Money Matters: The Role of Yields and Profits in Agricultural Technology Adoption

Jeffrey D. Michler, Emilia Tjernström, Simone Verkaart, and Kai Mausch

Despite the growing attention to technology adoption in the economics literature, knowledge gaps remain regarding why some valuable technologies are rapidly adopted, while others are not. This paper contributes to our understanding of agricultural technology adoption by showing that a focus on yield gains may, in some contexts, be misguided. We study a technology in Ethiopia that has no impact on yields, but that has nonetheless been widely adopted. Using three waves of panel data, we estimate a correlated random coefficient model and calculate the returns to improved chickpea in terms of yields, costs, and profits. We find that farmers' comparative advantage does not play a significant role in their adoption decisions and hypothesize that this is due to the overall high economic returns to adoption, despite the limited yield impacts of the technology. Our results suggest economic measures of returns may be more relevant than increases in yields in explaining technology adoption decisions.

JEL codes: C33, O13, Q16.

Key words: Technology adoption, heterogeneity, correlated random coefficients, Ethiopia.

An empirical puzzle persists around why smallholder farmers in developing countries rapidly adopt some valuable technologies while others, such as fertilizer and hybrid seed, are not. The adoption literature has tackled this question in a variety of ways, proposing answers to the puzzle that include imperfections in credit markets (Croppenstedt, Demeke, and Meschi 2003), property rights (Place and Swallow 2000), learning externalities (Conley and Udry 2010), and lack of commitment (Kremer, Duflo, and Robinson 2011). Additionally, agricultural input costs are relatively high in Sub-Saharan Africa, partly due to transportation costs and input market interventions (Byerlee and Deininger 2013). One explanation, proposed by Suri (2011), centers on heterogeneity. Even when average returns are high, farmers may face heterogeneous returns based on their own, unobservable, comparative advantage in adopting the new technology. Using a correlated random coefficient model, Suri (2011) confirms this hypothesis for hybrid maize adoption in Kenya. According to this result, the empirical puzzle is only a puzzle when researchers fail to adequately control for heterogeneity in returns

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to farmers. Suri (2011) shows that in her data, farmers with low net returns either fail to adopt or disadopt the technology. This explanation of the puzzle has gained strong traction in the adoption literature, as evinced by some 449 papers citing her results as of July 2018. Remarkably, though, no one has attempted to reproduce these findings in a different context.

In this paper, we conduct an extension test of Suri's (2011) findings, using the case of improved chickpea adoption in Ethiopia. Implementing panel data methods that are common in the literature, we show that adoption of the new technology does not increase yields compared to local varieties. This result presents a puzzle that is distinct from the one usually considered in the adoption literature—high adoption rates of a technology that does not significantly increase yields. We then explore whether the low average returns for yields hide substantial heterogeneity by testing to see if Suri's (2011) solution to the puzzle for maize in Kenya holds for chickpea in Ethiopia. To do this, we use a generalized Roy model in which the returns to adoption that drive adoption decisions are allowed to vary across individuals. The theoretical model implies an underlying yield function with correlated random coefficients (CRC). To estimate this model, we expand the Suri (2011) correlated random coefficient model to accommodate more time periods.[1] This approach allows households to have both an absolute advantage in farming (equivalent to a fixed effect) and a comparative advantage in adoption (a household effect that is correlated with the adoption decision). We find no evidence that controlling for unobserved heterogeneity in returns resolves the puzzle. In fact, for improved chickpea in Ethiopia, we find that a farmer's comparative advantage plays no significant role in the returns to adoption.

What, then, explains the high adoption rates of this non-yield-increasing technology? We propose that the adoption literature of the past couple decades, which often viewed the physical returns to adoption as the main explanatory factor, has been focused on the wrong outcome. To economists, agricultural technology adoption decisions should be the outcome of individuals' optimization of expected utility or profit, where returns are a function of land allocation, the production technology, the costs of inputs, prices of outputs, and the markets in which those prices are realized and obtainable (Feder, Just, and Zilberman 1985). Recent literature that has focused on physical output, or imputed a shadow value to unmarketed physical output, implicitly assumes that output can either be stored or sold at a profitable price (Evenson and Gollin 2003; Smale and Olwande 2014; Asfaw, Di Battista, and Lipper 2016; Emerick et al. 2016; Jutzi and Rich 2016; Njeru, Mano, and Otsuka 2016; Verkaart et al. 2017). If outputs are instead difficult to sell or store, this could explain why the adoption of so many high-yielding varieties remains low.[2] Conversely, the marketability of improved chickpea may be why adoption in Ethiopia has been so high. In the face of limited sales opportunities due to missing or poorly functioning markets, the assumed equivalence between yields and economic returns may have led the literature astray.[3]

To test this explanation, we explore the economic returns to technology adoption measured in terms of (*a*) production costs per hectare and (*b*) profits (net revenue from the sale of agricultural goods in the market) per hectare. Using standard panel data methods, we find that the adoption of improved chickpea significantly reduces production costs and significantly increases farm profits. Our results are robust to estimating returns using Suri's (2011) correlated random coefficient model. In fact, we find no evidence that heterogeneity in household comparative advantage explains differences in the returns to adoption. Rather, what drives adoption is the ability of households to lower costs by reallocating crop production out of more costly crops and into improved chickpea.

[1] This is in turn a generalization of the correlated random effects (CRE) model first outlined by Mundlak (1978) and Chamberlain (1984), as well as a generalization of the now standard fixed effects approach to panel data estimation.

[2] Burke and Falco (2015) show large price fluctuations in the maize market in East Africa, suggesting that some barriers exist that prevent farmers from storing their product and selling at more advantageous prices later on in the season. Potential barriers include limited post-harvest storage capacity (Ricker-Gilbert and Jones 2015) and liquidity constraints (Stephens and Barrett 2011).

[3] The sole recent study that we are aware of which explores this path is Olwande et al. (2015), which explicitly looks at the marketing of maize, kale, and dairy in Kenya. These authors find little evidence of market participation by households, except in the case of dairy. This suggests that farmers might struggle to convert the higher yields that improved inputs provide into profitable surplus.

Compounding these cost savings is the ability of households to increase profits through the sale of surplus quantities of improved chickpea.

Our estimation results imply that there is little heterogeneity in returns to the adoption of improved chickpea varieties among smallholder farmers in Ethiopia. This result, suggesting that returns are relatively homogeneous (not heterogeneous) across households, is likely due to the considerable economic benefits to be gained from the adoption of improved chickpea. Predicted returns, measured as reductions in cost and increases in profits, are large enough that all groups have positive returns to adoption, even though there is no yield gain. While the comparative advantage story proposed by Suri (2011) may explain some of the adoption puzzle in contexts like maize in Kenya, the importance of measuring returns in economically meaningful ways should not be overlooked. In regions of the world with missing or poorly functioning markets, the discrepancy between the shadow value assigned to unmarketed physical production and the actual market value of the product may be larger than previously assumed. Perhaps the empirical adoption puzzle is due to focusing on the wrong output measure, and a reorientation towards economic measures such as costs, revenues, or profits will make the puzzle less common, as is demonstrated for the case of chickpea in Ethiopia.

This conclusion supports earlier technology adoption work, especially by agricultural economists, that focuses more explicitly on profits and economic returns. Several of the early contributions to the literature on technology diffusion highlight the role of profitability, which is defined as a function of market access (Griliches 1957; Cochrane 1958; Kislev and Shchori-Bachrach 1973; Feder 1982). As early as Falcon (1970) and Hayami and Herdt (1977), there was recognition of the limits of yield-improving technologies in regions where pricing difficulties were common. The results of our empirical analysis should be interpreted as a return to the insights of these earlier studies. Our conclusions also support the suggestions made by Feder, Just, and Zilberman (1985), Binswanger and Townsend (2000), and Foster and Rosenzweig (2010), namely that research should reorient in a direction that considers not just the physical but also price effects, and therefore economic returns, as factors that influence the adoption of agricultural technologies.

Context and Data

The Technology

As part of the Tropical Legumes II (TLII) development program in Ethiopia, a chickpea improvement program bred new varieties and established seed grower associations for production and distribution.[4] Seed improvement specifically focused on key plant traits, including larger seeds, resistance to Ascochyta blight/Fusarium wilt, drought tolerance, early maturation, and yield increases (Eshete et al. 2017). Research reports on field trials of the new varieties suggest positive, but somewhat mixed results along the yield dimension: some reports claim that yields were two to three times those of landrace varieties (Eshete et al. 2017), but other research reported more modest yield gains (Daba et al. 2005; Gowda et al. 2011). Farm trials also revealed that the larger seed size added substantial value to the new variety since wholesalers who purchase chickpea for export look specifically for seed size and color. It is therefore reasonable to expect that farmers may have expected the new variety to constitute an improvement along both of these dimensions.

Cultivation of local and improved chickpea (and all other legumes, such as fava bean, field pea, and grass pea) takes place in the post-rainy season using residual moisture. Planting occurs several weeks before harvest of the main growing season cereal crop, meaning that households are unable to cultivate two crops in the same 12-month period. Households must therefore decide between (*a*) growing cereal during the main rains and leaving the plot fallow through the post-rainy season, and (*b*) leaving the plot fallow during the main rains and growing chickpea during the post-rainy season. Thus, chickpea competes with cereal crops for land and purchased inputs, but the timing implies that

[4] The TLII development program is a joint initiative lead by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), the International Institute of Tropical Agriculture (IITA), and the International Center for Tropical Agriculture (CIAT). More details regarding the chickpea improvement program can be found in Verkaart et al. (2017) and at http://www.icrisat.org/TropicalLegumesII/.

Table 1. Transitions across Local/Improved Varieties for the Sample Period

	Transition of Adoption			Fraction of Sample (%)
	2007	2010	2014	($N = 600$)
Always adopter	Y	Y	Y	24.50
Early adopter	N	Y	Y	30.67
Late adopter	N	N	Y	20.00
Mixed adopter	Y	N	Y	4.00
Mixed disadopter	N	Y	N	6.33
Late disadopter	Y	Y	N	1.50
Early disadopter	Y	N	N	1.17
Never adopter	N	N	N	11.83

Note: The table shows all possible adoption histories for the three years in our panel. In the middle three columns, the letters represent adoption status, where "Y" represents the adoption of improved chickpea varieties, while "N" represents non-adoption or disadoption.

competition for labor is minimal. In general, households in Ethiopia—like most farm households in Sub-Saharan Africa—apply inputs at levels well below those recommended by authorities.

Data Sources

We analyze the decision to adoption improved varieties of chickpea in Ethiopia using three rounds of panel data collected in 2007, 2010, and 2014 for the TLII program. The districts in this study were purposively selected for their suitable agro-ecology for chickpea production, and represent major chickpea growing areas in the country (Asfaw et al. 2012).

In each district, eight to ten villages were randomly selected and within these 150–300 households were randomly selected, allowing for both chickpea and non-chickpea growing farmers to be interviewed. We limit our analysis to households that were interviewed in all three rounds of the survey, providing a balanced sample of 600 households. Adopters are defined as households who plant an improved chickpea variety in the season surveyed.[5] The data include detailed input use information on a variety of crops, including purchased inputs, hired labor costs, and family labor time as well as demographic information.[6]

Overall, adoption rates of improved chickpea increased substantially during the study period. In 2007, 31% of households were recorded as growing improved varieties of chickpea. By 2014, the adoption rate had increased to 80% of households. Table 1 displays the transition history of adoption for households in the data. Of the 600 households in our sample, 25% always cultivate improved varieties of chickpea. A further 55% adopt improved varieties and remain adopters over the study period. Only 12% of households never adopt improved varieties, while 9% of households disadopt.

Adoption rates were not uniform across space or time. Figure 1 shows heterogeneity in the rate of adoption from round to round across the three districts in our study area. Adoption rates in Lume-Ejere were already over 50% when the survey began, and by the end of the survey over 90% of households had adopted improved varieties. Minjar-Shenkora saw the most dramatic growth in adoption, increasing from 12% of households in 2007 to 84% of household in 2014. Compared to these two districts, adoption rates were lower in Gimbichu, where the initial adoption rate was 22% and increased to 45% by the end of the study.

The TLII data is geo-coded at the household level, which allows us to match households to rainfall data sources using satellite imagery from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data. CHIRPS is a thirty-year rainfall dataset that spans 50° South latitude

[5] Misidentification of varietal types is a common problem in many studies of adoption of new seed technology. However, the improved varieties in this study are predominantly newly introduced Kabuli chickpea types (95% of improved varieties). Kabuli are easy to distinguish from traditional Desi varieties as they are larger and cream colored, while Desi are smaller and brown. Additionally, the two varieties produce different colored flowers. We are therefore confident that improved seed is correctly identified.

[6] See online appendix A for more details about the household-level data and relevant descriptive statistics.

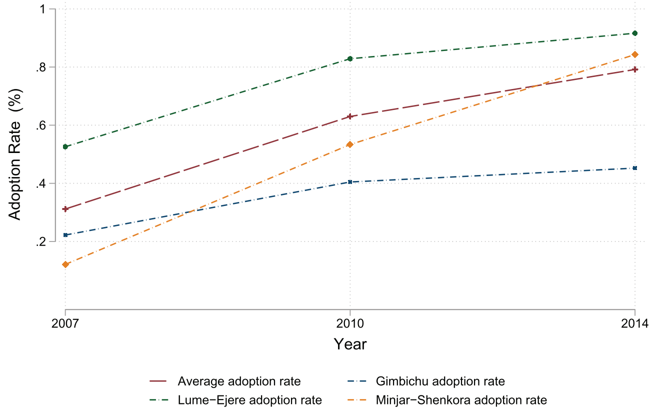

Figure 1. Average rate of adoption of improved varieties by district

Note: Figure displays the percentage of households cultivating improved chickpea varieties in a given year in the different study regions.

to 50° North latitude and incorporates 0.05° resolution satellite imagery with in-situ station data to create a gridded rainfall time series (Funk et al. 2015). The data provide daily rainfall measurements from 1981 through the present. We map households into the 0.05° grid cells and calculate the cumulative rainfall for the rainy season immediately preceding chickpea planting.[7] To measure rainfall shocks, we calculate normalized deviations in a single season's rainfall from average seasonal rainfall over the previous five years

$$(1) \quad \mathrm{R}_{jt} = \left|\frac{r_{jt} - \bar{r}_j}{\sigma_{r_j}}\right|.$$

Here, shocks are calculated for each grid cell j in year t where r_{jt} is the observed amount of rainfall for the season, $\bar{r}_j$ is the average seasonal rainfall for the grid cell over the past five years, and σ_{r_j} is the standard deviation of rainfall during the same period.

Theoretical Framework

We begin by using a Roy model in which the decision to adopt is the outcome of optimizing expected profit, where returns are a function of land allocation, the production technology, the costs of inputs, and prices of outputs (Feder, Just, and Zilberman 1985). Focusing on the production technology underlying the profit function, we assume Cobb-Douglas yield functions of the form of

$$(2) \quad Y_{it}^H = e^{\beta_t^H} \left(\prod_{j=1}^{k} X_{ijt}^{\gamma_j^H}\right) e^{u_{it}^H}$$

$$(3) \quad Y_{it}^L = e^{\beta_t^L} \left(\prod_{j=1}^{k} X_{ijt}^{\gamma_j^L}\right) e^{u_{it}^L}$$

where Y_{it}^H and Y_{it}^L are the yields of improved or hybrid (H) chickpea and local (L) varieties, respectively. Yields are a function of a set of inputs in per hectare terms (X_{ijt}), which we allow to have differential effects on yields, depending on the type of seed (γ_j^H and γ_j^L). The β's are variety-specific aggregate returns to production. Finally, the u_{it}^H and u_{it}^L terms are variety-specific compound error terms, in which

$$(4) \quad u_{it}^H = \theta_i^H + \varepsilon_{it}^H$$

$$(5) \quad u_{it}^L = \theta_i^L + \varepsilon_{it}^L.$$

Following Carneiro, Hansen, and Heckman (2003) and Suri (2011), we assume that households know θ_i^H and θ_i^L, which are farmer-specific productivity effects. We also assume that ε_{it}^H and ε_{it}^L are unknown to the farmer at planting and are uncorrelated with each other as well as with the X's.

Because θ_i^H and θ_i^L are unobserved, we follow Lemieux (1998) in decomposing the productivity effects as

[7] Given that we have household GIS coordinates and 0.05° grid cells, many households end up within the same grid cell (603 households, 111 grid cell observations). However, matching households to grid cells gives us significantly more variation in rainfall than simply using village rainfall measures as there are only 26 villages in the data.

$$\theta_i^H = b_H(\theta_i^H - \theta_i^L) + \zeta_i \tag{6}$$

$$\theta_i^L = b_L(\theta_i^H - \theta_i^L) + \zeta_i \tag{7}$$

where $b_H = (\sigma_H^2 - \sigma_{HL})/(\sigma_H^2 + \sigma_L^2 - \sigma_{HL})$, $b_L = (\sigma_L^2 - \sigma_{HL})/(\sigma_H^2 + \sigma_L^2 - \sigma_{HL})$, $\sigma_H^2 \equiv \text{Var}(\theta_i^H)$, $\sigma_L^2 \equiv \text{Var}(\theta_i^L)$, and $\sigma_{HL} \equiv \text{Cov}(\theta_i^H, \theta_i^L)$. The ζ_i is a household's absolute advantage in agricultural production and thus does not vary by the variety of chickpea under cultivation.

We then define $\phi \equiv b_H/b_L - 1$ and rewrite equations (6) and (7) as

$$\theta_i^H = (\phi + 1)\theta_i + \zeta_i \tag{8}$$

$$\theta_i^L = \theta_i + \zeta_i \tag{9}$$

where $\theta_i \equiv b_L(\theta_i^H - \theta_i^L)$. Our equation of interest is equation (8), which relates the productivity of a household in growing improved varieties of chickpea (θ_i^H) to a household's comparative advantage in growing improved varieties compared to local varieties (θ_i) and the household's absolute advantage in farming (ζ_i). The scaling term ϕ on θ_i is a measure of how important the comparative advantage is for growing improved varieties.

Returning to our Cobb-Douglas yield functions, we take logs to linearize the equations and replace the u_{it}^H and u_{it}^L terms with their decompositions:

$$y_{it}^H = \beta_t^H + X_{it}'\gamma_j^H + (\phi + 1)\theta_i + \zeta_i + \varepsilon_{it}^H \tag{10}$$

$$y_{it}^L = \beta_t^L + X_{it}'\gamma_j^L + \theta_i + \zeta_i + \varepsilon_{it}^L. \tag{11}$$

Using a generalized yield equation of the form $y_{it} = h_{it}y_{it}^H + (1 - h_{it})y_{it}^L$ and substituting in equations (10) and (11), we can define our empirical specification as

$$\begin{aligned} y_{it} = {} & \beta_t^L + X_{it}'\gamma_j^L + (\beta_t^H - \beta_t^L)h_{it} \\ & + X_{it}'(\gamma_j^H - \gamma_j^L)h_{it} + \theta_i + \phi\theta_i h_{it} \\ & + \zeta_i + \varepsilon_{it} \end{aligned} \tag{12}$$

where h_{it} is the decision by household i at time t to adopt improve chickpea and $\varepsilon_{it} \equiv h_{it}\varepsilon_{it}^H + (1 - h_{it})\varepsilon_{it}^L$.

The model defined by equation (12) is a CRC model because the coefficient $\phi\theta_i$ on the adoption term depends on the unobserved θ_i and will generally be correlated with the adoption decision. This is a generalization of the household fixed effects model (Suri 2006). Note that a fixed effects model is equivalent to restricting $\phi = 0$ so that the household unobservable θ_i has the same effect on yields regardless of the technology adopted. Intuitively, this assumes that the unobserved heterogeneity that makes the adoption decision endogenous is independent of a household's ability to use the technology. The CRC model relaxes this assumption and allows the unobserved effect to vary by chickpea variety.

In our estimation procedure, which is described in the next section, we estimate the distribution of θ_i, which is a measure of a household's productivity in improved varieties relative to local varieties, and ϕ, a measure of the importance of comparative advantage. The ϕ term describes the sorting of households into improved varieties. For $\phi > 0$, the sorting process leads to greater inequality in yields as households with relatively high values for θ_i select into the new technology and see increasing gains from their decision to adopt. Alternatively, for $\phi < 0$, the sorting process leads to less inequality as adoption of improved varieties will still be optimal for households with relatively small values for θ_i. When $\phi = 0$, a household's comparative advantage in cultivating improved varieties relative to local varieties is not important for the decision of whether to adopt the improved varieties.

Empirical Approach

Identification of the Yield Function

Identification of equation (12) requires two assumptions. The first is mean independence of the composite error and unobserved comparative advantage terms and the exogenous regressors. This amounts to

$$\text{E}[\zeta_i + \varepsilon_{it} | \theta_i; h_{i1}, \ldots, h_{iT}; X_{i1}, \ldots, X_{iT}]. \tag{13}$$

This assumption is not particularly strong, given that by differencing out $(\theta_i^H - \theta_i^L)$, we have ensured that ζ_i is independent of θ_i (Heckman and Honore 1990; Suri 2011). The second assumption is strict exogeneity of the idiosyncratic error term, which implies that transitory shocks do not affect the household's decision to adopt. We divide potential shocks into two categories—those that occur after the adoption decision, and those that occur prior to the adoption decision.

The timing of the household's decision is as follows. Prior to the rainy season, a household decides to either plant cereals before the rains or skip cereals and potentially plant legumes in the post-rainy season. If the household chooses to skip cereals, it observes rainfall and then decides to either plant legumes or leave the plot fallow for the entire year.[8] If the household chooses to plant legumes, it then prepares the land and chooses a seed technology based on forward-looking expectations regarding the availability of inputs (including budget constraints) and prospects for the sale of outputs. Having decided upon a seed technology, the household plants and then throughout the growing season applies labor and complementary inputs as non-rainfall shocks are realized. Finally, the household harvests and markets its production.

We are able to control for many of the shocks that occur prior to the adoption decision and affect both the decision to adopt and yields. We directly control for these potential shocks by including a variety of weather and household demographic variables. To control for weather shocks, we use seasonal rainfall as well as deviations from average rainfall. As Suri (2011) points out, the most likely type of non-weather shock is sudden sickness or death in the family.[9] We include variables to capture changes to the head of household, the household structure, and the household's access to off-farm income on the assumption that a death would impact any or all of these terms.

What remains are transitory shocks that occur after the adoption decision is made. We control for input use, as households will adjust their use of purchased inputs and the application of labor as seasonal shocks are realized. As panel A of table A1 in the supplementary appendix reveals, input use varies considerably over time. We interpret this as households adjusting their input use to the realization of transitory shocks after the adoption decision has been made. Given that we include input values in the regressions, we believe the possible presence of post-adoption transitory shocks is well controlled for.

By including a rich set of control variables, we have endeavored to reduce the potential for transitory shocks to affect both the adoption decision and outcomes. However, including controls still leaves the possibility that some unobserved transitory shocks remain. Such shocks, if they exist, most likely simultaneously reduce access to improved varieties and negatively impact outcomes, meaning the returns to improved varieties may be biased upward. Our results should be interpreted in the light of this limitation.

Estimating the CRC Model

To estimate equation (12) we use Suri's (2011) generalization of the correlated random effects (CRE) model pioneered by Chamberlain (1984). We return to Suri (2006) in order to expand the method to accommodate three years of data. For ease of exposition, we outline the estimation procedure for a three-period model without covariates. Assume the data generating process is given by

$$(14) \quad y_{it} = \delta + \beta h_{it} + \theta_i + \phi \theta_i h_{it} + \xi_{it}$$

where $\xi_{it} \equiv \zeta_i + \varepsilon_{it}$, $\beta \equiv \beta_t^H - \beta_t^L$, and all other terms are as previously defined. Note that the problem in estimating this equation comes from the fact that both h_{it} and θ_i are present in multiple places in the equation. As with the Chamberlain (1984) CRE model, we can replace the θ_i's with their linear projection on the history of the household's adoption behavior

$$(15) \quad \theta_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i3} + \lambda_4 h_{i1} h_{i2} + \lambda_5 h_{i1} h_{i3} + \lambda_6 h_{i2} h_{i3} + \lambda_7 h_{i1} h_{i2} h_{i3} + \nu_i.$$

Note that we must include the history of interaction because while the projection error ν_i is uncorrelated with each individual history by construction, it is not necessarily uncorrelated with the product of the histories.

Substituting equation (15) into equation (14) yields the following:

[8] As an anonymous reviewer pointed out, one may be concerned that the introduction of improved chickpea creates additional land pressure, reducing the incidence of fallowing and thereby reducing land quality (and by extension, yields) for those farmers who adopt the new technology. Three factors mitigate this concern. First, the crop cycle in Ethiopia means that the household decision to cultivate chickpea does not create additional pressure on land use (i.e., growing two crops on the same plot in the same year). Second, as Josephson et al. (2014) note, households in Ethiopia have by and large replaced fallowing with multi-crop practices. To the extent that the evidence in Josephson et al. (2014) is representative of a transition that has already occurred in Ethiopia, the introduction of improved chickpea does not introduce any new dynamics to soil management. Third, chickpeas fix nitrogen in the soil, making it unclear that fallowing is more nutrient-enriching than cultivating chickpeas.

[9] Note that if household members are chronically ill or if death is expected due to age or existing infection, those would not be transitory and are therefore controlled for by our absolute advantage term.

$$
\begin{aligned}
y_{it} = {} & \delta + \beta h_{it} + \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i3} + \lambda_4 h_{i1} h_{i2} \\
& + \lambda_5 h_{i1} h_{i3} + \lambda_6 h_{i2} h_{i3} + \lambda_7 h_{i1} h_{i2} h_{i3} + \nu_i \\
& + \phi(\lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i3} + \lambda_4 h_{i1} h_{i2} \\
& + \lambda_5 h_{i1} h_{i3} + \lambda_6 h_{i2} h_{i3} + \lambda_7 h_{i1} h_{i2} h_{i3} + \nu_i) h_{it} \\
& + \tau_i + u_{it}.
\end{aligned}
$$

The structure of the equation becomes easier to visualize when we write out each time period's yield function:

$$
\begin{aligned}
\text{(16a)}\quad y_{i1} = {} & (\delta + \lambda_0) + [\beta + \phi\lambda_0 + \lambda_1(1+\phi)] h_{i1} \\
& + \lambda_2 h_{i2} + \lambda_3 h_{i3} + [\phi\lambda_2 + \lambda_4(1+\phi)] h_{i1} h_{i2} \\
& + [\phi\lambda_3 + \lambda_5(1+\phi)] h_{i1} h_{i3} + \lambda_6 h_{i2} h_{i3} \\
& + [\phi\lambda_6 + \lambda_7(1+\phi)] h_{i1} h_{i2} h_{i3} \\
& + (\nu_i + \phi\nu_i h_{i1} + u_{i1})
\end{aligned}
$$

$$
\begin{aligned}
\text{(16b)}\quad y_{i2} = {} & (\delta + \lambda_0) + \lambda_1 h_{i1} + [\beta + \phi\lambda_0 \\
& + \lambda_2(1+\phi)] h_{i2} + \lambda_3 h_{i3} + [\phi\lambda_1 \\
& + \lambda_4(1+\phi)] h_{i1} h_{i2} + \lambda_5 h_{i1} h_{i3} \\
& + [\phi\lambda_3 + \lambda_6(1+\phi)] h_{i2} h_{i3} \\
& + [\phi\lambda_5 + \lambda_7(1+\phi)] h_{i1} h_{i2} h_{i3} \\
& + (\nu_i + \phi\nu_i h_{i2} + u_{i2})
\end{aligned}
$$

$$
\begin{aligned}
\text{(16c)}\quad y_{i3} = {} & (\delta + \lambda_0) + \lambda_1 h_{i1} + \lambda_2 h_{i2} \\
& + [\beta + \phi\lambda_0 + \lambda_3(1+\phi)] h_{i3} \\
& + [\phi\lambda_1 + \lambda_5(1+\phi)] h_{i1} h_{i3} \\
& + \lambda_4 h_{i1} h_{i2} + [\phi\lambda_2 + \lambda_6(1+\phi)] h_{i2} h_{i3} \\
& + [\phi\lambda_4 + \lambda_7(1+\phi)] h_{i1} h_{i2} h_{i3} \\
& + (\nu_i + \phi\nu_i h_{i3} + u_{i3}).
\end{aligned}
$$

These are the structural yield equations for each period. From these we can estimate the following three reduced form equations:

$$
\begin{aligned}
\text{(17a)}\quad y_{i1} = {} & \delta_1 + \gamma_1 h_{i1} + \gamma_2 h_{i2} + \gamma_3 h_{i3} \\
& + \gamma_4 h_{i1} h_{i2} + \gamma_5 h_{i1} h_{i3} + \gamma_6 h_{i2} h_{i3} \\
& + \gamma_7 h_{i1} h_{i2} h_{i3} + n_{i1}
\end{aligned}
$$

$$
\begin{aligned}
\text{(17b)}\quad y_{i2} = {} & \delta_2 + \gamma_8 h_{i1} + \gamma_9 h_{i2} + \gamma_{10} h_{i3} \\
& + \gamma_{11} h_{i1} h_{i2} + \gamma_{12} h_{i1} h_{i3} \\
& + \gamma_{13} h_{i2} h_{i3} + \gamma_{14} h_{i1} h_{i2} h_{i3} + n_{i2}
\end{aligned}
$$

$$
\begin{aligned}
\text{(17c)}\quad y_{i3} = {} & \delta_3 + \gamma_{15} h_{i1} + \gamma_{16} h_{i2} + \gamma_{17} h_{i3} \\
& + \gamma_{18} h_{i1} h_{i2} + \gamma_{19} h_{i1} h_{i3} + \gamma_{20} h_{i2} h_{i3} \\
& + \gamma_{21} h_{i1} h_{i2} h_{i3} + n_{i3}.
\end{aligned}
$$

These equations give 21 reduced form coefficients $(\gamma_1 - \gamma_{21})$ from which we can estimate ten structural parameters $(\beta, \phi, \lambda_0 - \lambda_7)$. Note that if we normalize the θ's so that $\sum \theta_i = 0$, we can eliminate λ_0 and only need to estimate nine structural parameters.[10] The restrictions necessary to identify the structural parameters are presented in table below.

$$
\begin{aligned}
\gamma_1 &= [\beta + \varphi\lambda_0 + \lambda_1(1+\varphi)] \\
\gamma_2 &= \lambda_2 \\
\gamma_3 &= \lambda_3 \\
\gamma_4 &= [\varphi\lambda_2 + \lambda_4(1+\varphi)] \\
\gamma_5 &= [\varphi\lambda_3 + \lambda_5(1+\varphi)] \\
\gamma_6 &= \lambda_6 \\
\gamma_7 &= [\varphi\lambda_6 + \lambda_7(1+\varphi)] \\
\gamma_8 &= \lambda_1 \\
\gamma_9 &= [\beta + \varphi\lambda_0 + \lambda_2(1+\varphi)] \\
\gamma_{10} &= \lambda_3 \\
\gamma_{11} &= [\varphi\lambda_1 + \lambda_4(1+\varphi)] \\
\gamma_{12} &= \lambda_5 \\
\gamma_{13} &= [\varphi\lambda_3 + \lambda_6(1+\varphi)] \\
\gamma_{14} &= [\varphi\lambda_5 + \lambda_7(1+\varphi)] \\
\gamma_{15} &= \lambda_1 \\
\gamma_{16} &= \lambda_2 \\
\gamma_{17} &= [\beta + \varphi\lambda_0 + \lambda_3(1+\varphi)] \\
\gamma_{18} &= \lambda_4 \\
\gamma_{19} &= [\varphi\lambda_1 + \lambda_5(1+\varphi)] \\
\gamma_{20} &= [\varphi\lambda_2 + \lambda_6(1+\varphi)] \\
\gamma_{21} &= [\varphi\lambda_4 + \lambda_7(1+\varphi)]
\end{aligned}
$$

We estimate equations (17a)–(17c) as seemingly unrelated regressions and preserve the 21 reduced form parameters in a vector $\boldsymbol{\pi}_{[21\times1]}$ and the variance-covariance matrices in a large symmetric block matrix $\mathbf{V}_{[21\times21]}$. The restrictions on the γ's can be expressed as $\boldsymbol{\pi} = \mathbf{H}\boldsymbol{\delta}$, where $\mathbf{H}_{[21\times9]}$ embodies the 21 restrictions on γ, and $\boldsymbol{\delta}_{[9\times1]}$ is a vector of our nine structural parameters.

We then use the optimal minimum distance (OMD) function to estimate the structural parameters. What remains is to calculate the variance-covariance matrix of the structural parameter estimates so we can compute the correct standard errors. This involves taking derivatives of each element in the product $\mathbf{H}\boldsymbol{\delta}$ with respect to each of the structural parameters; this gives us 63 derivatives in the construction of the variance-covariance matrix.[11] We automate the estimation procedure using a new Stata

[10] Normalizing θ_i results in $\lambda_0 = -\bar{h}_{i1}\lambda_1 - \bar{h}_{i2}\lambda_2 - \bar{h}_{i3}\lambda_3 - \bar{h}_{i1}\bar{h}_{i2}\lambda_4 - \bar{h}_{i1}\bar{h}_{i3}\lambda_5 - \bar{h}_{i2}\bar{h}_{i3}\lambda_6 - \bar{h}_{i1}\bar{h}_{i2}\bar{h}_{i3}\lambda_7$, where the bars are the averages of the adoption decision over time. Note that by the notation $\bar{h}_{i1}\bar{h}_{i2}$ we do not mean the product of each mean, but rather the mean of the interaction term.

[11] Note that there are more derivatives than restrictions because of the presence of λ_0, which is a function of all of the λ_i terms.

package described in Barriga Cabanillas et al. (2018).

Returns for Yields

Descriptive Evidence

At first glance, descriptive evidence of the impact of improved chickpea on yields appears to be unambiguously positive. Restricting our sample to households who cultivate chickpea, panel A in table 2 shows that in all three years yields from improved varieties are significantly higher than yields from local varieties.[12] In online supplementary appendix A, we calculate the marginal distribution of yields by adoption status. Returns are significantly higher for those who have adopted, and the yield distribution for adopters first-order stochastically dominates the distribution for non-adopters.

One obvious potential reason why improved chickpea might be associated with higher yields is if farmers increase the intensity of agricultural input application. Compared to traditional local varieties, the cultivation of improved varieties is associated with higher rates of fertilizer, chemical pesticide, and herbicide application. Similarly, cultivation of improved varieties is associated with higher costs for hired labor and for transportation of goods to market. The only input where we consistently see no difference in use across varieties is family labor. This may be due to binding family labor constraints, which force households to substitute hired labor or labor-saving technologies, such as chemical herbicide, for scarce family labor.

Given the prevalence of statistically significant differences in input use, we cannot tell if the improved varieties result in higher yields or if households use inputs more intensively when growing improved varieties, and this is what results in the higher yields. To address this issue, we first turn to a multivariate analysis employing Ordinary Least Squares (OLS) and fixed effects.

OLS and Fixed Effects Evidence

Our theoretical framework sets up the model in terms of a Cobb-Douglas yield function so we begin by estimating the generalized yield function with log of chickpea yield as the dependent variable.[13] To start, we test to see if yield response curves to inputs differ by chickpea variety by estimating yield using regressions in which we interact inputs with the adoption indicator (see table B1 in the supplementary online appendix).[14] The yield response is similar for both chickpea types; on the basis of this result, we believe that it is reasonable to pool all the seed varieties together in the yield function. Results from OLS and fixed effects versions of this generalized yield function, with various sets of controls, are presented in columns (1)–(4) of table 3.

In our OLS regression, the returns to adoption are 26%, which is slightly larger than the mean difference in yields presented in table 2. The inclusion of measured inputs reduces the returns to adoption, but the returns remain positive and significant. These results provide suggestive evidence that differences in input use do not fully explain the higher observed yields for improved chickpea.

However, when we include household fixed effects, returns to adoption are no longer significantly different from zero. While higher yields on improved chickpea clearly exist in our data, differences in mean outcomes can be explained by including either observables or by controlling for time-invariant unobservables. Once we control for input use decisions, regional environmental differences, or time-invariant differences across households (i.e., the absolute advantage, ζ_i), improved chickpea yields are indistinguishable from local chickpea yields. The main caveat of our interpretation of the fixed effects results is that estimation of the equations relies on a fairly restrictive assumption regarding the adoption process. Fixed effects is a special case of the CRC model in that it assumes the

[12] For each cultivation pair we first test for normality of the data using the Shapiro-Wilk test. In every case we reject the null that the data is normally distributed. Because of this, we rely on the Mann-Whitney (MW) test instead of the standard *t*-test to determine if differences exist within crops across cultivation practices. Unlike the *t*-test, the MW test does not require the assumption of a normal distribution. In the context of summary statistics we also prefer the MW test to the Kolmogorov-Smirnov (KS) test since the MW test is a test of location, while the KS test is a test for shape. Results using the KS test are equivalent to those obtained from the MW test.

[13] Given the prevalence of zero values in both input and output data, we use the inverse hyperbolic sine transformation to convert levels to logarithmic values.

[14] This also allows us to conduct a number of other tests regarding the potential endogeneity of some inputs as well as regarding the separability of labor. These tests are discussed in online appendices B and C.

Table 2. Production, Costs, and Returns of Improved and Local Chickpea

	2007			2010			2014		
	Local	Improved	MW-test	Local	Improved	MW-test	Local	Improved	MW-test
Panel A: Chickpea production									
Chickpea yield (kg/ha)	1,882	2,210	***	1,858	2,274	***	1,862	2,432	***
	(1,002)	(1,177)		(1,086)	(1,124)		(784.8)	(1,098)	
Chickpea area (ha)	0.435	0.755	***	0.337	0.654	***	0.367	0.593	***
	(0.385)	(0.567)		(0.253)	(0.465)		(0.292)	(0.415)	
Chickpea seed (kg/ha)	135.3	206.0	***	186.2	187.6		202.2	208.5	
	(83.22)	(225.3)		(97.98)	(73.86)		(92.61)	(111.0)	
Fertilizer (kg/ha)	3.420	24.14	***	13.20	8.534		9.697	20.17	**
	(31.42)	(68.39)		(63.41)	(56.19)		(71.91)	(136.5)	
Chemical cost (USD/ha)	17.11	18.95		13.62	31.23	***	13.44	58.75	***
	(31.80)	(47.68)		(44.41)	(41.95)		(34.59)	(81.33)	
Family labor (days/ha)	73.07	77.69		91.02	72.75		73.31	74.74	
	(40.18)	(48.11)		(132.2)	(34.78)		(48.20)	(47.20)	
Hired labor cost (USD/ha)	16.98	52.45	***	23.55	34.21	***	53.20	52.55	
	(65.29)	(88.11)		(73.65)	(75.73)		(111.7)	(98.36)	
Transportation cost (USD/ha)	2.095	8.995	***	1.392	5.601	***	1.877	2.123	**
	(8.566)	(32.04)		(5.045)	(15.75)		(10.56)	(8.176)	
Chickpea price (USD/kg)	1.449	1.961	***	0.972	1.751	***	0.763	0.955	***
	(0.336)	(0.671)		(0.197)	(0.432)		(0.156)	(0.140)	
Observations	207	187		106	378		55	475	
Panel B: Whole farm production									
Production costs (USD/ha)	555.9	680.2	***	575.9	546.3		633.0	540.2	***
	(301.2)	(268.3)		(258.4)	(221.9)		(273.9)	(210.8)	
Cultivated area (ha)	2.087	2.891	***	2.027	2.814	***	1.966	2.322	***
	(1.080)	(1.338)		(1.096)	(1.504)		(1.706)	(1.274)	
Seed cost (USD/ha)	185.1	254.4	***	173.3	195.4	***	154.7	141.1	**
	(97.29)	(91.93)		(90.71)	(72.41)		(67.89)	(70.47)	
Fertilizer cost (USD/ha)	304.8	313.3		336.7	272.6	***	393.7	297.6	***
	(197.1)	(170.1)		(160.6)	(142.0)		(178.8)	(130.7)	
Chemical cost (USD/ha)	14.21	13.72	***	6.346	13.54	***	15.93	26.87	***
	(86.59)	(30.08)		(15.43)	(14.67)		(40.67)	(31.89)	
Family labor (days/ha)	70.15	72.19		79.12	69.32	***	75.35	70.23	
	(28.43)	(28.93)		(34.24)	(26.82)		(39.53)	(31.35)	
Hired labor cost (USD/ha)	50.01	93.34	***	58.01	61.48	**	68.11	73.51	
	(63.83)	(89.08)		(97.76)	(66.91)		(103.6)	(86.96)	

Continued

Table 2. continued

	2007			2010			2014		
	Local	Improved	MW-test	Local	Improved	MW-test	Local	Improved	MW-test
Transportation cost (USD/ha)	1.717	5.502	***	1.605	3.218	***	0.569	1.098	**
	(7.832)	(12.54)		(8.158)	(7.393)		(2.507)	(3.820)	
On-farm profit (USD/ha)	2,058	2,475	***	1,784	2,242	***	1,434	1,749	***
	(893.0)	(1,122)		(906.6)	(1,154)		(797.4)	(722.1)	
Observations	413	187		222	378		125	475	

Note: Columns in table display means of production data by year and by type of chickpea cultivated, with standard deviations in parentheses. All monetary units are given in real terms. Columns headed "Local" are output and inputs used in cultivation of local varieties of chickpea, while columns headed "Improved" are output and inputs used in cultivation of improved varieties. The final column for each year presents the results of Mann-Whitney two-sample tests for differences in distribution. Results are similar if a Kolmogorov-Smirnov test is used. Significance of MW-tests are reported as * = p < 0.1; ** = p < 0.05; and *** = p < 0.01.

comparative advantage term is equal to zero. This assumption amounts to requiring that a household's experience or history of adoption has no effect on the outcome of interest, or that the effect is the same in every time period. Alternatively, if households are fully aware, or completely ignorant, of the potential gains from adoption, or behave myopically, it may be the case that their history of adoption has a time-invariant impact on their returns. Given that nearly 40% of the households in the sample do not change their adoption status, such an assumption may be reasonable.

Correlated Random Effects and CRC Evidence

To test for the possibility that adoption history has either no effect or a time-invariant effect on returns, we next estimate a correlated random effects (CRE) model (see table 4). To do this, we replace the time-invariant household fixed effect with its projection on the complete household adoption history. Coefficients on the returns to adoption are similar in the CRE model and in the fixed effects model.[15] Returns on yields are again not significant, regardless of whether or not we include measured inputs.

Across the fixed effects and CRE models, a robust set of outcomes show, controlling for observables and unobservables, that improved chickpea varieties have no statistically significant impact on yields. This result brings us back to our primary question—if improved chickpea varieties are not yield improving, why have so many households adopted them? One explanation is that a household's unobserved comparative advantage, left uncontrolled for in much of the existing adoption literature, is biasing our results. A test of whether or not such correlation exists can be constructed using the CRC model. Here, we not only estimate the returns to adoption (β) but the degree of selection due to heterogeneity in households' comparative advantage (ϕ). A *t*-test on the ϕ term is a test of the validity of the fixed effects assumption that unobserved heterogeneity is

[15] While the CRE and fixed effects estimates of returns are similar, the χ^2 values on the overidentification tests allow us to reject the fixed effects model in all cases. However, the overidentification test is an omnibus test, meaning that it has low power to reject any specific alternative. Thus, our ability to reject the fixed effects model is not particularly surprising or informative.

Table 3. Basic OLS and Household FE Specifications

	Ln chickpea yield (kg/ha)				Ln production cost (USD/ha)				Ln on-farm profit (USD/ha)			
	OLS (1)	OLS (2)	FE (3)	FE (4)	OLS (5)	OLS (6)	FE (7)	FE (8)	OLS (9)	OLS (10)	FE (11)	FE (12)
Improved chickpea	0.258***	0.127*	0.054	0.076	−0.017	−0.079***	0.054*	−0.045**	2.849***	2.814***	2.523***	2.379***
	(0.072)	(0.070)	(0.089)	(0.088)	(0.026)	(0.014)	(0.030)	(0.018)	(0.308)	(0.311)	(0.390)	(0.399)
Covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
District Controls	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Household FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations	1,408	1,408	1,408	1,408	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800
R^2	0.043	0.163	0.006	0.058	0.136	0.769	0.004	0.754	0.178	0.246	0.135	0.129

Note: Dependent variable is either log of chickpea yield, log of production costs per hectare, or log of on-farm profit per hectare. In specifications that include covariates, these include the set of inputs presented in table A1. Where the dependent variable is measured in dollar terms, we convert relevant covariates to value terms. Additional household controls include gender of household head, household size, off-farm income, land ownership, average rainfall for the season, and rainfall shock. Standard errors are reported in parentheses, while significance is as follows: * = $p < 0.1$; ** = $p < 0.05$; and *** = $p < 0.01$.

time-invariant and uncorrelated with the decision to adopt, or the experience of adoption.

Table 5 reports the OMD estimates of the structural parameters from the CRC model.[16] Returns to adoption for yields are again not significant, having controlled for observables and unobservables. Additionally, the estimates of ϕ are not statistically different from zero. If we believe that $\phi = 0$, this implies that selection into improved varieties is not based on any sort of unobserved comparative advantage. Intuitively, heterogeneity exists between households in that some households are better farmers than other households, regardless of crop type. This absolute advantage in farming is completely controlled for by the fixed effects model. What the CRC results show is that there is no detectable comparative advantage additional to a household's absolute advantage at farming that makes some households better at cultivating improved varieties compared to local varieties, and results in their selecting into improved varieties.[17]

To summarize our results thus far, our fixed effect and CRE estimates provide no evidence that the adoption of improved chickpea results in higher yields when compared to local varieties. This presents us with an empirical puzzle that is the converse of the one that motivates Suri (2011): high adoption rates of a technology that does not increase average yields. Estimating the CRC model, we find no evidence that Suri's (2011) explanation of the puzzle for maize in Kenya holds in the context of chickpea in Ethiopia.[18] The high adoption rate is not driven by selection based on comparative advantage. Thus, the question remains: why are so many households in Ethiopia adopting improved chickpea in the absence of yield gains?

[16] Estimates of the reduced form coefficients are presented in online appendix E.

[17] In online appendix D we estimate two-year pairwise versions of the CRC model to determine if our results are affected by the averaging over three years. Though coefficients are less precisely estimated, the results confirm those in the three-year model.

[18] We also estimate models with chickpea production value as the dependent variable. In the adoption literature, this is a common way to measure "economic" impact. However, it requires the assumption that, if a household wanted to, all production could be sold for that imputed value. Our results show that improved chickpea adoption has no significant impact on chickpea production value. Results of these alternative specifications are available from the authors upon request.

Table 4. CRE Reduced Form and Structural Estimates

Reduced Form Estimates

	Ln chickpea yield (kg/ha)						Ln production cost (USD/ha)						Ln on-farm profit (USD/ha)					
	Without covariates			With covariates			Without covariates			With covariates			Without covariates			With covariates		
	2007	2010	2014	2007	2010	2014	2007	2010	2014	2007	2010	2014	2007	2010	2014	2007	2010	2014
Improved,	0.102	0.154***	0.222**	0.020	−0.080	0.064	0.278***	0.228***	0.156***	−0.047**	0.001	0.012	0.834*	0.136	−1.480***	1.922***	−0.304	−0.551
2007	(0.078)	(0.060)	(0.105)	(0.081)	(0.060)	(0.116)	(0.046)	(0.050)	(0.041)	(0.024)	(0.023)	(0.017)	(0.441)	(0.529)	(0.574)	(0.454)	(0.565)	(0.545)
Improved,	0.044	0.023	−0.012	0.096	0.165**	−0.034	−0.073	−0.010	−0.060	−0.016	−0.039*	0.002	−0.387	3.004***	0.160	−0.263	2.526***	−0.650
2010	(0.101)	(0.077)	(0.136)	(0.095)	(0.070)	(0.137)	(0.044)	(0.049)	(0.040)	(0.023)	(0.023)	(0.017)	(0.430)	(0.516)	(0.560)	(0.443)	(0.551)	(0.532)
Improved,	0.425***	0.131	0.306*	0.194	0.302***	−0.035	−0.087*	−0.203***	0.139***	−0.008	−0.046	−0.063***	1.003**	2.299***	4.297***	0.529	1.398**	2.115***
2014	(0.128)	(0.098)	(0.173)	(0.149)	(0.111)	(0.216)	(0.052)	(0.057)	(0.046)	(0.029)	(0.029)	(0.021)	(0.501)	(0.601)	(0.651)	(0.558)	(0.695)	(0.670)

Optimal Minimum Distance (OMD) Structural Estimates

	Ln chickpea yield: Without covariates	Ln chickpea yield: With covariates	Ln production cost: Without covariates	Ln production cost: With covariates	Ln on-farm profit: Without covariates	Ln on-farm profit: With covariates
β	−0.041	0.057	0.054	−0.044**	2.487***	2.330***
	(0.074)	(0.073)	(0.037)	(0.017)	(0.407)	(0.407)
λ_1	0.163***	−0.046	0.198***	0.005	−1.064***	−0.427
	(0.049)	(0.050)	(0.029)	(0.013)	(0.342)	(0.344)
λ_2	0.045	0.084	−0.066**	−0.002	0.042	−0.252
	(0.068)	(0.066)	(0.027)	(0.013)	(0.311)	(0.311)
λ_3	0.259***	0.212**	−0.162***	−0.024	1.606***	0.549
	(0.072)	(0.083)	(0.033)	(0.017)	(0.348)	(0.385)
Observations	1,011	1,011	1,800	1,800	1,800	1,800
χ^2	1,472	1,651***	3,237***	1,069	11,513***	2,952***

Note: Dependent variable is either log of chickpea yield, log of production cost per hectare, or log of on-farm profit per hectare. In specifications that include covariates, these include the set of inputs presented in table A1. Where the dependent variable is measured in dollar terms, we convert relevant covariates to value terms. Additional household controls include gender of household head, household size, off-farm income, land ownership, average rainfall for the season, and rainfall shock. Standard errors are reported in parentheses, while significance is as follows: * = p < 0.1; ** = p < 0.05; *** = p < 0.01.

Table 5. Three Year CRC OMD Structural Estimates

	Ln chickpea yield (kg/ha)		Ln production cost (USD/ha)		Ln on-farm profit (USD/ha)	
	Without covariates	With covariates	Without covariates	With covariates	Without covariates	With covariates
β	−0.239	0.012	0.042	−0.047***	2.269***	2.360***
	(0.628)	(0.108)	(0.040)	(0.018)	(0.472)	(0.505)
φ	6.647	2.271	−0.241	0.909	1.202	4.325
	(18.86)	(4.109)	(0.265)	(1.667)	(1.335)	(9.198)
λ_1	0.237	0.068	0.039	−0.023	−0.141	−0.350
	(0.156)	(0.161)	(0.121)	(0.041)	(1.120)	(0.820)
λ_2	0.299***	0.173	−0.074	0.030	0.525	−0.212
	(0.109)	(0.107)	(0.060)	(0.026)	(0.651)	(0.598)
λ_3	0.272***	0.140	−0.164***	−0.002	1.638***	0.160
	(0.104)	(0.110)	(0.046)	(0.021)	(0.465)	(0.512)
λ_4	−0.297**	−0.237	0.246	0.020	0.275	0.361
	(0.120)	(0.179)	(0.173)	(0.050)	(1.244)	(0.840)
λ_5	−0.183	−0.035	0.159	0.035	0.008	0.271
	(0.265)	(0.187)	(0.144)	(0.046)	(1.157)	(0.743)
λ_6	−0.283***	−0.112	−0.028	−0.037	−0.479	0.130
	(0.103)	(0.118)	(0.074)	(0.030)	(0.713)	(0.532)
λ_7	0.267**	0.186	−0.165	−0.028	−0.846	−0.404
	(0.122)	(0.161)	(0.189)	(0.056)	(1.538)	(0.918)
Observations	1,011	1,011	1,800	1,800	1,800	1,800
χ^2	4,341***	4,504***	6,517***	3,112***	15,204***	7,403***

Note: Dependent variable is either log of chickpea yield, log of production cost per hectare, or log of on-farm profit per hectare. In specifications that include covariates, these include the set of inputs presented in table A1. Where the dependent variable is measured in dollar terms, we convert relevant covariates to value terms. Additional household controls include gender of household head, household size, off-farm income, land ownership, average rainfall for the season, and rainfall shock. Standard errors are reported in parentheses, while significance is as follows: * = p < 0.1; ** = p < 0.05; and *** = p < 0.01.

Returns for Costs and Profits

Descriptive Evidence

We now turn from a focus on the physical returns to improved chickpea adoption to the economic returns. We measure economic returns as per-hectare costs of production and as per-hectare profits from the sale of agricultural production. These specifications directly embed our yield function, with the Cobb-Douglas framework underpinning the cost or profit function. Households, when making their technology adoption decisions, are minimizing over cost functions or maximizing over profit functions for which the Cobb-Douglas technology is an input. We consider whole farm production as it allows us to capture reallocation of resources across crops and better mirrors household economic decision-making, which is ultimately concerned with household income and not income from a single crop.[19]

Similar to the descriptive evidence regarding production, we find significant differences in production costs between those who adopt improved chickpea and those who do not (see panel B in table 2). At first glance, we do not find strong evidence that adoption of improved chickpea lowers production costs, which is unsurprising, since improved chickpea cultivation is more resource intensive. In the first year of the survey, those who cultivate improved chickpea have significantly higher production costs. However, over the subsequent rounds of the survey, these costs fall, suggesting a learning process. The primary sources of the differences in production costs are seed, chemicals, and transportation. Despite these categories contributing to higher costs of on-farm production, the net result is that those who

[19] One may be concerned that the subsequent analysis is not directly comparable to our analysis of yields, since our sample is larger. To ensure that our results regarding costs and profits are not driven exclusively by the inclusion of households that never cultivate chickpea of any type, we also estimate cost and profit functions of just chickpea producers. We find that our fixed effects and CRE results do not change when we limit ourselves to the smaller sample. Our CRC results for costs and profits share the same sign but are not significant at conventional levels.

cultivate improved chickpea are significantly more profitable than those who do not.[20] The descriptive evidence suggests that while improved chickpea production can be more costly, these costs result in higher yields and that those yields can be profitably marketed.

OLS and Fixed Effects Evidence

Results from OLS and fixed effects versions of the cost and profit regressions with various sets of controls are presented in columns (5)–(12) of table 3. Recall that only our OLS estimates of the yield function resulted in positive returns to the adoption of improved chickpea. Comparably, the returns in terms of costs tend to be negative and significant and the impact on profit is always positive and significant. Households who adopt the technology experience around a 5% reduction in per hectare production costs, which helps contribute to around a 25% increase in profits per hectare. We take this as evidence that households are not adopting improved chickpea for the technology's potential yield gains. Rather, households adopt improved chickpea for the potentially significant returns gained as measured by lower costs and higher profits. This suggests the need to consider economic returns, not purely physical returns or some imputed value to physical returns, when seeking to understand the technology adoption decision in the context of developing country agriculture.

Correlated Random Effects and CRC Evidence

While our OLS and fixed effects results are encouraging, they may be biased if adoption is correlated with a household's comparative advantage in cultivating improved varieties of chickpea. We again estimate the CRE model, which returns values very similar to our fixed effects estimates (see table 4). Returns continue to remain significant when we estimate the CRC model (see table 5).[21]

The results from our cost and profit regressions tell a very different story than do our results from the estimation of the yield function. We find robust evidence that those who adopt improved chickpea had lower production costs and higher profits, even without seeing significant increases in yields. Despite this, we again find no evidence of selection into improved varieties based on a household's comparative advantage. There could be several explanations for this null result.[22] First, our set of control variables may have completely controlled for any comparative advantage that might remain unobservable if we had fewer controls. This seems unlikely since our results do not differ dramatically when we exclude/include covariates from our model. Second, our estimates may be too imprecise, meaning that a comparative advantage exists but we lack the power to detect it. Given that the standard errors on the estimates of ϕ tend to be larger than the standard errors on the other structural parameters, we cannot rule out this explanation. Third, the skill and knowledge to cultivate improved varieties may be extremely similar to that required to cultivate local varieties. If this is the case, no special advantage is required to shift a household from non-adoption to adoption. Given the relative simplicity of cultivating chickpeas, this explanation is plausible. Finally, it may be that the economic returns to improved varieties are so consistently large that it is rational for every household to adopt. Given the high adoption rates and that we consistently find that adoption increases profits in the range between 23% and 28%, we believe this explanation is the most likely. Additionally, this explanation does not preclude the existence of selection based on comparative advantage. Rather, what it says is that during this stage of the adoption cycle, the returns gained by all households from adoption greatly exceed any comparative advantage that some households might gain. If we were earlier or later in the adoption cycle, there may be more sorting based on a household's comparative advantage.

[20] In online appendix A, we separately calculate the marginal distributions of costs and profits by adoption status. Figure A2 shows that there is not much difference in the distribution of costs across adopters and non-adopters. Figure A3 shows the distribution of profits from adoption first-order dominates those from non-adoption.

[21] Estimates of the reduced form coefficients are presented in online appendix E.

[22] In addition to these explanations, we explore, in online appendices B and C, the potential for endogeneity in our explanatory variables as well as the issue of separability of labor.

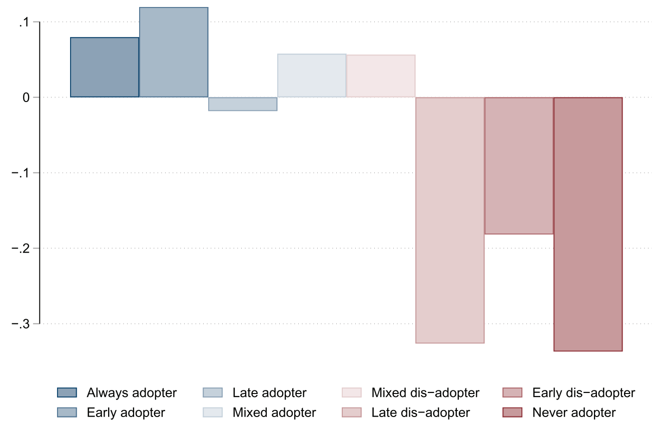

Figure 2. Distribution of returns for yields

Note: Figure displays predicted returns for yields by household history of adoption. Distribution of returns are calculated as $\hat{\beta}+\hat{\phi}\hat{\theta}_i$, where θ_i is the comparative advantage term for each household.

Discussion

Predicted Returns

To better understand why comparative advantage does not play a significant role in the adoption of improved chickpea, we predict the $\hat{\theta}$ term for a given adoption history. We can recover the $\hat{\theta}$ using equation (15) and our structural OMD estimates. Given that each history is binary, and given that we observe at least one household in each history, the projection is fully saturated (see table 1). This procedure results in eight mass points for the $\hat{\theta}$'s.

Once we have recovered the $\hat{\theta}$'s, we can predict the average returns for a given adoption history. This involves calculating $\hat{\beta}+\hat{\phi}\theta_i$, where $\hat{\beta}$ is the average return to improved varieties, and each i is a specific adoption history. The results can be viewed as the counterfactual returns for non-adopting households using weighted averages of all possible returns. In figures 2–4, we graph the returns to improved chickpea adoption for each adoption history.

Figure 2 displays returns to adoption in terms of chickpea yields. The predicted values align with what we would a priori expect in the adoption of new technologies: there are differences in returns based on adoption history. The households who adopt have higher returns to the technology, in terms of yields, than those who do not adopt or disadopt. However, given the evidence from our regressions, these differences are not statistically significant. We conclude that households who choose to adopt see positive but insignificant gains from adoption, while farmers who refrain from adoption or who disadopt may do so because their gains from adoption would be slightly negative.

Figures 3 and 4 display returns to adoption in terms of production costs and on-farm profits per hectare. Here we find consistently negative (positive) returns regardless of adoption history. Unlike the results from the yield regressions, we find reductions in costs for all groups. We interpret this result as evidence that while gains from adoption in terms of yields differ slightly based on who chose not to adopt or who disadopted, the reductions in production costs are significant for all groups. This translates into positive returns on profit regardless of a household's adoption history. We believe that the returns on profit, which are around 25%, are so large that the absolute advantage presented by improved varieties dwarfs any comparative advantage that some households might possess. We conclude that comparative advantage might be an important factor in determining adoption of technologies with lower average returns, such as maize and fertilizer in Suri (2011), where average returns were 9%. However, for technologies with large potential returns, such as the case of improved chickpea in Ethiopia, individual comparative advantage may not matter when measured against the absolute advantage all households would gain from adoption.

Potential Mechanisms

If households that adopt improved chickpea are not obtaining higher yields, then what is

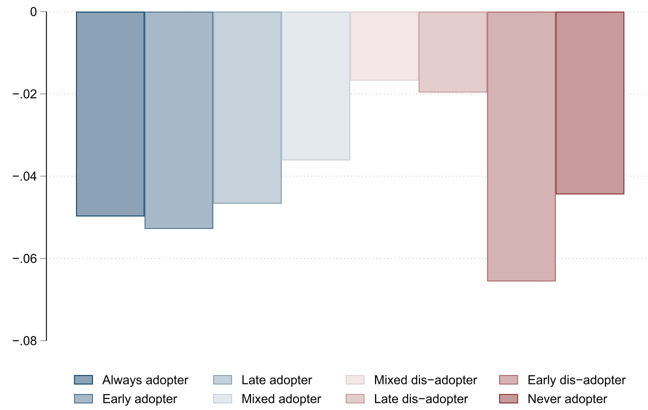

Figure 3. Distribution of returns for production costs

Note: Figure displays predicted returns for production costs per hectare by household history of adoption. Distribution of returns are calculated as $\hat{\beta} + \hat{\phi}\hat{\theta}_i$, where θ_i is the comparative advantage term for each household.

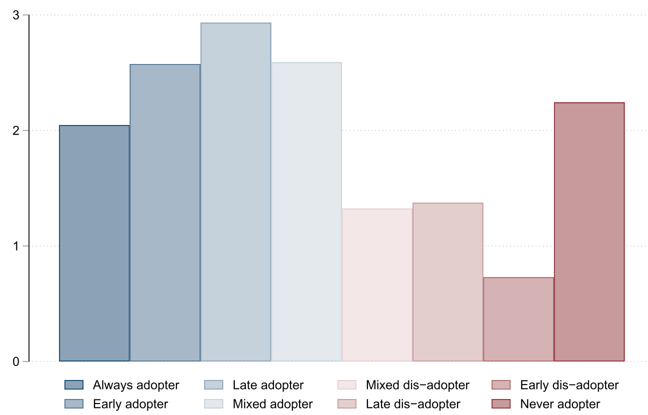

Figure 4. Distribution of returns for on-farm profits

Note: Figure displays predicted returns for on-farm profits per hectare by household history of adoption. Distribution of returns are calculated as $\hat{\beta} + \hat{\phi}\hat{\theta}_i$, where θ_i is the comparative advantage term for each household.

driving the large gains in profitability? We have shown that lower production costs explain some of this difference but where are these cost savings coming from since improved chickpea cultivation is more input intensive? In this final section we explore two potential mechanisms that may be driving the increase in profits. The first is changes in cropping patterns, and the second is increased marketability of crop production.

To understand how these mechanisms change in relation to adoption of improved chickpea, we construct two different "treatment" and "control" groups. In the first, we compare households who cultivate improved chickpea in all three rounds of the data with those who cultivate improved chickpea in round one but disadopt by the final round. In the second, we compare households who never adopt with those who adopt the technology in later rounds. The intuition behind comparing these adoption types is that in the first year, 2007, adopters and future disadopters should always have outcomes similar to each other, and so should never adopters and future adopters. By the last round, 2014, when adoption histories are different, these outcomes should have diverged.

To test the hypothesis that improved chickpea adoption translates into higher profits through the reallocation of crop production out of more costly or less profitable crops and into improved chickpea, we construct

Table 6. Crop Mix over Time

	2007			2014		
	Always adopter	Future disadopter	MW-test	Always adopter	Future disadopter	MW-test
Herfindahl Index	0.309	0.341		0.302	0.375	**
	(0.085)	(0.134)		(0.082)	(0.149)	
Shannon Index	−0.300	−0.329		−0.294	−0.361	**
	(0.078)	(0.118)		(0.076)	(0.129)	
Cultivated area allocated to chickpea (%)	27.14	29.02		25.81	21.32	
	(14.07)	(20.34)		(10.78)	(8.46)	
Agricultural sales income (USD)	4,874	4,350		2,098	918.6	***
	(3,915)	(4,493)		(2,336)	(1,064)	
Share of chickpea production sold (%)	63.61	59.91		48.65	22.22	***
	(29.37)	(24.51)		(24.63)	(9.94)	
Chickpea share of sales income (%)	38.97	31.82		31.94	25.04	
	(23.31)	(31.18)		(25.42)	(33.72)	
Observations	147	16		147	16	
	Never adopter	Future adopter	MW-test	Never adopter	Future adopter	MW-test
Herfindahl Index	0.393	0.409		0.409	0.331	***
	(0.126)	(0.141)		(0.151)	(0.093)	
Shannon Index	−0.377	−0.390		−0.391	−0.322	***
	(0.112)	(0.124)		(0.131)	(0.086)	
Cultivated area allocated to chickpea (%)	20.25	18.88		17.47	26.51	***
	(14.06)	(10.09)		(9.79)	(12.21)	
Agricultural sales income (USD)	2,227	2,727	*	683.0	1,521	***
	(1,724)	(2,212)		(875.7)	(1,253)	
Share of chickpea production sold (%)	59.23	58.90		29.56	57.77	***
	(14.42)	(23.17)		(18.67)	(25.30)	
Chickpea share of sales income (%)	24.42	22.67		18.25	39.24	***
	(23.00)	(18.36)		(29.74)	(27.09)	
Observations	71	304		70	304	

Note: Table displays the mean level of crop diversity and agricultural marketing variables by adoption type and year. In the upper panel, "Always adopters" are those who in every year adopt improved chickpea. These are compared to "Future disadopters," that is, those households who adopt in 2007 but disadopt in either 2010 or 2014. In the lower panel, "Never adopters" are those who in every year do not adopt improved chickpea. These are compared to "Future adopters," that is, those households who do not adopt in 2007 but adopt in either 2010 or 2014. The final column for each year presents the results of Mann-Whitney two-sample tests for differences in distribution. Results are similar if a Kolmogorov-Smirnov test is used. Significance of MW-tests are reported as * = p < 0.1; ** = p < 0.05; and *** = p < 0.01.

standard measures of crop diversity at the household level. Our data contains detailed information on the production of ten different crops. We calculate Herfindahl and Shannon indices using the share of land allocated to each crop.[23] When comparing always adopters to future disadopters as well as never adopters to future adopters in 2007, we find no significant difference in crop diversity (see table 6). By 2014, though, always adopters and future adopters have become more specialized when compared to their relevant counterfactual group. Always adopters and future disadopters, both of whom cultivate improved chickpea in 2007, have similar diversity indices while in 2014, after future disadopters have stopped cultivating improved chickpea, future disadopters are significantly more diversified. In a similar way, after future adopters have started to cultivate improved chickpea they are significantly more specialized than their counterfactual never-adopters. Looking across the same two groups, we find that these changes in diversity are associated with increases in the share of farmland allocated to chickpea production. We take this as evidence that cost savings occur as households

[23] The Herfindahl Index is calculated as $\mathcal{H} = \sum_{i=1}^{R} p_i^2$, where R is the total number of crop types and p_i is the proportion of cultivated area for each crop i. The Shannon Index is calculated as $\mathcal{S} = -\sum_{i=1}^{R} p_i \ln(p_i)$, where all terms are as previously defined.

shift production out of high-cost crops into relatively less costly improved chickpea.

To test the hypothesis that improved chickpea adoption translates into higher profits through increased sales of chickpea surpluses, we examine differences in agricultural sales income, share of chickpea sold, and share of chickpea in sales income. Starting in 2007, we find no differences in the baseline values of our two groups, with the exception that future adopters have higher agricultural sales income than never adopters. This suggests that our constructed counterfactual groups for always adopters and never adopters are broadly similar. When we look at sales outcomes in 2014, we find that households who disadopt now have significantly less income from agricultural sales than those who continue to cultivate improved chickpea. Additionally, the proportion of chickpea production that is sold into the market is significantly higher for those who continue to cultivate improved varieties. Those who disadopt sell less chickpea compared to their always-adopting counterparts, as well as to their past selves who cultivated improved varieties in 2007. A similar pattern exists when we compare never adopters to future adopters. Though similar to each other in 2007, by 2014 those who adopt have higher agricultural sales income, sell more of their chickpea crop, and have a larger proportion of their sales income from chickpea.

Verkaart et al. (2018) provide a detailed discussion on the cropping practices of households in Ethiopia using the same data. According to their calculations, the increase in cultivation of improved chickpea comes primarily at the expense of local chickpea, other legumes, and maize. Throughout the study period, there was no significant change to the number of households growing teff and wheat, nor to the area allocated to these two crops. This suggests that households have replaced traditional legumes with improved chickpea or have given up maize cultivation during the main growing season and replaced it with post-rainy season chickpea. Verkaart et al. (2018) also calculate total production costs by crop. These authors find that the production costs of improved chickpea are about half that for maize. They also find that the costs of production for all legumes (local and improved chickpea, fava beans, lentils, grass pea, and field pea) tend to be similar. Where differences appear is in the share of households selling improved chickpea and the sale price commanded by improved chickpea. It appears that as households move away from maize and into improved chickpea, they experience cost savings. At the same time, as households move away from traditional legumes and into improved chickpea, they are able to take advantage of the market.

Summarizing these results, we find that households who adopt improved chickpea reallocate production from costly crops, like maize, into relatively less costly improved chickpea. These cost savings are magnified by a household's ability to market their surplus chickpea crop, which captures profits that are unavailable when households cultivate local chickpea or other staple crops. In light of these large economic gains, the high adoption rates of improved chickpea make intuitive sense. An empirical puzzle only exists when we measure returns using the wrong metric, which in this case appears to be yields.

Conclusions and Policy Implications

Recent studies of agricultural technology adoption have focused on the physical returns (yields) or on the imputed value for these physical returns. This has created an empirical puzzle in which households choose not to adopt despite high average yields. Numerous potential solutions have been proposed, each of which contains elements to commend itself to the policymaker.

We propose a return to an older, alternative solution focused on economic returns to new agricultural technologies. We study a technology that appears to have no impact on yields yet has been widely adopted in Ethiopia. Using three years of panel data and a correlated random coefficient model, we calculate the returns to improved chickpea adoption in terms of yields, costs, and profits. Across a number of specifications, we find no evidence that adoption results in higher yields. This empirical puzzle—high adoption despite low to zero returns—disappears, however, once we measure returns in economic terms. We find that adoption results in significant reductions in total farm production costs and a significant increase in profits. Somewhat surprisingly, given its popularity as a potential solution since Suri (2011), we find no evidence of comparative advantage or heterogeneity in returns based on unobservables. Given that returns on profits are around 25%, we conclude that any comparative advantage some farmers may possess is dominated by the clear absolute advantage available to all farmers from adoption. This explains the high adoption rates (up to 80%) of improved chickpea.

To understand the potential mechanisms that allow households to convert a non-yield-increasing technology into a cost-reducing and profit-enhancing technology, we conduct a simple counterfactual analysis. While this analysis relies on non-random "treatment" and "control" groups, the results present a consistent picture regarding the potential mechanisms that have made adoption of improved chickpea varieties so popular. Despite not gaining higher yields relative to local varieties, those who adopt find adoption to be highly profitable. Adopters are able to sell more of their chickpea crop, gain more income from the increased sales, and reallocate cropland to specialize in improved chickpea production.

Our results imply that the divergent adoption rates across contexts may be explained by the quality of the markets for the output. Persistent low adoption rates of improved maize varieties that have been documented across Eastern Africa may be the result of a lack of markets where farmers can sell their surpluses. Without complementary economic gains, which require markets for surpluses, increased physical gains will likely be unattractive to potential adopters. This suggests that focusing policy solely on the yield aspect of genetic gains may be misguided. Examining traits other than yields, and improving households' ability to realize higher yields (perhaps through complementary investments that improve value chains and market access) should accompany yield-increasing breeding programs.

The context of our study is an extreme example of the extent to which money matter. Despite improved chickpea providing no statistically significant gains in yields, adoption of the technology has been extremely high. This adoption success has been the result of markets for the improved varieties in which farmers can sell their surpluses and reap economic benefits unavailable from growing and marketing less desirable traditional varieties. Policy and future research should reorient in a direction that considers both the physical and economic returns as factors that influence the adoption of agricultural technologies.

Supplementary Material

Supplementary material is available online at http://oxfordjournals.org/our_journals/ajae/online.

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