Money matters: The role of yields and profits in agricultural technology adoption*

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Abstract

Despite the growing attention to technology adoption in the economics literature, knowledge gaps remain regarding why some valuable technologies are slow to realize their full potential. This paper contributes to our understanding of agricultural technology adoption by showing that a focus on yield-increasing technologies 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.

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1 Introduction

An empirical puzzle persists around the fact that adoption rates of many proven technologies, such as fertilizer and hybrid seeds, remain low among smallholder farmers in developing countries. The adoption literature has tackled this question in a variety of ways, proposing answers to the puzzle that include imperfections in credit markets (Croppenstedt et al., 2003), property rights (Placen and Swallow, 2000), learning externalities (Foster and Rosenzweig, 1995; Conley and Udry, 2010), and lack of commitment (Kremer et al., 2011). 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 farmers' comparative advantage. Suri (2011) shows that in her data farmers with high returns adopt the technology while farmers with low returns either fail to adopt or dis-adopt the technology. This explanation of the puzzle has gained strong traction in the adoption literature, as evinced by some 395 papers citing her results as of October 2017. 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 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 yield 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 production 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

[1] This is in turn a generalization of the correlated random effects (CRE) model first outlined by Mundlak (1978) and

allows for 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 few 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 markets in which those prices are realized and obtainable (Feder et al., 1985). Recent literature that has focused on physical output, or imputed a shadow value to un-marketed physical output, implicitly assumes that output can either be stored or sold at a profitable price (Evenson and Gollin, 2003; Smale and Olwande, 2014; Jutzi and Rich, 2016; Asfaw et al., 2016; Emerick et al., 2016; Njeru et al., 2016; Verkaart et al., 2017). If the product is instead hard to sell or store, this may explain why adoption of so many high-yielding varieties remains low, and why improved chickpea adoption in Ethiopia has been so high.[2] 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 (i) production costs per hectare and (ii) profits (net revenue from the sale of agricultural goods in the market) per hectare. Using standard panel data methods we find that adoption of improved chickpeas significantly reduces production costs and significantly increases farm profit.

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. They 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.

These results do not appear to stem from bias introduced by unaccounted for household comparative advantage. 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. Compounding these cost savings is the ability of households to increase profits through the sale of surplus quantities of improved chickpea. Existing local varieties of chickpea produce small, brown seeds, which have limited marketability outside of Ethiopia. The newly introduced improved varieties produce large cream-colored seeds, which are prized both domestically and in Middle Eastern and South Asian markets.

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 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 un-marketed 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 that a re-orientation towards economic measures such as cost, revenue, or profit 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 return to the insights of these earlier studies. Our conclusions also support the suggestions made by Feder et al. (1985), Binswanger and Townsend (2000), and Foster and Rosenzweig (2010), namely that research should re-orient 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.

The rest of this paper is structured as follows. Section 2 describes the data sources and the history of adoption of improved chickpea varieties in Ethiopia. Section 3 outlines the theoretical model used to frame the adoption decision. In Section 4, we describe the empirical estimation of our theoretical model, including the necessary identifying assumptions. We then, in Section 5, investigate the impact of adoption on yields and if the inclusion of household comparative advantage explains adoption. We find no evidence of positive returns to adoption in terms of yield nor do we find evidence that returns to adoption are heterogeneous based on comparative advantage. These results motivate our empirical investigation of the economic returns to adoption in Section 6. Here we find that adoption reduces production costs and increases farm profit, though again we find no evidence of a significant role for comparative advantage in explaining adoption. To better understand why this might be the case, in Section 7 we calculate the returns to adoption based on each household's adoption history. We also discuss several mechanisms that may be driving the profitability of improved chickpea cultivation. Section 8 concludes.

2 Data on Adoption of Chickpea in Ethiopia

2.1 Sources of Data

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 Tropical Legumes II (TLII) program.[4]

[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). TLII has conducted chickpea research and development activities, including breeding of new varieties and the establishment of seed grower associations for production and distribution.

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). The districts are in the Shewa region, roughly 50km southeast of Addis Ababa. The study area is located in the central highlands and chickpea is grown during the post-rainy season using residual moisture.

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 and an attrition rate of 13 percent.[5] Adopters are defined as households who plant an improved chickpea variety in the season surveyed.[6] The data includes detailed input use information on a variety of crops, including purchased inputs, hired labor costs, and family labor time as well as demographic information (see Table 1).[7]

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°S-50°N 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 to the present. We map households into the 0.05° grid cells and calculate the cumulative rainfall for the rainy season immediately preceding chickpea planting.[8] To measure rainfall shocks, we calculate normalized deviations in a single season's rainfall from average seasonal rainfall over the previous five years:

[5]To check for non-random attrition we compare characteristics at baseline and found no significant differences. Results are available from the authors.

[6]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 coloured while Desi are smaller and brown. Additionally, the two varieties produce different colored flowers. We are therefore confident that improved seed is correctly identified.

[7]To enable comparisons across time, we deflated nominal Ethiopian Birr values to real values using the national consumer price index with 2005 as base following Verkaart et al. (2017). These constant 2005 data were subsequently converted from Ethiopian Birr to US dollars (USD) Purchasing Power Parity (PPP) values using rates extrapolated from the 2011 International Comparison Program (World Bank, 2015).

[8]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.

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

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.

2.2 History of Adoption

Overall, adoption rates of improved chickpea increased substantially during the study period. In 2007, 31 percent of households were recorded as growing improved varieties of chickpea. By 2014 the adoption rate had increased to 80 percent of households. Table 2 displays the transition history of adoption for households in the data. Of the 600 households in our sample, 25 percent always cultivate improved varieties of chickpea. A further 55 percent adopt improved varieties and remain adopters over the study period. Only 12 percent of households never adopt improved varieties, while nine percent of households dis-adopt.

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 percent when the survey began and by the end of the survey over 90 percent of households had adopted improved varieties. Minjar-Shenkora saw the most dramatic growth in adoption, increasing from 12 percent of households in 2007 to 84 percent of household in 2014. Compared to these two district, adoption rates remained relatively stagnant in Gimbichu, where the initial adoption rate was 22 percent and only increased to 45 percent by the end of the study.

One obvious explanation for heterogeneity in adoption is differences in agro-climatic zones across the districts. While all the districts are in the Shewa region, relatively close to each other, and well suited for chickpea production, there are significant differences in growing conditions from district to district. Gimbichu receives, on average, 100mm more rainfall in a season than Minjar-Shenkora (674mm compared to 565mm). Gimbichu is also at a much higher elevation than either district ($2,400$m compared to just under $2,000$m for the other two districts). We use district fixed effects along with cumulative seasonal rainfall and rainfall shocks to control for heterogeneity in returns induced by differences in agro-climatic zones.

3 Theoretical Framework

We begin by assuming that the decision to adopt is the outcome of optimizing expected profit, where returns are a function of land allocation, the production technology and the costs of inputs and prices of outputs (Feder et al., 1985). Focusing on the production technology underlying the profit function, we assume Cobb-Douglas production functions of the form

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

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

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 sets of inputs (X_{ijt}) which we allow to have differential effects on yield, 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

$$u_{it}^H = \theta_i^H + \varepsilon_{it}^H, \tag{4}$$

$$u_{it}^L = \theta_i^L + \varepsilon_{it}^L. \tag{5}$$

Following Carneiro et al. (2003) and Suri (2011), we assume households know θ_i^H and θ_i^L, which are farmer-specific productivity effects. We also assume 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

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

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

where $b_H = \left(\sigma_H^2 - \sigma_{HL}\right) / \left(\sigma_H^2 + \sigma_L^2 - \sigma_{HL}\right)$, $b_L = \left(\sigma_L^2 - \sigma_{HL}\right) / \left(\sigma_H^2 + \sigma_L^2 - \sigma_{HL}\right)$, $\sigma_H^2 \equiv \text{Var}\left(\theta_i^H\right)$, $\sigma_L^2 \equiv \text{Var}\left(\theta_i^L\right)$, and $\sigma_{HL} \equiv \text{Cov}\left(\theta_i^H, \theta_i^L\right)$. 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 $\theta_i \equiv b_N\left(\theta_i^H - \theta_i^L\right)$. Our equation of interest is (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 production 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:

$$y_{it} = \beta_t^L + X_{it}'\gamma_j^L + \left(\beta_t^H - \beta_t^L\right) h_{it} + X_{it}'\left(\gamma_j^H - \gamma_j^L\right) h_{it} + \theta_i + \phi\theta_i h_{it} + \zeta_i + \varepsilon_{it}, \tag{12}$$

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 correlated random coefficient (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 section 4, 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 in the decision to adoption the improved varieties.

4 Empirical Approach

4.1 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

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

This assumption is not particularly strong, given that by differencing out $(\theta_i^H - \theta_i^L)$, we have ensured 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. After the rainy season, a household decides to plant or leave a given plot fallow. If it chooses to plant in that year the household prepares the land. Following land preparation it chooses a seed technology based on forward-looking expectations regarding availability of inputs (including budget constraints), and prospects for the sale of outputs. Having resolved upon a seed technology, the household plants and then throughout the growing season applies labor and complementary inputs as shocks are realized. Finally, the household harvests and markets its production.

We are able to control for many of the 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 in Table 1 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.

What remains are transitory 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

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

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.

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 shock remains. 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.

4.2 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 begin by outlining the estimation procedure for a three-period model without covariates. Assume the data generating process is given by:

$$y_{it} = \delta + \beta h_{it} + \theta_i + \phi \theta_i h_{it} + \xi_{it}, \tag{14}$$

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:

$$\theta_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i3} + \lambda_4 h_{i1} h_{i2} + \lambda_5 h_{i1} h_{i3} + \lambda_6 h_{i2} h_{i3} + \lambda_7 h_{i1} h_{i2} h_{i3} + \nu_i, \tag{15}$$

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:

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

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

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

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

$$y_{i1} = \delta_1 + \gamma_1 h_{i1} + \gamma_2 h_{i2} + \gamma_3 h_{i3} + \gamma_4 h_{i1} h_{i2} + \gamma_5 h_{i1} h_{i3} + \gamma_6 h_{i2} h_{i3} + \gamma_7 h_{i1} h_{i2} h_{i3} + n_{i1} \quad \text{(17a)}$$
$$y_{i2} = \delta_2 + \gamma_8 h_{i1} + \gamma_9 h_{i2} + \gamma_{10} h_{i3} + \gamma_{11} h_{i1} h_{i2} + \gamma_{12} h_{i1} h_{i3} + \gamma_{13} h_{i2} h_{i3} + \gamma_{14} h_{i1} h_{i2} h_{i3} + n_{i2} \quad \text{(17b)}$$
$$y_{i3} = \delta_3 + \gamma_{15} h_{i1} + \gamma_{16} h_{i2} + \gamma_{17} h_{i3} + \gamma_{18} h_{i1} h_{i2} + \gamma_{19} h_{i1} h_{i3} + \gamma_{20} h_{i2} h_{i3} + \gamma_{21} h_{i1} h_{i2} h_{i3} + n_{i3} \quad \text{(17c)}$$

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 as follows:

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

We estimate equations (17a)-(17c) as seemingly unrelated regressions and preserve the 21 reduced form parameters in a vector $\pi_{[21\times1]}$ 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 $\pi = \mathbf{H}\delta$ where $\mathbf{H}_{[21\times9]}$ embodies the 21 restrictions on γ and $\delta_{[9\times1]}$ is a vector of our nine structural parameters.

The optimal minimum distance (OMD) function is:

$$\min_{\delta} = \{\pi - \mathbf{H}\delta\}' \mathbf{V}^{-1} \{\pi - \mathbf{H}\delta\}. \tag{18}$$

Solving for δ we get:

$$\delta^* = \left(\mathbf{H}'\mathbf{V}^{-1}\mathbf{H}\right)^{-1} \mathbf{H}'\mathbf{V}^{-1}\pi, \tag{19}$$

which is the optimal minimum distance estimator. 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 $\mathbf{H}\delta$ 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 package described in Barriga Cabanillas et al. (2017).

[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 than 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.

5 Returns for Yields

5.1 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 that cultivate chickpea, Panel A in Table 3 shows that in all three years yields on improved varieties are significantly higher than yields from local varieties.[12] Figure 2 shows the marginal distribution of yields by adoption status. Returns are significantly higher for those who have adopted, and adopters' yield distribution first-order stochastically dominates the distribution for non-adopters.

One obvious potential reason why improved chickpeas 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 OLS and fixed effects (FE).

5.2 OLS and FE Evidence

Our theoretical framework sets up the model in terms of a Cobb-Douglas production function so we begin by estimating the generalized yield function with log of chickpea yield as the dependent

[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 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.

variable.[13] Results from OLS and fixed effects versions of the production function with various sets of controls are presented in columns (1)-(4) of Table 4.

In our OLS regression, the returns to adoption are 26 percent, which is slightly larger than the mean difference in yields presented in Table 3. 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 does not fully explain the higher observed yields to 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 exists 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 yield is indistinguishable from local chickpea yield. 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. As outlined in Section 3, fixed effects is a special case of the CRE and CRC models in that it assumes the 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 percent of the households in the sample do not change their adoption status, such an assumption may be reasonable.

5.3 CRE 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 5). To do this, we replace the time-invariant household fixed effect with its projection on the complete household

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

adoption history. Coefficients on the return to adoption are similar in the CRE model and in the fixed effect model.[14] Returns on yield 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 returns us 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 time-invariant and uncorrelated with the decision to adopt or the experience of adoption.

Table 6 reports only the OMD estimates of the structural parameters from the CRC model. Returns to adoption for yields are again not significant once we have 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.

In case our analysis of the full panel is sensitive to the number of observations in each adoption trajectory (the three-wave version has more possible adoption histories), we adopt Suri's (2011) simpler two year model and estimate each two year pair. Given that adoption rates were so high

[14] 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.

during the period 2007 to 2010 it may be the case that our comparative advantage term, ϕ, is significant for that period but insignificant as adoption rates slow. Alternatively, we might expect a significant result over the longer time period 2007 to 2014. Table 7 displays the results from these pairwise regressions. Though our estimates are not particularly precise, due to low numbers of households in several of the adoption histories, neither the estimates of the returns to adoption nor of ϕ are statistically significant.

To summarize our results thus far, our fixed effect and CRE estimates provide no evidence that 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 this puzzle in the context of maize in Kenya holds in the context of chickpea in Ethiopia.[15] 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?

6 Returns for Costs and Profits

6.1 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 costs of production per hectare and as profits (per hectare) from the sale of agricultural production. These specifications directly embed our production 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[16] We con-

[15] We also estimate CRC 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 CRC 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.

[16] See Suri (2011) for more details on the connection between the adoption decision, the necessary assumptions for profit maximization, and the connection to our production framework.

sider 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.[17]

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 (Panel B in Table 3). 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. Figure 3 shows that there is not much difference in the distribution of costs across adopters and non-adopters. The primary source of the differences in production costs are seed, chemicals, hired labor, and transportation. Despite these categories contributing to higher costs of on-farm production, the net result is that those who cultivate improved chickpeas are significantly more profitable than those who do not. As Figure 4 shows, the distribution of profits from adoption first-order dominates those from non-adoption. The descriptive evidence suggests that while improved chickpea production can be more costly, these extra costs result in higher yields and that those yields can be profitably marketed.

6.2 OLS and FE Evidence

Results from OLS and fixed effects versions of the cost and profit functions with various sets of controls are presented in columns (5)-(12) of Table 4. Recall that only our OLS estimates of the production 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 that adopt the technology see around a five percent reduction in per hectare production costs, which helps contribute to around a 15 percent increase in profits

[17] 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.

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, when seeking to understand the technology adoption decision in the context of developing country agriculture.

6.3 CRE 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 5). Returns continue to remain significant when we estimate the CRC model (see Table 6). Point estimates in the CRC model are in fact larger, suggesting a downward bias when we do not control for a household's comparative advantage. Results from the two-year pairwise estimation of the CRC model are similar to the estimates on the full panel, though these coefficients are less precisely estimated (see Table 7).

The results from our cost and profit function estimation tell a very different story than do our results from the estimation of the production 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. 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 15 and 40 percent, 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.

7 Discussion

7.1 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 2). 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 $\hat{\beta} + \hat{\phi}\hat{\theta}_i$, 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 5 - 7 we graph the returns to improved chickpea adoption for each adoption history.

Figure 5 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. The households who adopt have higher returns to the technology, in terms of yields, than those who do not adopt or dis-adopt. Note though that returns to adopters are extremely similar across groups, with the exception of late dis-adopters, and range between 0.10 and 0.20. Given the evidence coming from our regressions and our predicted returns, we conclude that households who choose to adopt see positive but insignificant gains from adoption while farmers that refrain from adoption or dis-adopt may do so because their gains from adoption are even smaller.

Figures 6 and 7 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 large reductions in costs for all groups. We interpret this result as evidence that while gains from adoption in terms of yields tend not to be large, especially for those who chose not to adopt or dis-adopted, 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 35 percent, are so large that the absolute advantage presented by improved varieties dwarfs any comparative advantage that some households might posses. 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 where nine percent. 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.

7.2 Potential Mechanisms

If households that adopt improved chickpea are not getting higher yields, then what is 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 that cultivate improved chickpea in all three rounds of the data with those who cultivate improved chickpea in round one but dis-adopt 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, always adopters and future dis-adopters should have outcomes similar to each other as 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 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.[18] When comparing always adopters to future dis-adopters as well as never adopters to future adopters in 2007 we find no significant difference in crop diversity (see Table 8). By 2014, though, always adopters and future adopters have become more specialized when compared to their relevant counterfactual group. Always adopters and future dis-adopters, both of who cultivate improved chickpea in 2007 have similar diversity indices while in 2014, after future dis-adopters have stopped cultivating improved chickpea, future dis-adopters 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 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

[18] 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.

always adopters and never adopters are broadly similar. When we look at sales outcomes in 2014, we find that households that dis-adopt 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 dis-adopt sell less chickpea compared to their always adopting counterparts as well as to their past selves that 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.

Summarizing these results, households that adopt improved chickpea reallocate production from costly crops into relatively less costly improved chickpea. These cost savings are magnified by a household's ability to market their surplus chickpea crop, capturing 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.

8 Conclusions and Policy Implications

Recent studies of agricultural technology adoption have focused on the physical returns (yields) or the imputed total value of 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 posed, each of which contain 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 specification 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 38 percent, 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 percent) of improved chickpea.

To try and understand the potential mechanisms that allow households to convert a non-yield-increasing technology into a cost reducing and profit enhancing technology we construct 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 complimentary economic gains, which require markets for surpluses, increased physical gains will likely be unattractive to potential adopters. This suggests that policy focused on developing further genetic gains in terms of yields may be misguided. The context of our study is an extreme example of the extent to which markets matter. Despite improved chickpeas providing no statistically significant gains in yield, adoption of the technology has been extremely high. This adoption success has been the result of existing markets for the improved varieties in which farmers can market their surplus and reap economic benefits unavailable from growing and marketing less desirable traditional varieties. Policy and future research should re-orient in a direction that considers both the physical and the economic returns as factors that influence the adoption of agricultural technologies.

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Table 1: Descriptive statistics by year

	2007		2010		2014	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Panel A: Chickpea growers						
Chickpea yield (kg/ha)	2,038	(1,099)	2,183	(1,128)	2,372	(1,083)
Chickpea area (ha)	0.587	(0.505)	0.584	(0.447)	0.570	(0.410)
Chickpea seed (kg/ha)	168.9	(170.0)	187.3	(79.63)	207.9	(109.1)
Land preparation (USD/ha)	0.279	(5.531)	1.236	(14.06)	0.280	(6.272)
Fertilizer (kg/ha)	13.26	(53.28)	9.561	(57.82)	19.08	(131.2)
Chemical cost (USD/ha)	17.98	(40.08)	27.38	(43.08)	54.04	(79.00)
Family labor (days/ha)	75.26	(44.13)	76.75	(69.32)	74.59	(47.26)
Hired labor cost (USD/ha)	33.81	(78.89)	31.87	(75.34)	52.62	(99.72)
Transportation cost (USD/ha)	5.370	(23.15)	4.679	(14.22)	2.098	(8.443)
Observations	394		484		530	
Panel B: Whole farm production						
Production costs (USD/ha)	608.9	(326.1)	564.8	(273.5)	563.1	(233.0)
Cultivated area (ha)	2.338	(1.223)	2.523	(1.418)	2.248	(1.381)
Seed cost (USD/ha)	209.4	(114.1)	187.4	(80.46)	144.2	(72.48)
Land preparation (USD/ha)	3.531	(45.22)	2.804	(34.01)	1.972	(41.48)
Fertilizer cost (USD/ha)	1,129	(686.1)	1,257	(642.1)	2,228	(1,031)
Chemical cost (USD/ha)	20.46	(126.8)	10.87	(15.35)	24.79	(34.84)
Family labor (days/ha)	70.84	(28.61)	73.03	(30.18)	73.93	(51.96)
Hired labor cost (USD/ha)	64.45	(79.44)	62.40	(108.3)	73.16	(93.92)
Transportation cost (USD/ha)	3.435	(12.64)	4.891	(58.70)	0.987	(3.591)
On-farm profit (USD/ha)	2,189	(999.4)	2,079	(1,108)	1,696	(757.3)
Panel C: Household characteristics						
Male head (1 = yes)	0.938	(0.241)	0.943	(0.231)	0.917	(0.277)
Dependents ratio (%)	102.2	(75.48)	86.84	(66.28)	73.75	(64.81)
Off-farm income (1 = yes)	0.273	(0.446)	0.247	(0.431)	0.282	(0.450)
Land owned (ha)	2.215	(1.302)	2.255	(1.295)	2.116	(1.266)
Main season rainfall (mm)	609.4	(73.37)	500.4	(53.95)	572.7	(44.23)
Rainfall shock	0.321	(0.425)	2.214	(0.591)	0.355	(0.289)
Observations	600		600		600	

Note: Columns display means of data by year with standard deviations in parenthesis. Panel A reports production variables for chickpea growers. Panel B reports costs of production for the balanced sample while Panel C reports household characteristics for the balanced sample. All monetary units are given in real terms.

Table 2: 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 dis-adopter	N	Y	N	6.33
Late dis-adopter	Y	Y	N	1.50
Early dis-adopter	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 varities while "N" represents non-adoption or dis-adoption.

Table 3: Production, costs and returns of improved and local chickpeas

	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)	
Land preparation (USD/ha)	0.530	0.000		3.907	0.487	***	2.625	0.008	
	(7.631)	(0.000)		(24.05)	(9.463)		(19.46)	(0.126)	
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)	
Observations	207	187		106	378		55	475	
Panel B: Whole farm production									
Production costs (USD/ha)	569.7	695.6	***	590.3	549.8		640.2	542.8	***
	(337.2)	(282.1)		(340.9)	(223.9)		(276.5)	(216.0)	
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)	186.3	260.3	***	173.5	195.6	***	154.8	141.5	**
	(107.4)	(112.3)		(90.96)	(72.48)		(67.93)	(73.44)	
Land preparation ocst (USD/ha)	5.047	0.183		5.051	1.484	*	8.065	0.368	
	(54.43)	(2.498)		(42.03)	(28.24)		(90.00)	(6.606)	
Fertilizer cost (USD/ha)	1,120	1,151		1,428	1,156	***	2,786	2,081	***
	(712.0)	(626.5)		(668.3)	(605.0)		(1,235)	(916.8)	
Chemical cost (USD/ha)	21.42	18.34	***	6.304	13.54	***	15.94	27.12	***
	(146.86)	(63.40)		(15.43)	(14.67)		(40.78)	(32.75)	
Family labor (days/ha)	70.15	72.36		79.15	69.43	***	77.92	72.88	
	(28.43)	(29.02)		(34.31)	(26.87)		(56.95)	(50.58)	
Hired labor cost (USD/ha)	51.19	93.74	***	62.53	62.33	**	68.11	74.49	
	(70.74)	(89.38)		(153.1)	(70.07)		(103.6)	(91.27)	
Transportation cost (USD/ha)	1.866	6.899	***	7.599	3.301	***	0.569	1.098	***
	(9.192)	(17.62)		(96.05)	(7.706)		(2.507)	(3.820)	
On-farm profit (USD/ha)	2,057	2,480	***	1,786	2,252	***	1,457	1,758	***
	(901.9)	(1,136)		(940.0)	(1,162)		(836.9)	(723.0)	
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 parenthesis. 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; ***p<0.01.

Table 4: Basic OLS and household FE specifications

	Ln chickpea yield (kg/ha)				Ln production cost (USD/ha)				Ln on-farm profit (USD/ha)			
	OLS	OLS	FE	FE	OLS	OLS	FE	FE	OLS	OLS	FE	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Improved chickpea	0.258***	0.128*	0.054	0.077	−0.027	−0.090***	0.038	−0.047**	0.266***	0.280***	0.206***	0.152*
	(0.072)	(0.070)	(0.089)	(0.089)	(0.026)	(0.015)	(0.029)	(0.019)	(0.061)	(0.063)	(0.075)	(0.078)
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	0.005	0.056	0.146	0.732	0.003	0.709	0.046	0.088	0.033	0.032

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 in which include covariates, these include the set of inputs presented in Table 1. 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 (*p<0.1; **p<0.05; ***p<0.01).

Table 5: CRE reduced form and structural estimates

	Ln chickpea yield (kg/ha)						Ln production cost (USD/ha)						Ln on-farm profit (USD/ha)					
	Reduced Form Estimates																	
	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, 2007	0.102	0.154***	0.222**	0.023	−0.072	0.068	0.272***	0.218***	0.153***	−0.055**	−0.006	0.016	0.144***	0.185	0.133	0.235***	−0.061	0.204*
	(0.078)	(0.060)	(0.105)	(0.080)	(0.060)	(0.116)	(0.046)	(0.047)	(0.041)	(0.026)	(0.024)	(0.018)	(0.030)	(0.126)	(0.113)	(0.046)	(0.131)	(0.120)
Improved, 2010	0.044	0.023	−0.012	0.080	0.174**	−0.047	−0.058	−0.030	−0.054	−0.028	−0.039*	−0.014	0.030	0.350***	−0.059	0.079*	0.528***	−0.028
	(0.101)	(0.077)	(0.136)	(0.095)	(0.071)	(0.137)	(0.045	(0.046)	(0.040)	(0.025)	(0.023)	(0.018)	(0.044)	(0.123)	(0.111)	(0.044)	(0.127)	(0.117)
Improved, 2014	0.425***	0.131	0.306*	0.191	0.279**	−0.044	−0.077	−0.200***	0.149***	−0.006	−0.040	−0.065***	0.201***	0.121	0.429***	0.077	0.320**	0.04
	(0.128)	(0.098)	(0.173)	(0.149)	(0.111)	(0.216)	(0.053)	(0.054)	(0.046)	(0.033)	(0.030)	(0.022)	(0.051)	(0.143)	(0.129)	(0.056)	(0.161)	(0.148)

Optimal Minimum Distance (OMD) Structural Estimates

	Without covariates	With covariates	Without covariates	With covariates	Without covariates	With covariates
β	-0.041	0.066	0.038	-0.042**	0.140*	0.186**
	(0.074)	(0.073)	(0.036)	(0.018)	(0.073)	(0.076)
λ_1	0.163***	-0.046	0.090***	0.028	0.222***	0.171**
	(0.049)	(0.050)	(0.025)	(0.024)	(0.069)	(0.069)
λ_2	0.045	0.060	-0.004	0.009	0.041	0.039
	(0.068)	(0.067)	(0.022)	(0.022)	(0.050)	(0.046)
λ_3	0.259***	0.224***	0.074***	0.025	0.113**	0.066
	(0.072)	(0.082)	(0.027)	(0.027)	(0.056)	(0.055)
Observations	1,011	1,011	1,800	1,800	1,800	1,800
χ^2	1,472	1,652***	3,894***	1,426	4,013***	7,484***

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 in which include covariates, these include the set of inputs presented in Table 1. 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 (*p<0.1; **p<0.05; ***p<0.01).

Table 6: 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	2.311	0.187	−0.087	−0.039*	0.354**	0.383**
	(7.174)	(0.240)	(0.059)	(0.024)	(0.140)	(0.178)
ϕ	8.360	0.633	−0.046	−0.205	−0.323	−0.189
	(29.498)	(1.416)	(0.371)	(0.619)	(0.451)	(0.822)
λ_1	0.277***	0.073	−0.166**	0.015	0.515**	0.317*
	(0.102)	(0.135)	(0.067)	(0.041)	(0.234)	(0.187)
λ_2	0.283***	0.054	−0.078	0.004	0.120	0.117
	(0.107)	(0.137)	(0.056)	(0.027)	(0.089)	(0.089)
λ_3	0.260**	0.156	−0.132***	−0.011	0.243***	0.209***
	(0.111)	(0.118)	(0.048)	(0.027)	(0.067)	(0.067)
λ_4	−0.321*	−0.298	0.412***	0.036	−0.459	−0.359
	(0.182)	(0.215)	(0.137)	(0.061)	(0.334)	(0.316)
λ_5	−0.229	−0.048	0.291***	0.004	−0.176	−0.136
	(0.172)	(0.158)	(0.100)	(0.048)	(0.185)	(0.161)
λ_6	−0.265**	0.001	−0.018	−0.031	−0.088	−0.093
	(0.107)	(0.159)	(0.072)	(0.035)	(0.103)	(0.101)
λ_7	0.292**	0.244	−0.315**	−0.049	0.291	0.246
	(0.126)	(0.225)	(0.147)	(0.074)	(0.337)	(0.300)
Observations	1,011	1,011	1,800	1,800	1,800	1,800
χ^2	4,338***	5,175***	8,855***	4,299***	2,737***	3,519***

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 in which include covariates, these include the set of inputs presented in Table 1. 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 (*p<0.1; **p<0.05; ***p<0.01).

Table 7: Two year CRC OMD structural estimates

	Ln chickpea yield (kg/ha)			Ln production cost (USD/ha)			Ln on-farm profit (USD/ha		
	2007-10	2010-14	2008-14	2007-10	2010-14	2008-14	2007-10	2010-14	2008-14
β	−2.304	0.348	−0.049	−0.058***	−0.044	−0.043	0.148	0.231	−48.50***
	(79.84)	(0.244)	(0.161)	(0.018)	(0.046)	(0.050)	(2.841)	(0.261)	(0.109)
ϕ	60.41	−0.020	1.585	−2.089	0.833	−0.847	8.761	−0.391	−0.999***
	(1,969)	(4.790)	(8.156)	(2.530)	(4.512)	(0.834)	(112.2)	(6.652)	(0.000)
λ_1	0.123	−0.106	−0.124	0.011	0.018	0.048	0.057	0.217	0.343
	(0.162)	(0.274)	(0.374)	(0.047)	(0.033)	(0.049)	(0.244)	(0.210)	(0.304)
λ_2	0.128	−0.023	−0.001	−0.019	−0.002	−0.043	0.078	0.172	0.048
	(0.090)	(0.192)	(0.144)	(0.026)	(0.031)	(0.027)	(0.049)	(0.172)	(0.060)
λ_3	−0.126	0.138	0.189	0.016	−0.035	−0.031	−0.078	−0.142	170.2
	(0.089)	(0.447)	(0.575)	(0.049)	(0.069)	(0.139)	(0.049)	(0.676)	(0.000)
Observations	714	886	738	1,206	1,206	1,206	1,206	1,206	1,206
χ^2	219.6	1,654***	254.9	16.33***	0.290	160.0	295.1	6,469***	328.2

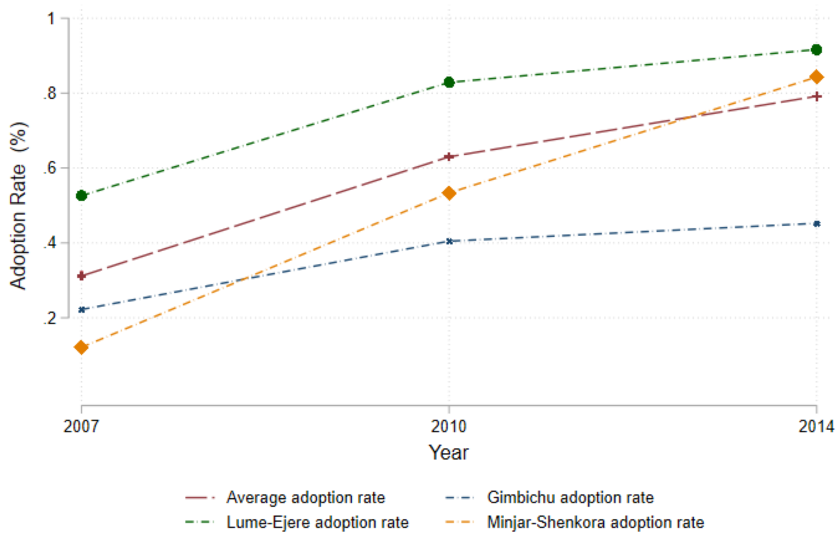
Note: Dependent variable is either log of chickpea yield, log of production costs per hectare, or log of on-farm profit per hectare. In specifications in which include covariates, these include the set of inputs presented in Table 1. Where the dependent variable is measured in dollar terms, we convert 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 (*p<0.1; **p<0.05; ***p<0.01).

Table 8: Crop mix over time

	2007			2014		
	Always adopter	Future dis-adopter	MW-test	Always adopter	Future dis-adopter	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	

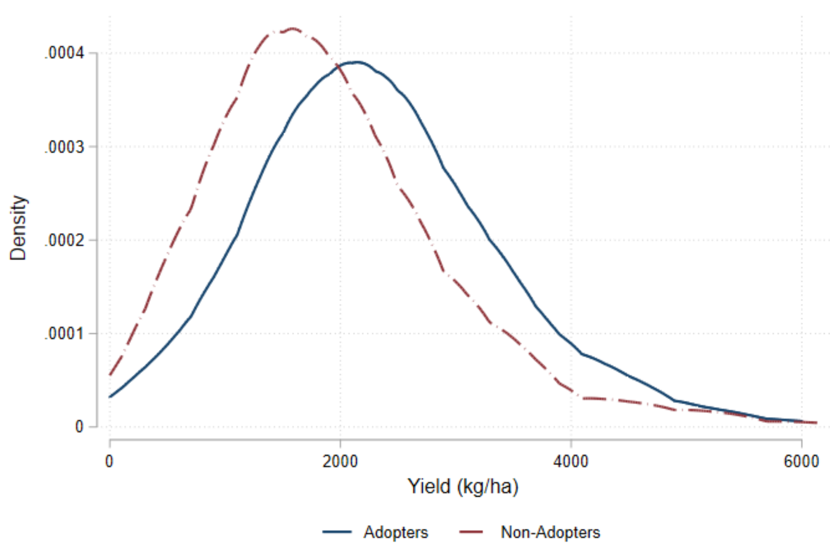
Note: Table displays the mean level of crop diversity and agricultural marketing variables by adoption type and year. In the upper panel, "Always adopters" are those who in every year adopt improved chickpea. They are compared to "Future dis-adopters," those households who adopt in 2007 but dis-adopt in either 2010 or 2014. In the lower panel, "Never adopters" are those who in every year do not adopt improved chickpea. They are compared to "Future adopters," those households who do not adopt in 2007 but adopt in either 2010 or 2014. 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. 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; ***p<0.01.

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



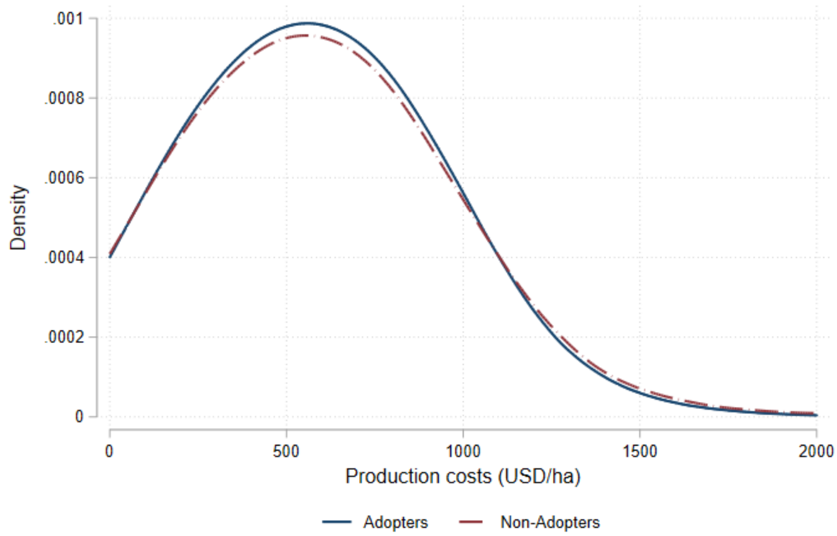
Note: Figure displays the average number of households cultivating improved chickpea varieties in a given year.

Figure 2: Marginal distribution of yields by adoption



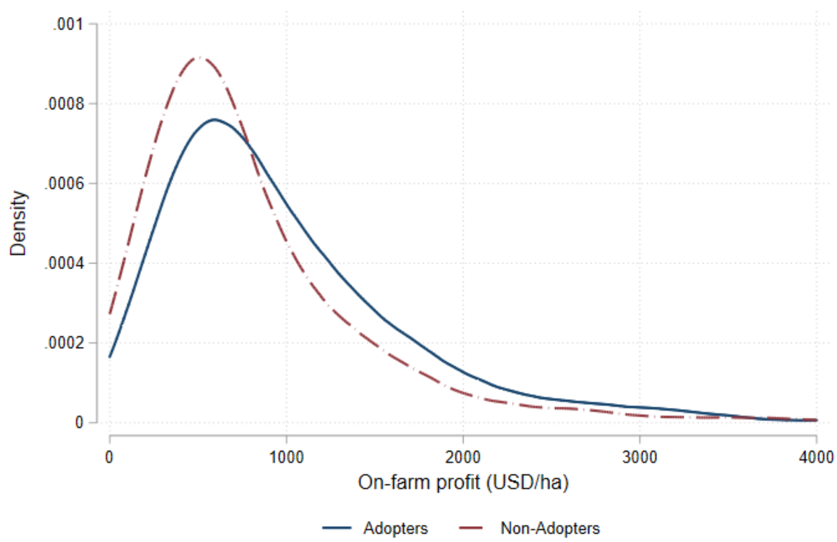
Note: Figure displays the kernel density for chickpea yields for adopters of improved varieties and non-adopters.

Figure 3: Marginal distribution of production costs by adoption



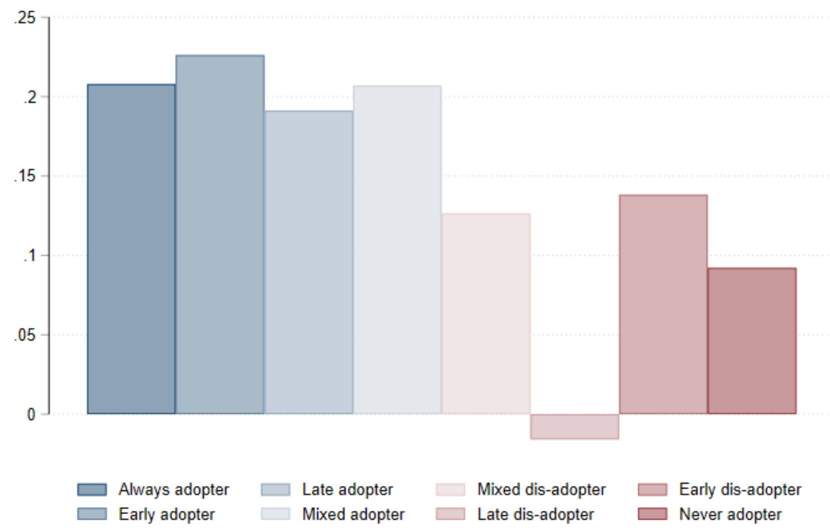
Note: Figure displays the kernel density for production costs per hectare for adopters of improved varieties and non-adopters.

Figure 4: Marginal distribution of on-farm profits by adoption



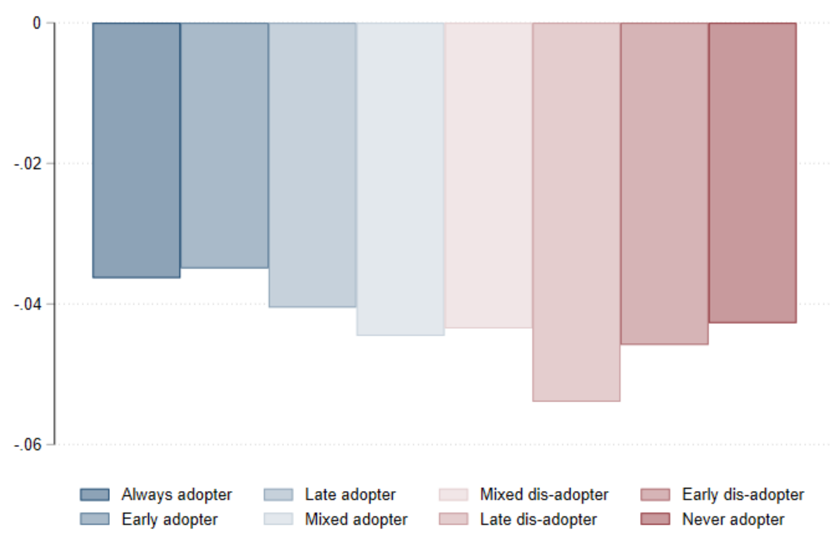
Note: Figure displays the kernel density for on-farm profits per hectare for adopters of improved varieties and non-adopters.

Figure 5: Distribution of returns for yields



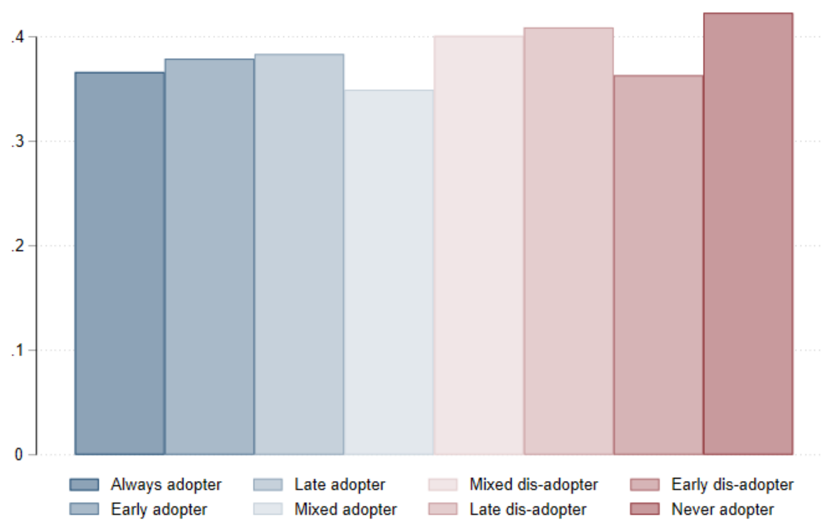
Note: Figure displays predicted returns for yields by household history of adoption. Distribution of returns are calculated as $\hat{\beta} + \hat{\phi}\hat{\theta}_i$, where θ_i is the comparative advantage term for each household.

Figure 6: 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 7: Distribution of returns for on-farm profit



Note: Figure displays predicted returns for on-farm profit 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.