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Estimating returns to fertilizer adoption with unobserved heterogeneity: Evidence from Ethiopia

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Abstract

This paper examines the relationship between chemical fertilizer adoption and agricultural productivity in Ethiopia. Our results suggest that average returns to fertilizer adoption are high. Further, we find substantial heterogeneity across farm households in returns to fertilizer adoption, with comparative advantage playing a significant role in the adoption decision of farmers. While the adoption decision of farmers was largely rational, fertilizer use across plots was sub-optimal. The results of this paper underscore the importance of improving farmers awareness about proper use of fertilizer through site-specific extension services for improving agricultural productivity.

KEYWORDS

comparative advantage, Ethiopia, fertilizer, heterogeneity, misallocation

1 | INTRODUCTION

The low adoption rate of modern agricultural inputs, such as fertilizer, is often suggested as the major reason for much of the stagnation in agricultural productivity across sub-Saharan African (SSA) countries (Bold, Kaizzi, Svensson, & Yanagizawa-Drott, 2017; Liverpool-Tasie, Omonona, Sanou, & Ogunleye, 2017). Various alternative explanations ranging from credit market constraints (Karlan, Osei, Osei-Akoto, & Udry, 2014), lack of agronomic knowledge (Liverpool-Tasie et al., 2017), information market constraints (Conley and Udry, 2010; Wossen, Berger, & Di Falco, 2015) to low returns (Duflo, Kremer, & Robinson, 2008; Suri, 2011) have been cited as the main reasons for the low adoption rates of profitable technologies. In this paper, we revisited the relationship between adoption of chemical fertilizer and agricultural productivity using cross-sectional and panel data from Ethiopia.

Estimation and identification of treatment effects of fertilizer adoption in the context of cross-sectional data is challenging as adoption decision is not necessarily random. In the absence of random assignment of adoption status, constructing a counterfactual is impossible as the same individual cannot be observed with and without fertilizer use simultaneously. In the impact evaluation literature, this is commonly regarded as the missing data problem and a range of approaches have been suggested to construct a reliable counterfactual distribution. These methods include matching approaches that consider observed sources of heterogeneities and instrumental variable (IV) approach that considers observed and unobserved sources of heterogeneities. Even though causal effects can be identified through IV approaches, identifying a relevant and exogenous instrument is often challenging. An important extension in this regard has been the use of panel data to estimate fixed effects by controlling for time-invariant sources of unobserved heterogeneities. However, building panel data sets is costly. As a result, many researchers in developing countries often resort to cross-sectional data to evaluate the effect of an intervention such as fertilizer use.

In this paper, we utilized an approach that exploits the typical decision-making behavior of farm households in developing countries in a cross-sectional data setting. Due to

prevalent insurance and credit market imperfections, many farm households engage in crop diversification activities as an *ex ante* risk reduction and *ex-post* consumption smoothing strategies. Thus, individual farm households often produce more than one crop on different plots with a specific technology being adopted in one plot and not on others. Under this context, technological choice is not a complete switch from adoption to non-adoption of a technology (e.g., fertilizer). In such settings, we can observe the productivity levels of the same individual farmer at the same point in time with and without fertilizer use as most farmers own more than one plot, and fertilizer may not necessarily be applied in all plots. For a farmer that has a fertilized and unfertilized plot, the unfertilized plot can be considered as a counterfactual if it has the same characteristics with the fertilized plot.[1] This paper, therefore, exploits this observed pattern of fertilizer use by farmers to estimate a cross-sectional fixed effect (CFE) model. The most attractive feature of the CFE model is that any household and village level heterogeneities or aggregate shocks (such as market and climate) are plot invariant. The only source of variation is plot-level heterogeneities. If such plot-level heterogeneities are considered, treatment effects can be estimated consistently.

This paper uses the World Bank's Living Standards Measurement Study-Integrated Surveys of Agriculture (LSMS-ISA) data from Ethiopia to estimate the relationship between fertilizer adoption and agricultural productivity. To verify the reliability of the CFE estimates, we also examined the relationship between fertilizer adoption and agricultural productivity using other treatment effect estimation approaches: ordinary least square (OLS), propensity score matching (PSM), IV and standard panel fixed-effect models. The remainder of the paper is structured as follows: Section 2 presents overview of the fertilizer sector in Ethiopia. Section 3 outlines the empirical strategy and the description of the data source. Section 4 presents and discusses the main results and section 5 concludes.

2 | OVERVIEW OF FERTILIZER USE IN ETHIOPIA

It is widely recognized that improving agricultural productivity is central to poverty reduction. Cognizant of this fact, the government of Ethiopia has envisaged the agricultural sector as the engine of growth and transformation. For example, Ethiopia has implemented the Sustainable Development and Poverty Reduction Program (SDPRP) (2000/01–2004/05), Plan for Accelerated and Sustained Development to End Poverty (PASDEP) (2005/06–2009/10), the first Growth and Transformation Plan (GTP) (2010/11–2014/15) and the second GTP since 2015. In all of the above programs, the main focus was the agricultural

sector, and improving the adoption rate of fertilizer and improved seed being sought as the main pathways for improving productivity. This was done by setting annual cereal production and fertilizer use targets in the first and second GTPs.

Despite such renewed efforts by the government, the marketing and distribution system of fertilizer is rather inefficient and costly (Rashid, Tefera, Minot, & Ayele, 2013; Spielman, Kelemework, & Alemu, 2012). Currently, the Agricultural Inputs Supply Enterprise (AISE) plays a key role in fertilizer importation and to some extent in the distribution of fertilizer across the different regions of the country. At the regional level, often cooperative unions selected by the AISE are the main distributers. Importation is done based on demand assessment at the district level and targets set by the GTP of the country (Rashid et al., 2013; Spielman et al., 2012). Imported fertilizer is often transported to the warehouses of regional cooperatives and when this is not possible, to the central AISE warehouses (Spielman et al., 2012). During the planting season, the cooperative unions distribute fertilizer to the primary cooperatives. Fertilizer is then sold to smallholders by the primary cooperatives. In regions that have no cooperative unions or are inaccessible, AISE takes the responsibility to deliver, with primary cooperatives acting as wholesalers (Rashid et al., 2013). In addition, large commercial farmers (both state-owned and private) directly access fertilizer from AISE (Figure 1).

Data from the Central Statistical Authority (CSA, 2017a) suggest that in 2015/2016 cropping season more than 1.1 million metric ton of fertilizer was used by 14.7 million farmers across the country (Figure 2). The most common fertilizers being NPS (19% N, 38% P2O5 and 7% S), Diammonium Phosphate (DAP: 46% P2O5 and 18% N), and urea. Farmers apply fertilizer in different combinations, the best combination being NPS + urea followed by DAP + urea. For example, 45% of the fertilizer use in the country is in the form of NPS + urea while about 25% is a combination of DAP + urea. The rest is mostly urea or DAP independently. In terms of allocation of fertilizer for major crops, cereals account about 88% of the total fertilizer use of the country (CSA, 2017a).[2]

Contrary to conventional wisdom, the LSMS-ISA 2015/16 data also suggests that about 42% of the farmers use chemical fertilizer (this rate is about 73% when manure use is included). In terms of the regional distribution, more than 70% of the country's fertilizer consumption is concentrated in the two largest regions of the country: Oromia and Amhara regions. However, the use of chemical fertilizer in these regions is still low. For example, only 54% of the farmers in Oromia and 48% of the farmers in Amhara region have used chemical fertilizer in the 2015/16 cropping season. The highest fertilizer application rate is reported in Tigray and Harari regions (about 59%).
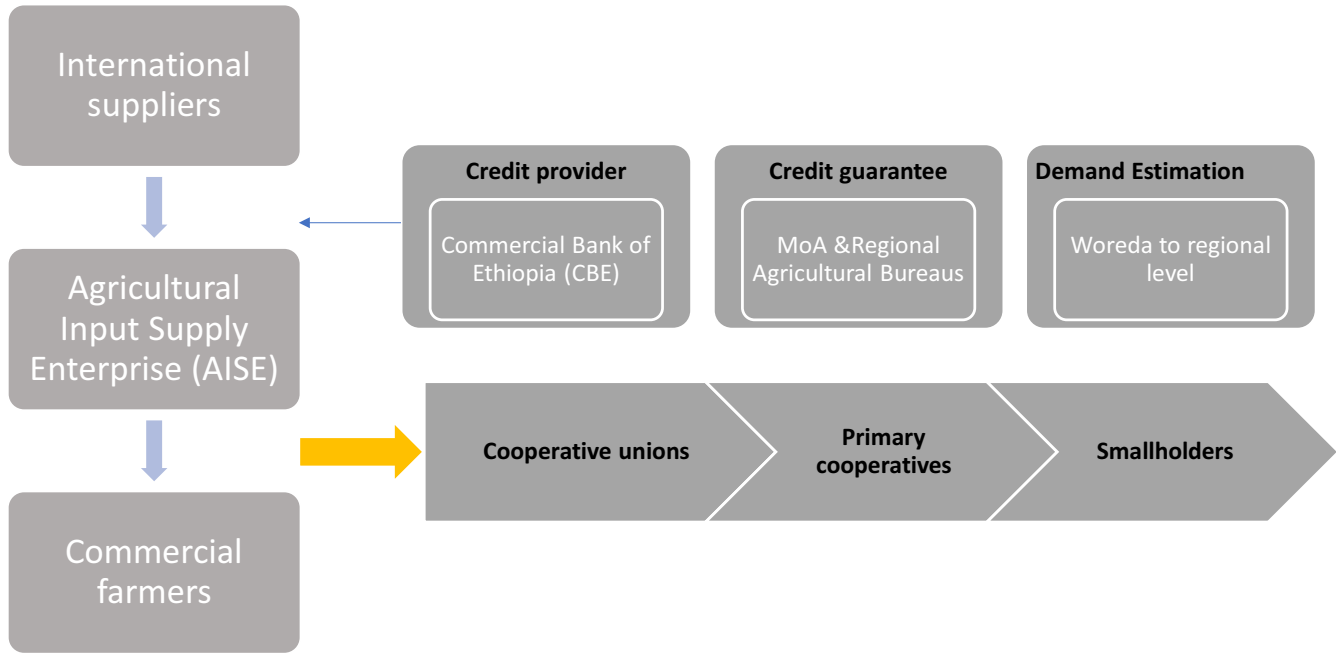
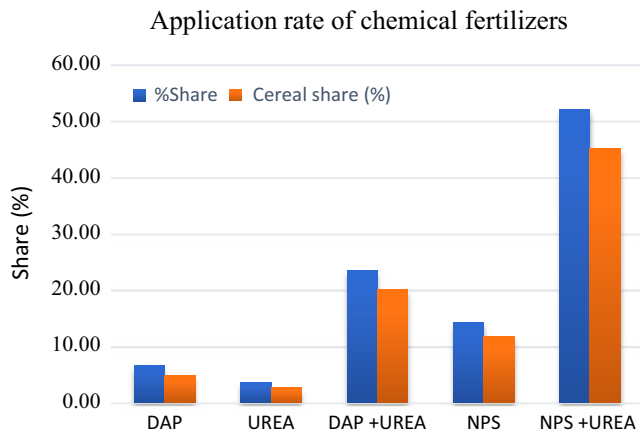**FIGURE 1** Overview of the fertilizer distribution system in Ethiopia: (Source, ATA, 2014)

FIGURE 2 Fertilizer use in 2015/16 season (CSA, 2017a,b)

3 | CONTEXT, EMPIRICAL STRATEGY AND DATA SOURCES

3.1 | Theoretical context

In this section, we present the theoretical framework employed to examine the effect of fertilizer adoption on the value of crop production. In our context, we defined the plot-level average treatment effect (ΔP) of adopting fertilizer by household i on a specific plot p (T_{ip}) on the value of production (V_{ip}) as:

$$\Delta P = (V_{ip}|T_{ip} = 1) - (V_{ip}|T_{ip} = 0) \qquad (1)$$

The above relationship implies that ΔP for a given farmer in a specific plot (T_{ip}) would be the difference between the value of production with and without fertilizer at the same point in time. This, however, is impossible as the same plot cannot be observed with and without fertilizer at the same time. On the other hand, the farmer that owns the plots can be observed with and without fertilizer use at the same moment in time as fertilizer is not necessarily applied in all of the plots owned by the farmer. We therefore exploit this fertilizer use behavior of farmers to estimate a model that controls for plot-level heterogeneities. Our approach mimics the standard fixed-effect model in panel data settings as the same farmer often has more than one plot.[3] Household-level heterogeneities will play no role as they are fixed for a given household across plots. However, fertilized and unfertilized plots could be different in both observed and unobserved characteristics. For example, a farmer may apply fertilizer in less fertile plots to improve productivity. Other general biophysical factors, such as weather shocks, market and other village-level general characteristics will be fixed as they are plot invariant. Therefore, by estimating a CFE model that considers plot-level heterogeneities, treatment effects can be estimated consistently.

3.2 | Empirical strategy

Our empirical strategy closely follows the approach of Bellemare (2013). Let V_{pi} be the value of output per hectare for plot p and household i. The effect of fertilizer use (F_{pi}) on V_{pi} is then estimated as follows:

$$V_{pi} = f(F_{pi}, Q_{pi}, Z_{pi}, w_{pi}, \gamma) \qquad (2)$$

Q_{pi} represents a vector of plot-specific land quality indicators for a given household (such as soil types, soil fertility, wetness index, slope, etc.). The variable F_{pi} is a dummy variable that takes on a value of one if farmer i applies fertilizer in plot p and zero otherwise. The variable Z_{pi}, captures a vector of household and village-level variables (such as rainfall, farm assets, age education, etc.). Finally, $w_{pi} = e_{pi} + h_i$ is a composite error term of household specific/plot invariant (h_i) unobserved characteristics and plot-varying unobserved characteristics (e_p). γ is a vector of parameters to be estimated.

In the above specification, adoption decision can be endogenous due to omitted variables bias. For example, farmers who choose to adopt fertilizer may have better farming skills and management abilities, which are clearly correlated with productivity. Therefore, OLS estimates would be biased. To account for such unobserved household level heterogeneities, we employed two approaches. First, we employed an IV regression approach. In our identification strategy, we used spatial variation in the number of fertilizer suppliers as an identifying instrument. This variable affects farmers' decision to use fertilizer but it does not affect the value of crop production through any channel other than fertilizer use. We constructed the number of fertilizer suppliers across the different regions of the country using data from the Ethiopian Statistical Authority (CSA, 2017a). The variable, number of fertilizer suppliers, is arguably exogenous to household characteristics. However, it is expected to affect fertilizer adoption positively. Our first stage regression result also suggests that this variable is relevant as it was significant at 1% level.[4]

Second, we estimated a CFE model by introducing household fixed effects. The inclusion of household fixed effects overcomes potential biases from unobserved heterogeneities at the household level by exploiting variation in fertilizer use within a household as shown in the following specification:

$$V_{pi} = f(F_{pi}, Q_{pi}, Z_{pi}, D_i, w_{pi}, \varphi) \qquad (3)$$

Equation 3 extends Equation 2 by incorporating household fixed effects (D_i). The introduction of household fixed effects eliminates endogeneity biases that stems from unobserved household level heterogeneity.[5] Our parameter of interest (φ) can therefore be estimated consistently in the presence of household level observed/unobserved heterogeneities. However, unobserved plot-level heterogeneities may still bias parameter estimates of φ[6]. As an alternative approach, we also extended the above specification to panel data settings. This is possible in our settings since households and parcels were tracked over time.

$$V_{pit} = f(F_{pit}, Q_{pit}, Z_{pit}, D_{jk}, w_{pit}, \delta) \qquad (4)$$

By estimating a standard fixed-effect model at the plot level (Equation 4), we will be able to obtain consistent estimates for δ as the correlation between the time-invariant plot-level unobservables and adoption of fertilizer is fully controlled.

After establishing the average return from the use of chemical fertilizer, we then examine the distribution of such returns by explicitly accounting for comparative advantage in the use of fertilizer using the correlated random coefficient (CRC) model (Michler, Tjernstro, Verkaart, & Mausch, 2018; Suri, 2011). Considering such heterogeneity is important as there might be significant heterogeneity in returns across fertilizer adopters.[7] Using the CRC model, we estimated effects for farmers that always use fertilizer (always adopters), farmers that never used fertilizer (never-adopters), farmers that used fertilizer in the current production season but not in the previous season (adopters), and farmers that used fertilizer in the previous production season but not in the current production season (dis-adopters). Following Suri (2011) and Barriga Cabanillas, Michler, Michuda, and Tjernström (2017), the CRC model is presented as follows:

$$V_{it} = \alpha + \beta f_{it} + \theta_i + \vartheta \theta_i f_{it} + \tau_i + u_{it} \qquad (5)$$

In the above specification, β measures average return from fertilizer adoption; θ_i captures the key unobservables that determine selection into fertilizer adoption and measures the relative productivity of a farmer with and without fertilizer. ϑ, denotes the sorting of farmers in fertilizer adoption (θ_i) and measures the importance of comparative advantage (Michler et al., 2018; Suri, 2011). For example, if a farmer with high θ_i's has lower gains from adoption, then $\vartheta < 0$ (Michler et al., 2018; Suri, 2011). Similarly, if $\vartheta > 0$ then the self-selection process leads to greater inequality in returns as farmers with high θ_i's has higher gains from adoption. Finally, τ_i is a household fixed effect which measures absolute advantage.[8] In the above specification, the parameter (θ_i), is correlated with the adoption decision of farmers (f_{it}). Therefore, the correlation between θ_i and f_{it} is eliminated by projecting θ_i onto the full adoption history of farmers (Michler et al., 2018; Suri, 2011). In our case, since we have two rounds of panel data, the projection coefficient is given by:

$$\theta_i = \delta_0 + \delta_1 f_{i1} + \delta_2 f_{i2} + \delta_3 f_{i1} f_{i2} + u_i \qquad (6)$$

The parameter θ_i is recovered by inserting Equation 6 into Equation 5. Once θ_i and ϑ are determined, returns are estimated as ($\beta + \vartheta \theta_i$)). These values are the predicted counterfactual returns for non-adopters using weighted averages of all possible returns (Michler et al., 2018; Suri, 2011).

3.3 | Data and descriptive statistics

For this study, we utilized the LSMS-ISA data. We used the 2015/16 survey round for our main analysis. In addition, data from the previous round (2013/14 round) is used to build a panel data set. The survey provides detail plot- and household-level information on crop production and adoption of new technologies, including the use of fertilizer at the plot level. In addition, the post-planting and post-harvest questionnaire solicited information on land ownership, labor use, and other inputs. Our main data set, the 2015/16 round contains detail data from about 5,000 households. Of these, about 66% are from rural areas and 9% from small towns. The remaining sample, about 25%, are from medium and large towns. For our purpose, we utilized data from rural areas and small towns.[9] Agricultural output is recorded in physical quantities (kilograms) of different crops at the plot level. Plot size is measured using GPS. In addition, the data also contains detail information on the full set of inputs used at the plot level.

The main treatment variable, adoption of chemical fertilizer, is constructed using the following question from the survey instrument, "Is fertilizer used on this field?" If yes, then the survey collected information on the type of fertilizer used by farmers. We defined the treatment variable (chemical fertilizer adoption) if the farmer uses either DAP, urea, NPS, or other inorganic fertilizers. In particular, we constructed a dummy variable that takes on a value of one if chemical fertilizer was applied in the plot and zero otherwise. The data contains extensive plot-varying variables. These include mostly agronomic practices and land quality indicators. The data provide labor use (family labor, hired labor, and unpaid labor from other households) for each plot. In addition, the data contains other agronomic practices such as the use of pesticide, herbicide, irrigation, and fallowing. The survey also contains information on land ownership (as measured by the certification status of the plot). Since our approach requires controlling for plot level heterogeneity, we used extensive land quality indicators. These variables include: soil fertility measurements, erosion level, elevation, slope, wetness index, distance of each plot from homestead and soil types of the plot. Some of these variables were constructed using georeferenced plot and household locations in conjunction with various geospatial databases (CSA, 2017b).[10]

Table 1 presents characteristics of fertilized and unfertilized plots. The data shows agronomic synergy since in plots where fertilizer is used, there is more herbicide and pesticide application. Farmers also tend to apply fertilizer in less sloppy plots, self-owned plots and to those closer to the homestead.

TABLE 1 Plot characteristics by fertilizer use status

	Full sample (N = 14,366)	Plots with fertilizer (N = 3,299)	Plots without fertilizer (N = 11,067)	Mean diff
Value of production per ha (in ETB)	12,046	19,307	9,881	9,426***
Use of pesticide (Yes = 1)	0.036	0.073	0.025	0.05***
Use of herbicide (Yes = 1)	0.11	0.27	0.06	0.21***
Slope of the plot (%)	13.1	10.1	14	−3.9***
Elevation of the plot (m)	1,989	2,121	1949.7	171***
Wetness index of the plot	12.6	12.97	12.5	0.48***
Good soil fertility level (Yes = 1)	0.33	0.33	0.332	−0.002
Fair soil fertility level (Yes = 1)	0.523	0.54	0.52	0.025***
Poor soil fertility level (Yes = 1)	0.147	0.13	0.15	−0.02***
Plot under extension program (Yes = 1)	0.217	0.63	0.094	0.54***
Plot under irrigation (Yes = 1)	0.027	0.027	0.028	−0.001
Plot Tenure (Plot owned = 1)	0.66	0.73	0.64	0.09***
Plot prevented from erosion (Yes = 1)	0.61	0.80	0.55	0.25***
Plot fallowed (Yes = 1)	0.087	0.08	0.09	−0.012***
Labor (hr)	139	188	124	64*
Manure (1 = yes)	0.28	0.216	0.30	0.08***
Compost (1 = yes)	0.044	0.054	0.04	0.01***
Leptosol soil type (Yes = 1)	0.108	0.101	0.11	−0.008
Cambisol soil type (Yes = 1)	0.024	0.033	0.02	0.012***
Vertisol soil type (Yes = 1)	0.352	0.357	0.35	−0.006
Luvisol soil type (Yes = 1)	0.346	0.362	0.34	−0.02***

ETB: Ethiopian birr. ***, ** and * refer to significance at 1%, 5% and 10% respectively.

TABLE 2 Household characteristics by adoption status

	Full sample	Fertilizer adopter	Fertilizer non-adopter	Mean diff
Household size	5.6	5.67	5.58	0.09***
Drought shock (1 = yes)	0.22	0.28	0.21	0.07***
Ownership of sickle	2.02	2.41	1.91	0.5***
Ownership of axe	0.65	0.62	0.77	0.155***
Ownership of pick axe	0.71	0.52	0.75	−0.18***
Ownership of traditional plough	0.84	0.68	0.88	−0.20***
Ownership of modern plough	1.06	1.24	1.0	0.24***
Ownership of water pump	0.06	0.057	0.065	0.008
Median plot distance (km)	84.5	13.6	147.8	134.2

***, ** and * refer to significance at 1%, 5% and 10% respectively.

Such differences in plot characteristics suggest selection bias at the plot level. The outcome variable, value per ha, is also reported in Table 1. Value of production is computed by multiplying total production by crop-specific prices. We used household-specific farm gate prices as reported in the survey. For cases where the household-specific farm gate prices were not reported, community-level crop prices were used. The plot-specific value of crop production was then converted into hectare equivalent and transformed into logarithmic form for estimation.[11] Values reported in Table 1 suggest that the value of production in fertilized plots is significantly higher than the value of production in unfertilized plots.

In Table 2, we present household-level variables. In this case, fertilizer adopter refers to a farmer that uses fertilizer at least in one of the plots. Table 2 suggests the presence

of significant heterogeneity at the household level between adopters and non-adopters.

4 | RESULTS

4.1 | Effect of fertilizer use on value of production

Table 3 reports our main results (the CFE model results) as well as OLS, PSM, and IV regression estimates. In our estimation, we included plot-specific soil types as additional controls. In addition, we also controlled for crop-specific fixed effects. These include the type of crop grown in a specific plot as well as the type of variety grown (improved or local varieties). Results in Table 3 show that parameter

TABLE 3 Estimated results using cross-section data (2015/16 LSMS-ISA round)

	CFE	PSM	OLS	IV	PFE
	(1)	(2)	(3)	(4)	(5)
Use of fertilizer	0.30***	0.542***	0.498***	0.329**	0.246***
	(0.067)	(0.078)	(0.093)	(0.174)	(0.067)
Soil type controls	Yes	Yes	Yes	Yes	Yes
Household level controls	No	Yes	Yes	Yes	Yes
Regional fixed effects	No	No	Yes	Yes	-
Crop fixed effects	Yes	Yes	Yes	Yes	Yes
R2	0.42		0.11	0.10	–
N	14,336	14,336	14,336	14,336	9,234

Standard errors clustered at the enumeration area-level are reported in parentheses. ***, ** and * refer to significance at 1%, 5% and 10% respectively. Standard controls include: use of pesticide, herbicide, labor, plot slope, plot elevation, plot wetness index, plot soil fertility level, erosion level, plot tenure status, plot management (irrigation, fallowing, etc.). Household fixed effects not reported include: household size, drought shock, ownership of farm assets (sickle, axe, plough and water pump). Soil type fixed effects include: Leptosol, Cambisol, Vertisol and Luvisol. Crop fixed effect are: Teff, Maize, Barley, Wheat, sorghum and a dummy for the use of improved varieties. Regional fixed effects include location dummies (Tigray, Amhara, Oromia, Somalia, SNNP, Afar, Benshangul Gumz, Harrar, Diredawa and Gambela).

estimates of the CFE model are very different from those obtained using OLS and PSM. The CFE estimates show a coefficient of 0.30 implying that adoption of fertilizer increases gross return by 35%.[12] However, treatment effects from OLS and PSM are much higher, the effect size being between 65–72%. The coefficient for IV is about 0.33, suggesting that fertilizer use increase gross return by about 39%, which is close to the CFE estimates. Note that, IV estimates are local average treatment effects. The effect size from the fixed-effect estimator (PFE) is 0.28, implying a 32.3% increase in gross-returns.[13] If we use IV and PFE estimates as a benchmark, then the CFE estimator can be a reliable estimation strategy in the absence of panel data and reliable instruments.

4.2 | Considering heterogeneity in returns

In this section, we present estimates from the CRC model. Estimated structural parameters of the CRC model are presented in Table 4. In the first two columns, we presented estimates at the household level (with and without covariates). While estimating effects at the household level, a farmer is considered as an adopter if fertilizer is used in at least one of the plots and zero otherwise. These structural estimates are then used to recover θ_i which is a farmer-specific productivity effect (comparative advantage). In the next two columns, estimates at the parcel level are reported as some households and parcels were tracked over time. In this case, the θ_{ip} measures parcel-specific unobserved productivity effects (comparative advantages). In recovering θ_{ip} in Equation 5 and Equation 6, we estimated the model with the assumption that the unobserved heterogeneity that makes the adoption decision endogenous depends on the farmers ability to use fertilizer and unobserved quality of the specific parcel of land. As such, the θ_{ip} measures the relative productivity of a

parcel of land with and without fertilizer while the θ_i measures the relative productivity of a farmer with and without fertilizer use. Note that, the household and parcel level estimates are not directly comparable as parcel and household combinations that were not present in the two survey rounds were dropped while estimating structural parameters of the parcel-level model. Across all household level estimates, ϑ is positive and statistically significant suggesting the existence of selection into fertilizer adoption based on comparative advantage (i.e., farmers that do better on average, do relatively well with fertilizer). Similarly, at the parcel level, ϑ is positive and significant with and without covariates (parcels that are productive on average will be more productive with fertilizer).

Using the above household level structural estimates, we presented the distribution of predicted counterfactual returns to fertilizer adoption $(\beta + \vartheta\theta_i)$ in Figure 3. The distribution is presented for the following group of farmers: always-adopters, never-adopters, adopters, and dis-adopters. As shown in Figure 3, adopters and always-adopters have a higher return from adoption compared to dis-adopters and never-adopters. This suggests that farmers adoption decision of fertilizer is rational in the sense that farmers with high returns adopt fertilizer while those with low returns do not.

Figure 4 shows the distribution of predicted returns at the parcel level $(\beta + \vartheta\theta_{ip})$.[14] The distributions of returns in Figure 4 suggest that the adoption decision of current adopters and dis-adopters is rational. However, returns in parcels where fertilizer is always applied is smaller than the returns in parcels where fertilizer was never applied. In 17% of the parcels, fertilizer was applied in both survey rounds while in about 58% of the parcels fertilizer was never applied.

Farmers decision not to use fertilizer despite large potential returns in some parcels is puzzling. The result may imply

TABLE 4 Structural parameters of the CRC model

	Household level		Parcel level	
	Without covariates	With covariates	Without covariates	With covariates
Optimal Minimum Distance (OMD) Structural Estimates				
β	0.366***	0.363***	0.360***	0.311***
	(0.079)	(0.073)	(0.088)	(0.075)
ϑ	0.69**	0.77**	1.74*	1.26*
	(0.35)	(0.38)	(0.94)	(0.76)
δ_1	−0.126*	−0.087	−0.22***	−0.20***
	(0.074)	(0.073)	(0.065)	(0.065)
δ_2	0.41***	0.407***	0.043	0.075
	(0.057)	(0.056)	(0.05)	(0.052)
δ_{12}	−0.20***	−0.193***	0.11**	0.10**
	(0.079)	(0.053)	(0.047)	(0.05)
N	2,338	2,338	4,174	4,174

Standard errors are reported in parentheses. ***, ** and * refer to significance at 1%, 5% and 10% respectively.
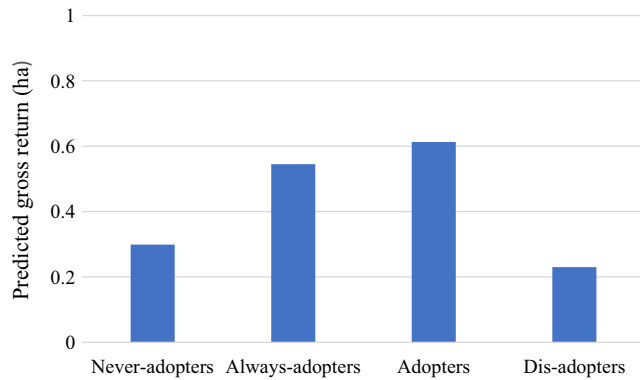
FIGURE 3 Household specific distribution of return per ha
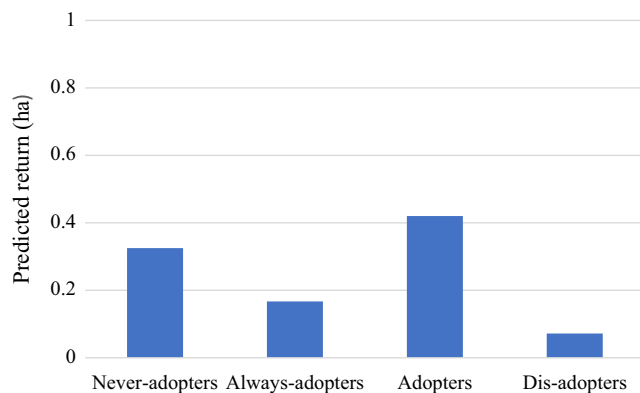
FIGURE 4 Parcel specific distribution of return per ha

evidence of misallocation, suggesting significant productivity gain from reallocation of fertilizer across plots. It also suggests that by applying fertilizer in unfertilized parcels, aggregate productivity can be improved. Low returns in always fertilized plots may also imply that the use of chemical fertilizer without other soil fertility enhancing practices may not increase productivity substantially. The continuous use of fertilizer despite lower potential returns in some parcels may also be due to insufficient knowledge about plot-specific returns of fertilizer among farmers. In this regard, improving farmers awareness about precision farming through site-specific extension services would be vital to improve overall agricultural productivity.

5 | CONCLUSIONS

This paper examined returns to fertilizer adoption in the presence of unobserved heterogeneity by exploiting cross-sectional variations in plot-specific characteristics. The CFE estimates suggest that adoption of fertilizer increases gross return by about 35%. Using standard panel fixed-effect and IV estimates as a bench mark, we show that the CFE estimator performs better than other approaches (OLS and PSM) that do not take unobserved heterogeneities into account. It worth noting that, despite our best effort to control for extensive

land quality indicators at the plot level, unobserved plot-level heterogeneities may still bias estimates of the CFE model.

Further, results from the correlated random coefficient model suggest substantial heterogeneity in returns to fertilizer adoption. We also find that comparative advantage plays a key role in the adoption decision of farmers. In particular, we find that farmers with high returns from adoption use fertilizer while those with low returns do not. However, fertilizer allocation across parcels was sub-optimal, implying evidence of misallocation. This sub-optimal decision may be due to difference in specific plot characteristics and insufficient knowledge about plot-specific returns to fertilizer use. Overall, the results underscore the importance of improving farmers awareness about proper use of fertilizer through site-specific extension services.

ENDNOTES

[1] Assuming the same plot quality in both observed and unobserved plot characteristics.

[2] Of the total fertilizer use in the country, 27% is applied to teff, 25% for maize and 22% for wheat.

[3] In our data, the average number of fields/plots is about four per farmer and only few farmers operate a single plot. In this paper a plot is defined as a unit of land within a parcel which is clearly demarcated by a hedge or path.

[4] These results are reported in the appendix. Note that, we have not extended the CFE to IV-CFE approach by using IV as the available instruments are measured at the household/region level. IV-CFE requires an IV that affects the decision to apply fertilizer at the plot-level but not plot level productivity. Our data, does not have a relevant and exogenous instrument at the plot level.

[5] $Cov(D_{jk}, \varepsilon_{pjk}) = 0$. This is what is estimated by the CFE approach.

[6] To overcome this bias, an instrument is required to control unobserved plot level heterogeneities.

[7] Controlling the type of crop-grown in each specific plot is vital as farmers may apply fertilizer based on crop type instead of specific qualities of the plot.

[8] Detail treatment of the CRC model is presented in Suri (2011).

[9] Medium and large towns were excluded as agriculture is not their source of livelihood.

[10] In principle, this land quality indicators will allow controlling for the unobserved heterogeneity between plots. Although precise measures of soil quality are observed here, they are typically unobservable.

[11] In order to make reasonable comparisons across survey rounds, we converted nominal value of production into real values by using the regional spatial price index as provided in the LSMS-ISA data. Note that, our focus is on gross returns instead of net-returns due to issues associated with the measurement of shadow wages.

[12] Note that, effects are calculated as 100[exp(coef.)−1] as the dependent variable is expressed in logarithm.

[13] In the PFE model, effects were estimated at the parcel level as the data tracked parcels and households instead of households and plots. A parcel is defined as a unit of land (which contains more than one

plot) that is owned by a single household and surrounded by a land owned by another household or demarcated by natural boundaries.

[14] Note that, Figures 3 and 4 are not directly comparable due to difference in sample size.

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