Revisiting Correlated Random Coefficient Model in Technology Adoption

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January 12, 2024

Abstract

This article revisits a correlated random coefficient model to estimate heterogeneous returns to technology and investigates its validity. I construct a canonical model of a profit-maximizing farmer and show that the identification assumption is violated if the farmer behaves following the model. I also demonstrate that with the existence of transitory shocks farmers know at the time of technology adoption, the method from the previous studies cannot remove the bias of estimates. I argue the importance of a theoretical model in discussing identification assumptions in empirical research.

Keywords: technology adoption, agriculture, productivity, estimation method

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1 Introduction

The low adoption rates of productive technologies among small agricultural producers in developing economies has been a long-lasting issue in development economics. The literature has explored the answer to this puzzle from a variety of perspectives. For example, learning about a new technology and its externality incentives farmers to wait for their neighbors to adopt first (Conley and Udry, 2010; Foster and Rosenzweig, 1995), and credit constraints can prevent farmers from borrowing enough funds to adopt a new technology (Giné and Klonner, 2006).[1] Given the importance of improved productivity from new technologies, it is crucial to understand the reason for the slow adoption of such technology and explore the solution for more rapid technological diffusion in developing areas.

One possible explanation for a low adoption rate is heterogeneity in returns to technology. Whereas it may seem that a given technology is productive and may improve income of households on average, this might not be the case for everyone. In particular, farmers with low returns may decide not to adopt the new technology as a result of profit-maximization behavior. To explore this possibility, Suri (2011) proposes an estimation method for heterogeneous benefits from new technology. This newly developed method reveals that cost difference drives differential adoption of the hybrid seeds across farmers in Kenya. Applying this method, Michler et al. (2019) show that returns for profits to improved chickpea cultivation in Ethiopia are different across adopters and non adopters. They also discusses that rather than the return in terms of yield, the return in profit matters for adoption of new technology in their research context.

In this article, I revisit the model and estimation method proposed by Suri (2011), namely, a correlated random coefficient (CRC) model, and investigate when the identification assumption can be satisfied or violated. I find that while the proposed estimation method is of use in situations where identification assumptions are satisfied to identify differences in returns to a new technology, users should be aware that this does not come without any cost. In particular, I develop a canonical model of a profit-maximizing farmer and explicitly derive the farmer's profit maximization condition. This article provides two findings on a CRC model.

[1] This topic is surveyed in detail by Foster and Rosenzweig (2010).

First, I show that a CRC model's assumption is violated according to the economic model when there are technology-specific costs. I demonstrate that a correlation between technology adoption choice and a farmer's general productivity leads to biased estimates. Simulation results are presented to strengthen this argument by showing biased estimates of heterogeneous returns to technology.

Second, I show the issue that arises when there are transitory shocks that farmers can observe before they decide which technology to adopt. Previous studies in the literature dealt with such situations by controlling for the observed transitory shocks directly. I use a model and simulation results to show that this solution is insufficient to fix the problem and the bias in estimates remains.

This article mainly contributes to the literature of technology adoption and particularly the literature of estimating returns to technology. As a process for low-income people to get out of poverty and mitigate food insecurity in developing economies, productive technology and its adoption have attracted a great attention in the literature (Feder et al., 1985; Foster and Rosenzweig, 2010). Existing studies have explored various drivers of the adoption behaviors, such as education (Weir and Knight, 2000), wealth (Moser and Barrett, 2006), and risks (Dercon and Christiaensen, 2011). In terms of heterogeneity in returns, some studies look at observable differences across farmers, such as education (Foster and Rosenzweig, 1996). More recent work has pointed out the importance of unobserved differences in determining the returns, such as soil quality (Foster and Rosenzweig, 2010; Munshi, 2004) and farmer-specific comparative advantages (Michler et al., 2019; Suri, 2011). I contribute to this literature by pointing out issues in an existing methodology for future development of methods precisely estimating heterogeneous returns to technology.

It should be emphasized that this study does not intend to criticize particular papers. As I will show, a canonical economic model implies that the identification assumption in the CRC model is not satisfied. However, as is often said, "all models are wrong but some are useful," and different models reflect realities in different contexts. For example, recent studies have found the behavior deviating from a standard economic model and the importance of behavioral effect in technology adoption in developing economies, such as present bias (Duflo et al., 2011) and a sunk-cost effect (Ashraf et al., 2010). The goal of this article is to demonstrate how useful a simple economic model can be to guide identification assumptions in empirical analyses.

The article proceeds as follows. Section 2 explains the model setup and discusses the first issue about the correlation between technology adoption and a farmer's productivity. The issue related to the observed transitory shocks at the time of adoption decision making is explored in Section 3. Section 4 concludes.

2 Correlation between technology adoption and unobserved productivity

2.1 Model setup

In this section, I construct a two-period model of a profit-maximizing farmer who decides whether to adopt a new technology. Consider the following Cobb-Douglas production functions of new and traditional technologies:

$$Y_{it}^N = e^{\beta^N}\left(\prod_{j=1}^{k} X_{ijt}^{\gamma_j^N}\right)e^{u_{it}^N}$$
$$Y_{it}^T = e^{\beta^T}\left(\prod_{j=1}^{k} X_{ijt}^{\gamma_j^T}\right)e^{u_{it}^T},$$

where N and T stand for new and traditional, respectively. The production outputs of a farmer i at time t are Y_{it}^N and Y_{it}^N. Inputs are denoted as X_{ijt} $(j = 1, \ldots, k)$. Technology-specific productivity is captured by β^N and β^T, and I assume there is no uncertainty in them.

Following Suri (2011), the unobserved productivities, u_{it}^N and u_{it}^T, are assumed to have the following structures:

$$u_{it}^N = \theta_i^N + \xi_{it}^N$$
$$u_{it}^T = \theta_i^T + \xi_{it}^T.$$

Without loss of generality, I assume that $E[u_{it}^N] = 0$ and $E[u_{it}^T] = 0$.[2] I also assume, without loss of

[2] If the expectation values are non zero, then I can add the means to β_t^N (or β_t^T) to make the expectations of u_{it}^N

generality, that $E[\theta_i^N] = 0$, $E[\theta_i^T] = 0$, $E[\xi_{it}^N] = 0$, and $E[\xi_{it}^T] = 0$, since $E[u_{it}^N] = 0$ and $E[u_{it}^T] = 0$.[3] The per area profit functions are

$$\pi_{it}^k = pY_{it}^k - \sum_{j=1}^{k} w_{ijt} X_{ijt}^k$$

where p is the output price, for both new and traditional technologies.[4] For simplicity, I ignore the uncertainty and seasonality of the price. The superscript k indicates the new or traditional (that is, $k \in \{N, T\}$). The amount of an input j per area and its price are denoted as X_{ijt}^k and w_{ijt}, respectively. The input prices differ across farmers and time due to, for example, differential distances from farmers to shops and the degree of competitiveness in the input market. I assume that input prices are independent of the farmer's productivity.

To focus on the identification problem due to the unobserved heterogeneity, I make a simplifying assumption that the inputs are exogenous. That is, the inputs are technology-specific and fixed per area. This allows us to ignore the additional endogeneity caused by input decisions. In particular, by defining the followings,

$$A^N = \prod_{j=1}^{k} \left(X_{ijt}^N\right)^{\gamma_j^N}, \quad A^T = \prod_{j=1}^{k} \left(X_{ijt}^T\right)^{\gamma_j^T},$$
$$C_{it}^N = \sum_{j=1}^{k} w_{ijt} X_{ijt}^N, \quad C_{it}^T = \sum_{j=1}^{k} w_{ijt} X_{ijt}^T,$$

the production functions and profit functions are represented by

$$Y_{it}^k = e^{\beta^k} A^k e^{u_{it}^k} = e^{B^k} e^{u_{it}^k}$$
$$\pi_{it}^k = pY_{it}^k - C_{it}^k,$$

where $B^k = \beta^k + \log(A^k)$.

Following Suri (2011), I make the following two assumptions. First, farmer-specific unobserved

and u_{it}^T be 0.

[3] Again, if their expectations are not zero, I can add appropriate numbers to make them zero.

[4] Suri (2011) also assumes that the price of hybrid and non hybrid maizes are identical.

productivities, θ_i^N and θ_i^T, are known to the farmer before the production decision. Second, ξ_{it}^N and ξ_{it}^T do not affect the hybrid decisions and input decisions. These can include rainfall shocks realized after these decisions are made.[5]

I follow Lemieux (1998) to decompose θ_i^N and θ_i^T as follows:

$$\theta_i^N = b_N(\theta_i^N - \theta_i^T) + \tau_i,$$
$$\theta_i^T = b_T(\theta_i^N - \theta_i^T) + \tau_i,$$

where

$$b_N = \frac{\sigma_N^2 - \sigma_{NT}}{\sigma_N^2 + \sigma_T^2 - 2\sigma_{NT}}, \quad b_T = \frac{\sigma_{NT} - \sigma_T^2}{\sigma_N^2 + \sigma_T^2 - 2\sigma_{NT}},$$
$$\sigma_{NT} = Cov(\theta_i^N, \theta_i^T), \quad \sigma_N^2 = Var(\theta_i^T), \quad \sigma_T^2 = Var(\theta_i^T).$$

The term τ_i is interpreted as farmer i's absolute advantage, which affects his productivity in the same manner regardless of the technology he uses. By defining the farmer-specific comparative advantage, θ_i, as $\theta_i = b_T(\theta_i^N - \theta_i^T)$, I obtain

$$\theta_i^N = (\phi + 1)\theta_i + \tau_i,$$
$$\theta_i^T = \theta_i + \tau_i,$$

where $\phi = \frac{b_N}{b_T} - 1$. Note that since $E[\theta_i^N] = 0$ and $E[\theta_i^T] = 0$, $E[\theta_i] = 0$ and thus $E[\tau_i] = 0$.

[5]This is in contrast to the specification in Olley and Pakes (1996), in which the transitory errors are decomposed into two parts: anticipatory shock and non anticipatory shock. The former affects decision making of firms. The case in which the time-variant shocks affect the technology adoption choice is discussed in Section 3.

Using these notations, I can write the observed log yield function as[6]

$$
\begin{aligned}
y_{it} &= h_{it} y_{it}^N + (1 - h_{it}) y_{it}^T \\
&= h_{it}(B^N + u_{it}^N) + (1 - h_{it})(B^T + u_{it}^T) \\
&= h_{it}(B^N + (\phi + 1)\theta_i + \tau_i + \xi_{it}^N) + (1 - h_{it})(B^T + \theta_i + \tau_i + \xi_{it}^T) \\
&= B^T + \theta_i + (B^N - B^T) h_{it} + \phi \theta_i h_{it} + \tau_i + \epsilon_{it}, \qquad (1)
\end{aligned}
$$

where $\epsilon_{it} = h_{it}\xi_{it}^N + (1 - h_{it})\xi_{it}^T$. Notice that in this equation, the "treatment variable," h_{it}, is correlated with its coefficient, θ_i, unobserved heterogeneity. Therefore, this is in the class of the CRC model.[7]

2.2 Definition of a return to technology

I define the return of the new technology as the percentage change in yield. With Equation (1), the return of new technology for the farmer i is

$$
\begin{aligned}
R_{it} &\equiv \frac{Y_{it}^N - Y_{it}^T}{Y_{it}^T} \\
&\approx log(Y_{it}^N) - log(Y_{it}^T) \\
&= (B^N - B^T) + \phi\theta_i + (\xi_{it}^N - \xi_{it}^T),
\end{aligned}
$$

where the approximation in the second line is valid when the difference between Y_{it}^N and Y_{it}^T is not large. Thus, defining $B \equiv B^N - B^T$, the expected return is

$$E_i[R_{it}] = B + \phi\theta_i.$$

The expectation is over the random productivity shocks (ξ_{it}^N and ξ_{it}^T).[8]

To explore the heterogeneous returns to the new technology, I consider the difference in returns

[6] Lowercase variables represent log of corresponding variables.

[7] Wooldridge (2003) (p.185) states that in a correlated random coefficient model, "one or more 'treatment variables', which could be continuous or discrete, or some combination, interact with unobserved heteroeneity - also called 'random coefficients' - and the treatment variables and unobserved heterogeneity are allowed to be correlated."

[8] Suri (2011) uses the same definition for returns to technologies.

across farmers who adopted/did not adopt the new technology. Because there are two periods in the data, the goal is to identify

$$E[R_{it}|h_{i1}, h_{i2}] = B + \phi E[\theta_i|h_{i1}, h_{i2}].$$

2.3 Technology adoption decision

The farmer adopts the new technology if the expected profit from it is higher than that of the traditional technology:

$$\begin{aligned}
& E[\pi_{it}^N] \geq E[\pi_{it}^T] \\
\Leftrightarrow\ & pE\left[e^{\xi_{it}^N}\right] e^{B^N} e^{\theta_i^N} - C_{it}^N \geq pE\left[e^{\xi_{it}^T}\right] e^{B^T} e^{\theta_i^T} - C_{it}^T \\
\Leftrightarrow\ & pE\left[e^{\xi_{it}^N}\right] e^{B^N} e^{(\phi+1)\theta_i+\tau_i} - pE\left[e^{\xi_{it}^T}\right] e^{B^T} e^{\theta_i+\tau_i} \geq C_{it}^N - C_{it}^T.
\end{aligned}$$

Therefore, the technology adoption function is represented as

$$h_{it} = \mathbb{1}\left\{pE\left[e^{\xi_{it}^N}\right] e^{B^N} e^{(\phi+1)\theta_i+\tau_i} - pE\left[e^{\xi_{it}^T}\right] e^{B^T} e^{\theta_i+\tau_i} \geq C_{it}^N - C_{it}^T\right\}. \quad (2)$$

Unless production costs in the two technologies coincide (that is, $C_{it}^N = C_{it}^T$), h_{it} depends on τ_i.[9] However, previous studies have found that there are technology-specific inputs. For instance, fertilizers and irrigation played a huge role in the Green Revolution, and, all else equal, high-yielding varieties use more fertilizer than traditional varieties (Heisey and Norton, 2007). In the context studied by Suri (2011), fertilizer usage is higher in the hybrid variety of maize. Depending on the context, it is likely that the input cost differs across technologies, which makes the technology choice dependent on τ_i.

[9] If $C_{it}^N = C_{it}^T$,

$$\begin{aligned}
& pE\left[e^{\xi_{it}^N}\right] e^{B^N} e^{(\phi+1)\theta_i+\tau_i} - pE\left[e^{\xi_{it}^T}\right] e^{B^T} e^{\theta_i+\tau_i} \geq 0 \\
\Leftrightarrow\ & \log\left(pE\left[e^{\xi_{it}^N}\right]\right) + B^N + (\phi+1)\theta_i + \tau_i \geq \log\left(pE\left[e^{\xi_{it}^T}\right]\right) + B^T + \theta_i + \tau_i,
\end{aligned}$$

hence τ_i cancel out and h_{it} does not depend on τ_i any more.

2.4 Estimation of a correlated random coefficient model

To identify the differential returns to technology, θ_i is projected onto the history of the technology adoption and their interactions:

$$\theta_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i1} h_{i2} + v_i. \tag{3}$$

Note that by the property of linear projection, $E[v_i] = 0$, $E[h_{i1} v_i] = 0$, $E[h_{i2} v_i] = 0$, and $E[h_{i1} h_{i2} v_i] = 0$. Substituting this θ_i into Equation (1), I obtain the reduced-form equations

$$y_{i1} = \delta_1 + \gamma_1 h_{i1} + \gamma_2 h_{i2} + \gamma_3 h_{i1} h_{i2} + (v_i + \phi v_i h_{i1} + \tau_i + \epsilon_{i1})$$
$$y_{i2} = \delta_2 + \gamma_4 h_{i1} + \gamma_5 h_{i2} + \gamma_6 h_{i1} h_{i2} + (v_i + \phi v_i h_{i2} + \tau_i + \epsilon_{i2}),$$

where

$$\gamma_1 = B + \lambda_1 + \phi(\lambda_0 + \lambda_1), \quad \gamma_2 = \lambda_2, \quad \gamma_3 = \lambda_3 + \phi(\lambda_2 + \lambda_3)$$
$$\gamma_4 = \lambda_1, \quad \gamma_5 = B + \lambda_2 + \phi(\lambda_0 + \lambda_2), \quad \gamma_6 = \lambda_3 + \phi(\lambda_1 + \lambda_3).$$

Based on the reduced-form parameter estimates and their relationships with the structural parameters, I obtain the latter with the minimum distance method.[10]

There are four terms in the error term: v_i, $\phi v_i h_{it}$, τ_i, and ϵ_{it}. Because v_i is the error term in the linear projection of v_i, v_i does not cause an endogeneity problem. Also, since h_{it} is a binary variable, $\phi v_i h_{i1}$ cannot be a source of endogeneity.[11] Therefore, the identification assumption for

[10] One requirement to estimate the structural parameters is $\gamma_2 \neq \gamma_4$ since otherwise $\phi = (\gamma_6 - \gamma - 3)/(\gamma_4 - \gamma_2)$ is not identified. In most simulation exercise shown later in the article, I confirm that $\widehat{\gamma_2}$ and $\widehat{\gamma_4}$ are statistically significantly different in most simulations.

[11] For instance, h_{i1} and $\phi v_i h_{i1}$ are uncorrelated because $E[h_{i1} \cdot \phi v_i h_{i1}] = \phi E[v_i h_{i1}] = 0$.

consistent estimates of γ's is[12]

$$E[\epsilon_{it}h_{i1}] = 0, \quad E[\epsilon_{it}h_{i2}] = 0, \quad E[\epsilon_{it}h_{i1}h_{i2}h_{i2}] = 0, \tag{4}$$

$$E[\tau_i h_{i1}] = 0, \quad E[\tau_i h_{i2}] = 0, \quad E[\tau_i h_{i1}h_{i2}] = 0. \tag{5}$$

With the consistently estimated parameters, γ's, I can obtain the consistent estimates of the structural parameters and hence the heterogeneous returns of a new technology.

2.5 Violation of the identification assumption

Remember that $\epsilon_{it} = h_{it}\xi_{it}^N + (1-h_{it})\xi_{it}^T$, and ξ_{it}^N and ξ_{it}^T are assumed not to affect the hybrid decisions and input decisions. Due to the independence between h_{it} and ξ_{it}, $E[\epsilon_{it}h_{i1}] = E[\epsilon_{it}h_{i2}] = E[\epsilon_{it}h_{i1}h_{i2}] = 0$. On the other hand, Equation (6) shows that with the existence of technology-specific costs, the technology adoption decision, h_{it}, depends on the farmer's absolute advantage, τ_i. Due to the correlation between h_{it} and τ_i, $E[\epsilon_{it}h_{i1}]$, $E[\epsilon_{it}h_{i2}]$, and $E[\epsilon_{it}h_{i1}h_{i2}h_{i2}]$ are not equal to zero. In other words, assuming that the canonical model from the previous section reflects the reality, I cannot identify the structural parameters with the CRC model and thus cannot identify the heterogeneous returns to a technology.

2.6 Simulation results

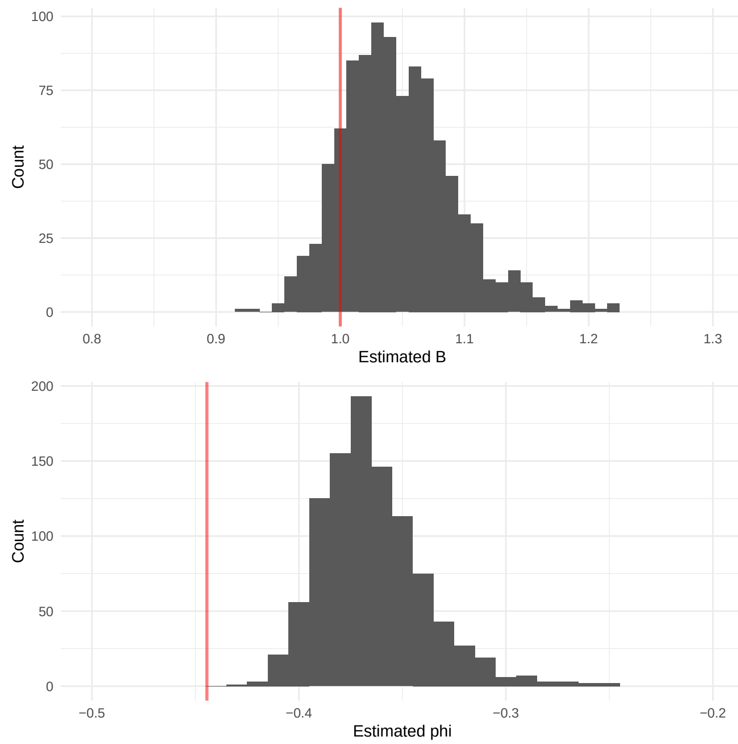
The discussion so far indicates the potential bias in the estimated returns to technology by a CRC model. I simulate data based on the behavioral model described above and use a CRC model to estimate returns to technology. Through this exercise, I demonstrate that these methods are biased due to the dependence of technology choice on absolute advantage of farmers. The parameters in the simulations are reported in Appendix. In each exercise, data are simulated 1,000 times.

Before showing the estimated returns to technology, I show the estimated structural parameters. The results are shown in Figure 1. The estimated B is not distributed around the true value,

[12] These conditions are different from the mean-independence assumptions used in Suri (2011) and Michler et al. (2019). Whereas the mean-independence is sufficient for unbiased estimates of the reduced-form parameters, it does not guarantee the unbiasedness of the structural parameters due to non-linear relationships between them.

and the estimates of ϕ are substantially different from the true parameter value. This suggests that the returns to technology, which are calculated based on these parameters, are biased as well.

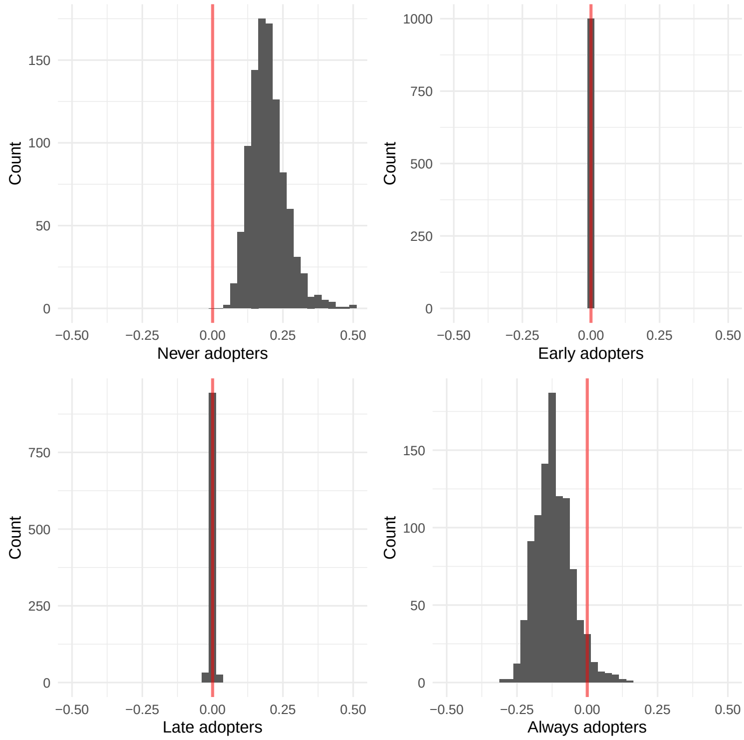
Figure 1: Estimated B and ϕ (true values: $B = 1$, $\phi = -0.44$)



Notes: The figures show the estimated B and ϕ. The red vertical lines show the true parameter values.

Figure 2 presents the estimated returns to technology of each farmer type: never adopters, who never adopted the new technology; early adopters, who used the new technology only in the first period; late adopters, who used the new technology only in the second period; and always adopters, who used the new technology in both periods. The estimated returns are severely biased for never adopters and always adopters. Those of the early and late adopters are consistently estimated, which is not surprising. Since these farmers use both technologies in different periods, simple differences in average yields in the two technologies provide consistent estimates of returns to technology. The real challenge is the estimate of returns for those who have experienced only one of the two technologies (that is, never adopters and always adopters), and Figure 2 shows that their returns are not consistently estimated.

Figure 2: Biases in returns to technology

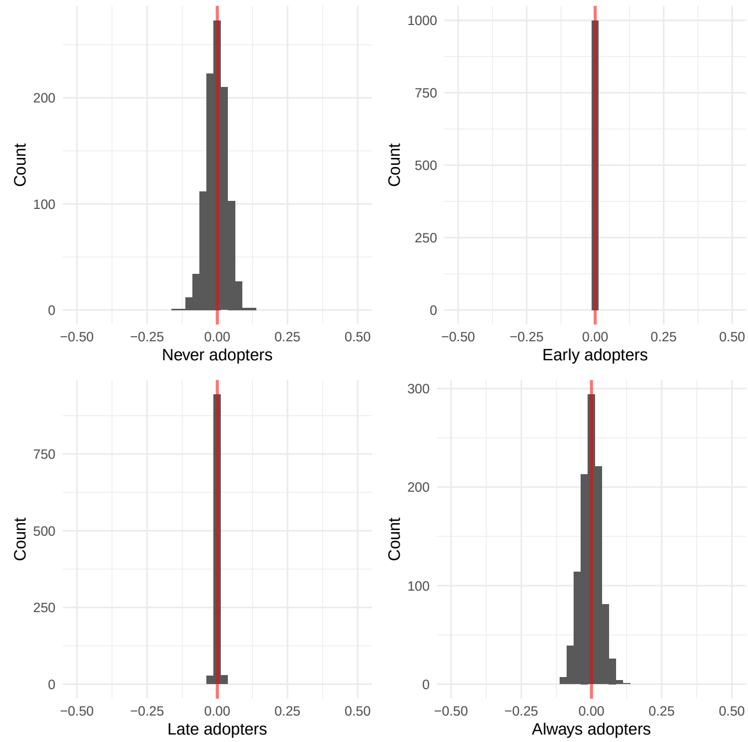


Notes: The figures show the differences between the estimated and true returns to technology by farmers' types. Red vertical lines are for a 0 difference from the true return to technology. Returns are defined as $B+\phi E[\theta_i|h_{i1}, h_{i2}]$, where B is the difference in technology-specific productivity between new and traditional technologies, θ_i is farmer-specific comparative advantage. Farmers are grouped into the following four categories based on their technology adoption histories: never adopters: $h_{i1} = h_{i2} = 0$, early adopters: $h_{i1} = 1,\ h_{i2} = 0$, late adopters: $h_{i1} = 0,\ h_{i2} = 1$, and always adopters: $h_{i1} = h_{i2} = 1$.

To demonstrate that this bias is caused by the dependence of the technology adoption decision on the absolute advantage of farmers, τ_i, I provide a CRC model results with data simulated assuming that farmers ignore τ_i when deciding which technology to use. The results are shown in Figure 3. As expected, the estimated returns are not biased and distributed around the true returns.[13]

[13]The structural parameter estimates in this scenario are shown in Appendix Figure A.1.

Figure 3: Biases in returns to technology when a farmer ignores his absolute advantage in technology adoption decisions



Notes: The figures show the differences between the estimated and true returns to technology by farmers' types. Red vertical lines are for a 0 difference from the true return to technology. Returns are defined as $B+\phi E[\theta_i|h_{i1}, h_{i2}]$, where B is the difference in technology-specific productivity between new and traditional technologies, and θ_i is farmer-specific comparative advantage. Farmers are grouped into the following four categories based on their technology adoption histories: never adopters: $h_{i1} = h_{i2} = 0$; early adopters: $h_{i1} = 1,\ h_{i2} = 0$; late adopters: $h_{i1} = 0,\ h_{i2} = 1$; and always adopters: $h_{i1} = h_{i2} = 1$.

3 Covariates observed before technology adoption decisions

In the previous section, it is assumed that the unobserved productivity is decomposed into time-invariant heterogeneity, θ_i^k, which is known to a farmer, and time-variant shocks, ξ_{it}^k, which is unknown before his technology adoption decision. The timing of the latter is essential to guarantee that the technology adoption is uncorrelated with technology adoption and to guarantee that the identification assumptions in Equation (4). However, there could be time-variant shocks that farmer knows before the decision on which technology to use. For instance, farmers allocate labor in response to rainfall shocks before planting (Fafchamps, 1993). Suri (2011) points out that family demographic changes due to death of adult members can affect the quality of labor and hence affect both technology adoption decisions and productivity. Ignoring such shocks, the technology adoption decision and time-variant shocks are correlated; even if I assume that the absolute advantage, τ_i, does not cause a bias, the estimates of returns to technology still suffer biases.

To deal with this situation, previous studies in the literature directly included variables to control for such shocks. Michler et al. (2019) includes such variables as household head gender, dependents ratio in a household, and off-farm income in regressions to control for shocks realized before planting decision. In this section, I demonstrate that this is imperfect in solving the issue and the bias remains even after controlling for pre decision shocks.

3.1 Model

Consider that a time-variant shock consists of two parts: ξ_{it} and Z_{it}. Whereas the former is unknown to a farmer when he decides technology, the latter is known by a farmer before his technology adoption decision. I assume that Z_{it} has a zero mean and is independent of a farmer's productivity. The Cobb-Douglas production functions become

$$\begin{aligned} Y_{it}^N &= e^{B^N} e^{(\phi+1)\theta_i+\tau_i+\rho Z_{it}+\xi_{it}^N} \\ Y_{it}^T &= e^{B^T} e^{\theta_i+\tau_i+\rho Z_{it}+\xi_{it}^N}, \end{aligned}$$

where for simplicity, the coefficient of Z_{it} is assumed to be the same in the two equations. The observed log yield function is

$$y_{it} = B^T + \theta_i + Bh_{it} + \phi\theta_i h_{it} + \rho Z_{it} + \tau_i + \epsilon_{it},$$

and an adoption function becomes

$$h_{it} = \mathbb{1}\left\{pE\left[e^{\xi_{it}^N}\right] e^{B^N} e^{(\phi+1)\theta_i+\rho Z_{it}+\tau_i} - pE\left[e^{\xi_{it}^T}\right] e^{B^T} e^{\theta_i+\rho Z_{it}+\tau_i} \geq C_{it}^N - C_{it}^T\right\}. \tag{6}$$

By using the linear projection in Equation (3), I obtain a similar reduced-form regression equations as before:

$$y_{i1} = \delta_1 + \gamma_1 h_{i1} + \gamma_2 h_{i2} + \gamma_3 h_{i1} h_{i2} + \rho Z_{i1} + (v_i + \phi v_i h_{i1} + \tau_i + \epsilon_{i1}),$$
$$y_{i2} = \delta_2 + \gamma_4 h_{i1} + \gamma_5 h_{i2} + \gamma_6 h_{i1} h_{i2} + \rho Z_{i2} + (v_i + \phi v_i h_{i2} + \tau_i + \epsilon_{i2}).$$

The relationships between the reduced-form parameters and structural parameters remain the same.

To consistently estimate the parameters, on top of the identification assumptions in Equations (4) and (5), Z_{it} and each variable in the error terms need to be uncorrelated as well. However, Z_{it} and v_i are correlated for the following reason. Remember that Z_{it} is independent of a farmer's productivity. Hence, Z_{it} and θ_i are independent, and from Equation (3),

$$\begin{aligned} E[Z_{it} v_i] &= E[Z_{it}\theta_i] - \lambda_0 E[Z_{it}] - \lambda_1 E[h_{i1} Z_{it}] - \lambda_2 E[h_{i2} Z_{it}] - \lambda_3 E[Z_{it} h_{i1} h_{i2}] \\ &= -\lambda_1 E[h_{i1} Z_{it}] - \lambda_2 E[h_{i2} Z_{it}] - \lambda_3 E[Z_{it} h_{i1} h_{i2}]. \end{aligned}$$

Because Z_{it} and h_{it} are correlated, this means that $E[Z_{it} v_i] \neq 0$.

Therefore, even if the pre decision shocks are sufficiently controlled for by Z_{it} and τ_i is not correlated with the technology adoption, the estimates of the model are inconsistent. This causes a bias in returns to technology, as shown in the numerical simulations below.

3.2 Simulation results

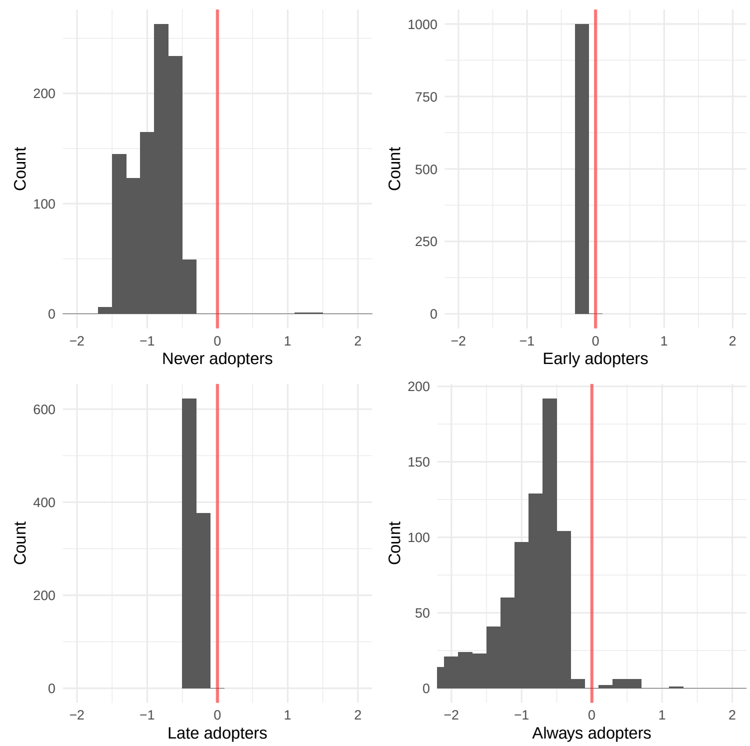
As in Section 2.6, I simulate the data, but this time with transitory shocks realized before technology adoption. In this simulation, farmers ignore τ_i in technology adoption decisions so that the issue raised in Section 2 is ignored and the focus is on the discussion of the impact of transitory shocks.

I show estimated results with a CRC model where the observed part of transitory shocks are controlled for in the reduced-form regressions. The results are presented in Figure 4.[14] Consistent

[14] The results without controlling for such shocks are obviously biased because farmers make technology adoption decisions after a part of transitory shocks, which necessarily correlate technology adoption and the unobserved shocks. Appendix Figure A.2 present the results.

with what was shown in the economic model in the previous section, the returns are estimated inconsistently.[15] This indicates that with the existence of time-variant shocks that are observable to farmers before decision making, simply controlling for such shocks in the reduced-form equations does not solve the problem in a CRC model.

Figure 4: Biases in returns to technology with pre decision shocks controlled for



Notes: The figures show the differences between the estimated and true returns to technology by farmers' types. Red vertical lines are for a 0 difference from the true return to technology. Returns are defined as $B+\phi E[\theta_i|h_{i1}, h_{i2}]$, where B is the difference in technology-specific productivity between new and traditional technologies, and θ_i is farmer-specific comparative advantage. Farmers are grouped into the following four categories based on their technology adoption histories: never adopters: $h_{i1} = h_{i2} = 0$; early adopters: $h_{i1} = 1,\ h_{i2} = 0$; late adopters: $h_{i1} = 0,\ h_{i2} = 1$; and always adopters: $h_{i1} = h_{i2} = 1$.

4 Conclusion

Low adoption rates of new and productive technologies and precise estimation of returns to technology have been a central topic in development and agricultural economics for a long time. To answer this puzzle, Suri (2011) proposes a method to estimate heterogeneous returns to technology,

[15]The coefficient of the observed part of the transitory shocks, ρ, is estimated with a bias as well (Figure A.3).

and the method has been used by other researchers (Michler et al., 2019; Wossen et al., 2019). I show that the identification assumption of the estimation model, a CRC model, is inconsistent with a canonical model of a profit-maximizing farmer. With a model and simulation results, I demonstrate that if a farmer behaves as described in the model developed here, the estimation results for returns to technology are biased. I also demonstrate that when there are time-variant shocks that farmers can observe before technology adoption, a simple solution used in the previous studies to control for such observed shocks does not fix the biased estimates.

The purpose of this study is not to criticize specific papers. Indeed, the farmers are likely to behave in different ways in different contexts, and the canonical model developed here may not reflect the reality in the study contexts in the previous research. Instead, my goal is to demonstrate the value of explicitly developing a theoretical model even in empirical studies to discuss the validity of identification assumptions. The model I present is greatly simplified to clearly convey the main points, and different and more complex models can be more relevant in some contexts: potential model extensions may include endogenous input choices, utility maximization with a risk-averse farmer, and correlated input prices with productivities). Different models should be considered and used as a guide for empirical analyses.

Unfortunately, although I point out several issues in a CRC model, I do not yet propose a solution to obtain consistent estimates of returns to technology. As pioneered by Suri (2011), heterogeneous returns to technology are a promising avenue to explain slow adoption of productive technology in developing economies. Developing an improved CRC model for precise estimates of the returns is of great importance and is left for future research.

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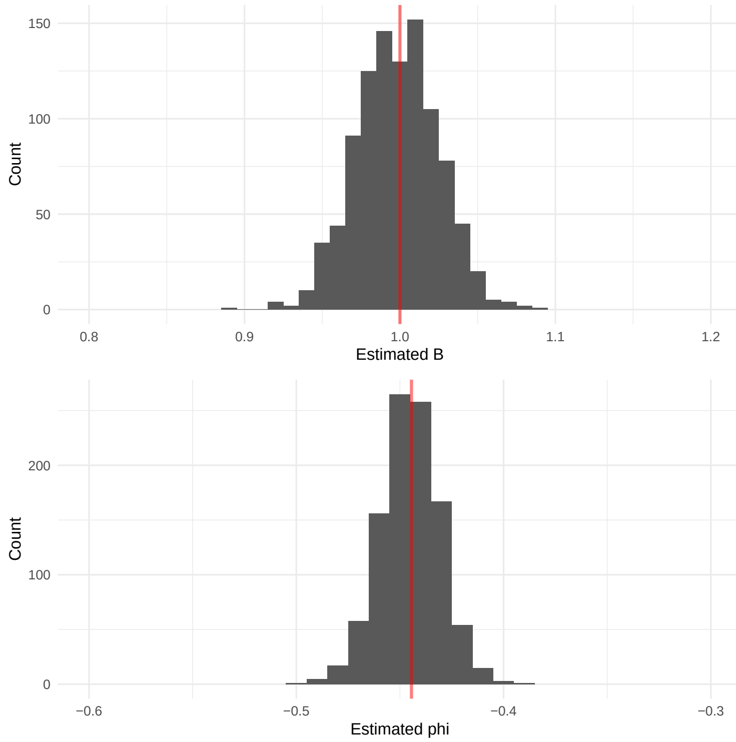
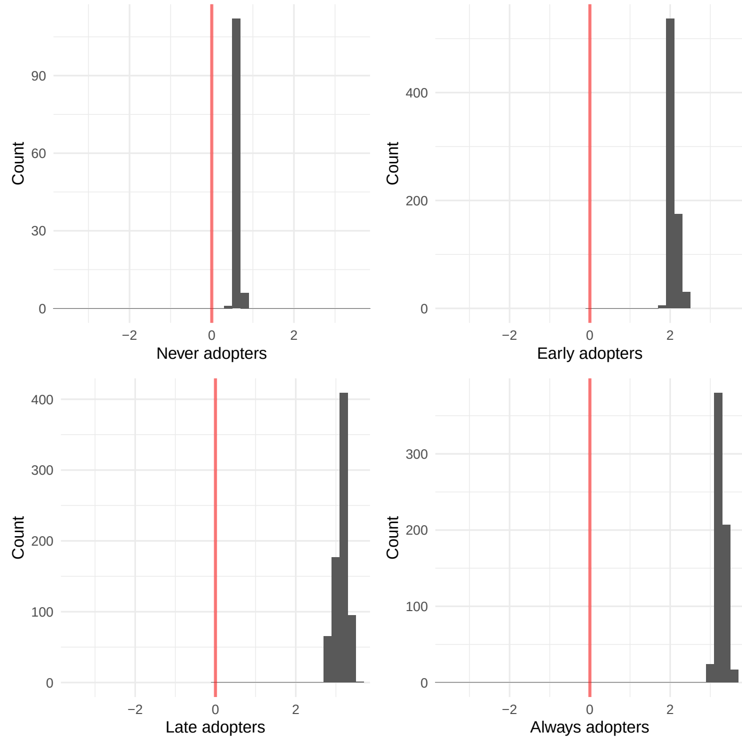
A Appendix figures

Figure A.1: Estimated B and ϕ when a farmer ignores his absolute advantage in technology adoption decisions (true values: $B = 1$, $\phi = -0.44$)



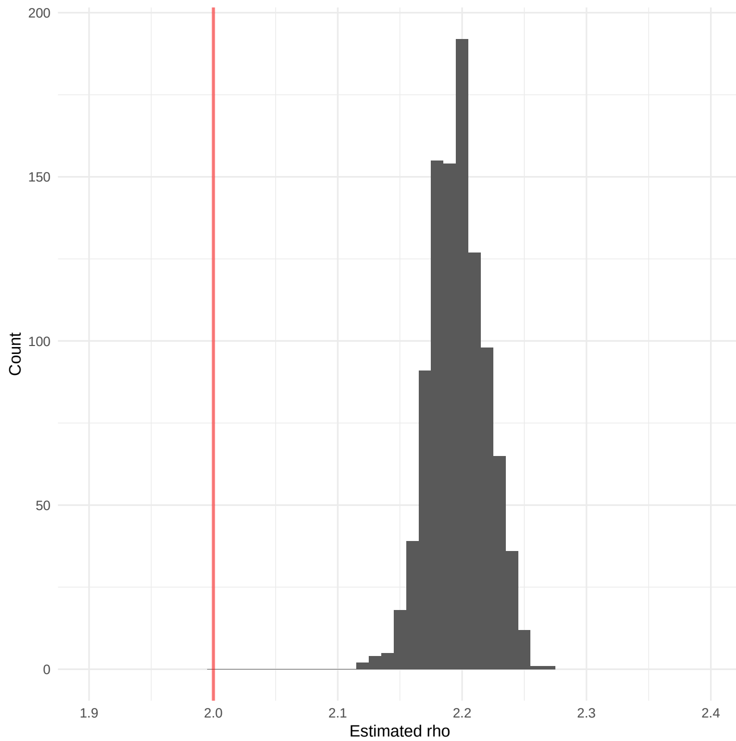
Notes: The figures show the estimated B and ϕ. The red vertical lines show the true parameter values.

Figure A.2: Biases in returns to technology without controlling for pre-decision shocks



Notes: The figures show the differences between the estimated and true returns to technology by farmers' types. Red vertical lines are for a 0 difference from the true return to technology. Returns are defined as $B+\phi E[\theta_i|h_{i1}, h_{i2}]$, where B is the difference in technology-specific productivity between new and traditional technologies, θ_i is farmer-specific comparative advantage. Farmers are grouped into the following four categories based on their technology adoption histories: never adopters: $h_{i1} = h_{i2} = 0$, early adopters: $h_{i1} = 1$, $h_{i2} = 0$, late adopters: $h_{i1} = 0$, $h_{i2} = 1$, and always adopters: $h_{i1} = h_{i2} = 1$. Since a hypothesis $\gamma_2 = \gamma_4$ was not rejected in more than half simulations, in this figure, I only show the results in which a hypothesis $\gamma_2 = \gamma_4$ is rejected at a 10% significance level.

Figure A.3: Estimated ρ when there are pre-decision shocks (true value: $\rho = 2$)



Notes: The figures show the estimated ρ. The red vertical line shows the true parameter value.

B Parameters for data simulation

$$B^T = 0.3 + U[0, 0.1]$$

$$B = 1$$

$$\sigma^{N2} = 3.5$$

$$\sigma^{T2} = 10.5$$

$$\sigma^{NT} = 6.0$$

$$\xi_{it}^N \sim N(0, 0.1)$$

$$\xi_{it}^T \sim N(0, 0.1)$$

$$\log C_{i1}^N \sim U[0, 1.1]$$

$$\log C_{i2}^N \sim U[1.76, 2.86]$$

$$\log C_{it}^T \sim N(0, 1.1)$$

$$Z_{it} \sim N(0, 1)$$

$$\rho = 2.0$$