thériault, and Eva Weltzien. 2018. "Farm Family Effects of Adopting Improved and Hybrid Sorghum Seed in The Sudan Savanna of West Africa." *Food Policy* 74: 162–171. <https://doi.org/10.1016/j.foodpol.2018.01.001>.
- Smith, R. J., and R. W. Blundell. 1986. "An Exogeneity Test for a Simultaneous Equation Tobit Model with an Application to Labor Supply." *Econometrica* 54(3): 679–685.
- Tabé-Ojong, Martin Paul, Michael Hauser, and Kai Mausch. 2022. "Does Agricultural Commercialisation Increase Asset and Livestock Accumulation on Smallholder Farms in Ethiopia?" *The Journal of Development Studies* 58: 1–21. <https://doi.org/10.1080/00220388.2021.1983170>.
- Tabé-Ojong, Martin Paul, Lina Marcela Ibarra, Robert Santiago Andrade, and Ricardo Labarta. 2023. "Soil Conservation and Smallholder Welfare under Cassava-Based Systems in Thailand." *Land Degrad Dev* 34(6): ldr.4569. <https://doi.org/10.1002/ldr.4569>.
- Tabé-Ojong, Martin Paul, J. C. Lokossou, B. Gebrekidan, and H. D. Affognon. 2023. "Adoption of Climate-Resilient Groundnut Varieties Increases Agricultural Production, Consumption, and Smallholder Commercialization in West Africa." *Nature Communications* 14: 5175. <https://doi.org/10.1038/s41467-023-40781-1>.
- Tabé-Ojong, Martin Paul, Kai Mausch, Tesfaye B. Woldeyohanes, and Thomas Heckelee. 2022. "Three Hurdles towards Commercialisation: Integrating Subsistence Chickpea Producers in the Market Economy." *European Review of Agricultural Economics* 49(3): jbab023. <https://doi.org/10.1093/erae/jbab023>.

- Tabe-Ojong, Martin Paul, Ernest L. Molua, Marco Alberto Nanfouet, Cynthia J. Mkong, Vanessa Kiven, and Venant Atem Ntegang. 2023. "Oil Palm Production, Income Gains, and off-Farm Employment among Independent Producers in Cameroon." *Ecological Economics* 208: 107817. <https://doi.org/10.1016/j.ecolecon.2023.107817>.
- Tabe-Ojong, Martin Paul, Melinda Smale, Nelissa Jamora, and Vania Azevedo. 2022. "Genebanks and Market Participation: Evidence from Groundnut Farmers in Malawi." *CABI Agric Biosci* 3(1). <https://doi.org/10.1186/s43170-022-00082-x>.
- Tabe-Ojong, Paul Jr Martin, Ernest L. Molua, Siri B. Ngoh, and Samuel E. Beteck. 2021. "Production, Consumption and Market Diversification of Grain Legumes in the Humid Forest Agroecology of Cameroon." *Sustainable Production and Consumption* 27: 193–202. <https://doi.org/10.1016/j.spc.2020.10.023>.
- Tesfay, Menasbo Gebru. 2020. "Does Fertilizer Adoption Enhance smallholders' Commercialization? An Endogenous Switching Regression Model from Northern Ethiopia." *Agriculture & Food Security* 9(1): 1–18. <https://doi.org/10.1186/s40066-020-0256-y>.
- Tessema, Y. M., J. Asafu-Adjaye, M. Kassie, and T. Mallawaarachchi. 2016. "Do Neighbours Matter in Technology Adoption? The Case of Conservation Tillage in Northwest Ethiopia." *African Journal of Agricultural and Resource Economics* 11(3): 211–225.
- Timmer, Peter. 2008. "Agriculture and Pro-Poor growth: An Asian Perspective." *Asian Journal of Agriculture and Development* 5(1): 1–23.
- Vaiknoras, Kate, and Catherine Larochelle. 2021. "The Impact of Iron-Biofortified Bean Adoption on Bean Productivity, Consumption, Purchases and Sales." *World Development* 139: 105260. <https://doi.org/10.1016/j.worlddev.2020.105260>.
- van Asselt, Joanna, and Pilar Useche. 2022. "Agricultural Commercialization and Nutrition; Evidence from Smallholder Coffee Farmers." *World Development* 159: 106021. <https://doi.org/10.1016/j.worlddev.2022.106021>.
- Verkaart, S., B. G. Munyua, K. Maus, and J. D. Michler. 2017. "Welfare Impacts of Improved Chickpea Adoption: A Pathway for Rural Development in Ethiopia?" *Food Policy* 66: 50–61. <https://doi.org/10.1016/j.foodpol.2016.11.007>.
- von Braun, Joachim. 1995. "Agricultural Commercialization: Impacts on Income and Nutrition and Implications for Policy." *Food Policy* 20(3): 187–202. [https://doi.org/10.1016/0306-9192\(95\)00013-5](https://doi.org/10.1016/0306-9192(95)00013-5).
- Wooldridge, J. M. 2013. In *Introduction to Econometrics: A Modern Approach*, 5th ed., edited by J. Sabatino. Michigan: South Western Educational Publishing.
- Wooldridge, J. M. 2015. "Control Function Methods in Applied Econometrics." *Journal of Human Resources* 50(2): 420–445.
- World Bank. 2019. *Maximizing Finance for Development in Agriculture and Food Systems in Ethiopia: An Analysis of Beef, Coffee, and Maize* W. Bank. <https://openknowledge.worldbank.org/handle/10986/32102>
- World Bank. 2021. World Bank Country Overview: Ethiopia W. Bank. <https://www.worldbank.org/en/country/ethiopia/overview>

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Tabe-Ojong, Martin Paul Jr., and Ababayehu Girma Geffersa. 2024. "Complementary Technology Adoption and Smallholder Commercialization: Panel Data Evidence from Ethiopia." *Applied Economic Perspectives and Policy* 46(3): 1151–74. <https://doi.org/10.1002/aepp.13439>