Understanding the impact of agricultural technology adoption: K-factors, pitfalls and spillovers.* [DRAFT: DO NOT QUOTE.....YET]

Aliou Diagne[†] and Ben Groom[‡]

October 8, 2012

Abstract

Large impacts stemming from the adoption of modern varieties are difficult to find in Africa. This paper shows that this paucity of evidence can be understood once one disentangles the impact measured by specific treatment indicators. Average Treatment Effects measured using a binary adoption indicator are shown to comprise of adoption intensity, the $k-$factor, and the impact of adoption on traditional varieties. Hence ATE may well be zero or negative even in the presence of large $k-$factors. Methods used to evaluate treatment effects are developed to identify these individual components. Caution is required when estimating marginal treatment effects using *proportion of land in modern varieties* to define adoption, since if farmers are profit maximising, the treatment effect will be zero by definition. If non-zero, the treatment effect will not reflect the impact of modern varieties but other factors, like non-separability. An empirical analysis using data from Tanzania illustrates the theoretical results and paints a richer picture of the impact of adoption of modern rice varieties.

JEL: C8; O3; Q12; Q16; Q55

Keywords: Technology Adoption, Treatment Effects, Spillovers.

1 Introduction

It is widely hoped that technological change in agriculture, such as the adoption of modern varieties of crops, will kickstart a 'Green Revolution' in Africa. So far, the significant increases in yields and overall production witnessed in Asia have failed to materialise in Sub

***Acknowledgements**: This work has been undertaken as part of the Diffusion and Impact of Improved Varieties in Africa (DIIVA) project funded by a grant from the Gates Foundation to Bioversity (formerly IPGRI) on behalf of the CGIAR Special Panel on Impact Assessment (SPIA). The authors would also like to thank Tebila Nakelse and Paul Jasper for their research assistance, and Kei Kajissa and Yuko Kakano at the International Rice Research Institute, Tanzania for allowing us to use the Tanzania data. The paper has also benefited from being presented at the SPIA - International Association of Agricultural Economists Impact Assessment pre-conference, Foz de Iguacao, Brazil, 18th August 2012.

[†]Impact Assessment Economist, Africa Rice Centre, Cotonou, Benin. A.Diagne@cgiar.org.

[‡]Department of Geography and Environment, London School of Economics. b.groom@lse.ac.uk.

Saharan Africa, which still lags behind other regions in terms of agricultural productivity (e.g. Evenson and Gollin, 2001, Adekambi et al, 2009). Obviously it is important to understand why the increases in yields associated with modern varieties, that are well documented at the experimental plot level, have not always translated into increases at the farm level and in aggregate. Put another way, the magnitude of the $k-$factor at the experimental level is not generally reproduced at the farm level and in aggregate supply. Answers to this question require a coherent analysis of the determinants and impact of technology adoption. A necessary condition for this is a robust empirical strategy which builds on a clear definition of technology adoption itself and the impact measures of interest. Only then will it be possible to make sense of the factors which drive the success of adoption and the constraints to progress in African agriculture.

In this paper we take a counterfactual approach to ex-post evaluation of impact of the technological change. In the context of the adoption of modern varieties, we evaluate the theoretical measure of impact associated with two popular interpretations of technology adoption currently employed in empirical work on adoption and impact assessment (Doss, 2003, 2006). The first is a binary measure of technology adoption, which indicates whether a farmer has adopted any modern varieties at all. The second is the proportion of land allocated to modern varieties, which is a continuous measure of technology adoption and commonly interpreted as a measure of 'adoption intensity' (Suri, 2011; Kaguonga et. al, 2012). The latter reflects the fact that the adoption of new varieties is often partial, and traditional varieties are still grown by adopters.

Couched within production theory and the counterfactual approach we show that the Average Treatment Effect (ATE) of technology adoption measured by the binary interpretation reflects the interplay of several key farm level decisions: the adoption decision, the intensity of adoption and decisions concerning traditional varieties. For instance, if the outcome variable is yield, ATE is a combination of the yield $k-$factor, the proportion of land allocated to modern varieties and the difference in traditional yields between adoption and non-adoption states. This result extends to other outcome measures such as profit, revenue, cost and production. By disentangling these different aspects of impact this paper makes two important theoretical contributions to ex-post impact assessment. Firstly, the magnitude of impact can be specifically attributed to its underlying components: the farm level yield $k-$factor, the intensity of adoption, and the impact of adoption on traditional yield. That ATE is the net effect of all of these components explains in part why ATE^y may be zero despite the advantages that modern varieties provide at the farm level, as reflected by large yield $k-$factors. Secondly, with the components of ATE disentangled, the pathway of impact can be investigated in more detail. In particular, with the relationship between ATE and the $k-$factor clearly defined, typical empirical methods which identify ATE can be used to identify the $k-$factor, which is a key input into the measurement of economic surplus.

Extending the theoretical analysis of impact to the case when adoption is interpreted as *the proportion of land devoted to improved varieties* gives rise to a cautionary tale. Several studies in Sub Saharan Africa (SSA) employ this interpretation of technology adoption, or intensity of adoption (e.g. Degu et al., 1998; Gemida et al., 2001; Doss 2006; Kajissa et al 2011) and in some quarters it is considered a valid measure of adoption for impact analysis (Shideed and Mourid 2005; Suri, 2011). Looking at the associated measure of impact through the lens of production theory shows that this interpretation of adoption should be excluded from the toolbox of impact analysis. If it is assumed that farmers are profit maximising it can be shown that, irrespective of the actual impact of modern varieties on yields, revenues or profits, one would expect the theoretical measure of impact, and hence well identified empirical estimates, to be precisely zero. When impact is non-zero in this case, it is purely a reflection of differences in factor prices between modern and traditional varieties, market imperfections, transactions costs or deviations from the behavioural or other assumptions of production theory. It is not evidence of the impact of adoption per se. This renders this particular interpretation of technology adoption virtually useless for impact analysis.

The theoretical contributions naturally lead to their empirical counterparts. The relationship between ATE and the $k-$factor suggests several potential estimators for yield and production $k-$factors. Furthermore, disentangling the components of ATE theoretically informs empirical strategies to estimate each component in turn. This provides a richer picture of the impact of technology adoption than previously available. Empirical analyses of each of the theoretical points is undertaken using data on the adoption of new rice varieties from Tanzania.

The paper also contributes to an emerging literature pertaining to the empirical puzzle of low adoption and low impact of high yielding varieties. In a recent article, Suri (2011) explains the puzzle as a consequence of a positive correlation between potential net benefits and the fixed costs of adoption which results in adopters being those with low expected net benefits . This paper provides a complementary explanation for the puzzle which is rooted in the intensity of adoption and plot level spillovers to traditional agriculture. The paper also provides insights for the interesting results of a randomised control trial found in Bulte et al. (2012) in which placebo new varieties produced the same impact on yields as improved varieties. This speaks to a behavioural response in the process of adoption, which are characterised as a component of impact in this paper.

The paper is organised as follows. In Section 2 we outline a simple model of production. Section 3 discusses the $k-$factor and its relationship with typical treatment effects. In Section 4 we critically evaluate the theoretical measures of impact stemming from different interpretations of technology adoption. Section 5 provides empirical examples of the theoretical results using data on the adoption of new rice varieties in Tanzania. Section 6 concludes.

2 Simple Model of Production

In this section we develop a simple model of agricultural production. Through this lens it will then be possible to interpret the measures of impact stemming from alternative definitions of technology adoption. The outcome measures of interest are typically production, yield, revenue and profits.

Suppose that production of a single crop, say rice, can be specified for the j^{th} farmer by the following production functions for modern and traditional varieties respectively:

$$Y_j^M = f^M\left(L_j^M, \mathbf{z}_j^M\right) \tag{1}$$

$$Y_j^T = f^T\left(L_j^T, \mathbf{z}_j^T\right) \tag{2}$$

Where L_j^M, is land cultivated with modern varieties, L_j^T is land cultivated with traditional varieties, and $\mathbf{z}_j^i$ is a vector of inputs to modern and traditional production $(i = M, T)$. Assume that $f_k^i > 0$, $f_{kk}^i \leq 0$ and $f^i(0,0) = 0$.[1] For simplicity, assume that the production function is identical across farmers, while the inputs in z^i can overlap, possibly completely. Ignoring the j subscripts for simplicity, total production is given by:

$$Y = Y^M + Y^T \tag{3}$$

Now let the output price of modern and traditional varieties be p^M and p^T respectively, and the prices of non-land inputs to modern and traditional production be given by the vectors $\mathbf{p}_z^M$ and $\mathbf{p}_z^T$. Define the rental price of land as p_L^M and p_L^T respectively. The variety specific cost of production is given by $C^M = \mathbf{p}^M \mathbf{z}^M$ and $C^T = \mathbf{p}^T \mathbf{z}^T$, where $\mathbf{p}^i = [p_L^i, \mathbf{p}_z^i]$ and $\mathbf{z}^i$ contains L_j^i.[2] Total cost is then given by $C = C^T + C^M$. Variety specific revenues and profits are then given by $R^i = p_Y^i Y^i$ and $\Pi^i = p_Y^i Y^i - C^i$ and total profits and revenues are given by $R = R^M + R^T$ and $\Pi = \Pi^M + \Pi^T$, respectively.

In addition, let y_L^i, r_L^i, π_L^i and c_L^i represent the measures of output, revenue, profit and cost per unit of land, and r_Y^i, π_Y^i and c_Y^i be the equivalent per unit output.[3] this leads to the following definition for yield:

$$y_L = \frac{Y^M + Y^T}{L^M + L^T} = \alpha y_L^M + (1 - \alpha) y_L^T \tag{4}$$

This simple theoretical background assists in interpreting the measures of impact, as well as their identification and estimation.

3 The "$k-$factor"

One crucial measure of the impact is the so-called "k-factor", which measures productivity increases induced by technological change. Unfortunately, in the literature it has escaped a single definition and there are several candidates which are commonly used and seen as equally valid. The k-factor sometimes refers to a rightwards shift in the supply curve, and hence represents the 'raw' increase in output resulting from technological change (Fulginiti, 2008; p1). A related definition of the $k-$factor is the reduction in cost associated with technological change, which is a measure of the vertical shift in the supply curve (Masters et al., 1996; de Janvry and Sadoulet 2010).[4] Sometimes the $k-$factor is reported in levels, other times it is reported as a percentage change. For instance, in a review paper of the concept, Alston et al. (1995) define it as "the vertical shift of the supply function, expressed as a proportion of the initial price." (Ibid., p. 210).[5] In each case the $k-$factor consists

[1] Where $f_k^i = \frac{\partial f^i}{\partial k}$ for input k, and technology i.

[2] $\mathbf{p}^T \mathbf{z}^T$ is the dot product.

[3] That is, $y_{jL}^i = Y_j^i / L_j^i$ and $r_{jY}^i = R_j^i / Y_j^i$. The same notation is used for totals $y_j = Y_j / L_j$, and so on.

[4] Another early example is Peterson (1967) who defines the k-factor as "the percentage decrease in the supply function of poultry products that would occur should the new inputs used by poultry farmers to obtain greater efficiency suddenly disappear,..." (Ibid., p. 657)

[5] Master's et al. (1996), define k as the vertical shift in the supply curve or the net gain from research in terms of a decrease in production costs. (Masters et al 1996, p. 13) More specifically, and for estimation

of two components at the level of the farmer: a) a pure technology shift holding the input mix constant, and; b) a shift due to re-optimisation of the input mix upon adoption.[6] Estimates of the $k-$factor from experimental trials only capture the first of these components, and therefore tend to provide biased estimates of the 'true' $k-$factor associated with the "economically optimal yield increase." (Ibid., p. 329).

Whichever measure is used, it is clear that the $k-$factor is central to the estimation of changes in economic surplus due to the adoption of technology and for this reason remains important in applied agricultural economics (e.g. Alston et al., 1995). Recent estimations include Fulginiti (2008) who estimates the $k-$factor, interpreted as the horizontal shift in supply, for wheat, corn, soybeans and beef in the US. No matter how the $k-$factor is defined, as the reduction in cost associated with the adoption of agricultural techology (vertical shift in supply curve), or a pure production increase (horizontal shift), an estimate can be retrieved by combining estimates of the increase in yield associated with adoption of modern varieties with estimates of the relevant elasticities.

In this paper we focus on some particular interpretations of the $k-$factor which prevail in the literature, while distinguishing between production and yield $k-$factors. From the perspective of estimating the aggregate impact on supply from farm level data, the quantity of interest is the observed additional production or yield. The ATE from typical programme evaluation techniques is the appropriate measure here. As we show below however, the $k-$factor is an important component of ATE, yet specifically reflects the potential that a farmer obtains from the adoption of modern varieties by comparing production or yield from modern varieties between adoption and non adoption states. Estimates of the the average yield and production $k-$factors are therefore interest in their own right.

Taking first the yield $k-$factor, there are potentially three possible definitions of interest. Taking a counterfactual approach and using subscripts 1 and 0 to denote adoption and non-adoption status, the potential measures are: i) The observed yield $k-$factor : $K_y = E\left[y^M - y^T\right]$, where we have dropped the L subscript; ii) The average yield $k-$factor under adoption (i.e. conditional on adoption): $AK_1^y = E\left[y_1^M - y_1^T\right]$, which measures the additional yield for a particular farmer should they adopt;and, iii) The average yield $k-$factor across adoption states : $AK_{10}^y = E\left[y_1^M - y_0^T\right]$, which measures the difference in yield between the modern variety under adoption and the traditional variety under non-adoption. AK_1^y and AK_{10}^y are useful inputs to the estimation of economic surplus, as are their conditional counterparts. K_y, on the other hand, is typically contaminated with selection bias and confounders and not directly useful in this sense.

The *production* $k-$factors are slightly more complicated. The potential measures are: i) The average production $k-$factor: $AK_{10}^Y = E\left[Y_1^M + Y_1^T - Y_0^T\right]$, which measures the expected difference in production between adoption and non-adoption status;and, ii) The average production $k-$factor when only modern varieties are cultivated in the adoption state: $AK_{10}^Y(\alpha = 1) = E\left[Y_1^M - Y_0^T|\alpha = 1\right]$. This measures the difference in production between the modern varieties and traditional varieties when adoption is "complete". The observed $k-$factor, K_Y, is not a sensible measure when looking at production, since it does not control

purposes, this is later referred to as "the net reduction in production costs induced by the new technology, combining the effects of increased productivity and adoption costs." (Ibid., p.17)

[6] At the aggregate level, general equilibrium effects are also important. We make the Stable Unit Variable Treatment Assumption throughout.

for differences in the intensity of adoption and hence the land allocated to traditional and modern varieties.[7]

Apart from AK_{10}^{Y}, these different definitions of the $k-$factor attempt to capture the impact of modern varieties on yields and production irrespective of the intensity of adoption. In this sense they capture the "pure" effect of technology adoption. The following section shows how these conceptual measures are related to traditional measures of the impact of technology adoption in the case of modern varieties, which capture the impact of both the adoption and the intensity of adoption.

4 The impact of technology adoption: What impacts are we measuring exactly?

The definition of technology adoption has been the subject of debate in the agricultural literature (Doss 2006). In the context of adopting new varieties several possible measures have been suggested and employed in empirical analysis. One binary example of technology adoption assumes that adoption has taken place if any modern varieties whatsoever have been adopted. Another common measure is the proportion of land cultivated with modern varieties. This is often thought of as a measure of the intensity of adoption. [8] But what impacts do these definitions actually measure when looking at yields, production, revenue and profit? We first analyse the binary measure of adoption and then provide a cautionary tale about interpreting proportion of land cultivated as a measure of adoption for impact analysis.

4.1 The Adoption Dummy: A counterfactual approach

A common definition of technology adoption in the context of modern varieties is the presence or absence of new modern varieties among the crops grown by a given farmer. Here, the treatment variable is represented by an adoption dummy. $D_j : D_j = 1$ if $\alpha_j > 0$ and $D_j = 0$ otherwise. This treatment variable is best understood in the context of the counterfactual/potential outcomes approach in which it is an indicator of adoption status and determines which of the potential outcomes for each individual farmer are observed. With Q_1 and Q_0 defined as the potential outcomes in the treated and untreated states for outcome $Q \in \{\Pi, R, Y, y_L\}$ a typical treatment effect of interest is that which measures the averaeg impact of changing status, such as the Average Treatment Effect (ATE^Q):

$$ATE^Q = E\left[Q_1 - Q_0\right]$$

[7] It is a simple matter to convert the production $k-$factor into a measure of the cost reduction associated with technology adoption by multiplying by the inverse of the price elasticity of supply ε_{CY}. E.g. using measure ii):

$$K_{CY} = E\left[Y_1^M - Y_1^T\right](1 + \varepsilon_{CY})$$

[8] Other adoption variables might include the number of new varieties used (e.g. Diagne 2006).

with associated measures for the treated and untreated sub-populations.[9] Estimates of these treatment effects are required to establish the impact of the adoption of modern varieties on production, yields, profits and so on. The question is, what does the measure of impact coming from this interpretation of technology adoption tell us?

4.1.1 Treatment effect parameters and $k-$factors for production and yield

For brevity we focus on the cases where Q is equal to total production (Y) or yield (y_L). It is straightforward to extend the results to revenue (R) and profit (Π). When $Q = Y$ the counterfactual outcomes can be defined as:

$$\begin{aligned} Y_1 &= Y_1^M + Y_1^T \\ Y_0 &= Y_0^M + Y_0^T \end{aligned}$$

Noting that Y_0^M will typically be zero given our definition of adoption the observed outcomes are realised according to the following switching equation:

$$Y = Y_0 + D\left(Y_1 - Y_0\right) = Y_0^T + D\left(Y_1^M + Y_1^T - Y_0^T\right)$$

Similarly, the counterfactual $k-$factors can be defined as K_0^Y and K_1^Y for the non-adoption and adoption states respectively. The observed $k-$factor is realised according to:

$$K^Y = K_0^Y + D\left(K_1^Y - K_0^Y\right)$$

The Average Treatment Effect on production, ATE^Y, is given by:[10]

$$ATE^Y = E\left[Y_1 - Y_0\right] = E\left[Y_1^M + Y_1^T - Y_0^T\right] \tag{5}$$

ATE^Y measures the average increase in production should a farmer allocate some land to modern varieties rather than traditional varieties. This is equivalent to the $k-$factor AK_{10}^Y defined in the previous section. Furthermore, in the case that the adoption is "complete" $\left(Y_1^T = 0\right)$ this collapses to $E\left[Y_1^M - Y_0^T\right]$, which is equivalent to the $k-$factor $AK_{10}^Y(\alpha = 1)$ defined above.

This establishes the relationship between the different interpretations of the $k-$factor and ATE^Y typically estimated using the binary measure of technology adoption. It suggests that, in either case, ATE^Y is a justifiable measure of impact. Nevertheless, where adoption

[9] For simplicity we focus on ATE^Q. The analysis extends simply to the Average Treatment on the Treated and Untreated: ATT^Q and ATU^Q. The results derived below also apply to impact parameters such as Late and the MTE (see Heckman and Vytlacil, 2008).

[10] One could also define the Average Treatment Effect on the $k-$factor is: ATE^K, is given by:

$$ATE^{YK} = E\left[K_1^Y - K_0^Y\right] = E\left[Y_1^M - Y_1^T + Y_0^T\right]$$

This defines the relationship between the production $k-$factor and the average treatment effect as follows:

$$ATE^Y = ATE^{YK} + 2ATE^{YT}$$

where ATE^{YT} is the treatment effect on traditional production: $ATE^{YT} = E\left[Y_1^T - Y_0^T\right]$.

is not complete, the magnitude of ATE^Y will depend on the proportion of land allocated to modern varieties: α. It is also worth noticing that output from traditional production in the adoption state need not be equal to the counterfactual level of traditional production: $Y_1^T \neq Y_0^T$, due to the different proportions of land and other inputs allocated to traditional production in each case. Internal spillovers could also plausibly affect traditional production. For example, the modern variety may come with a package that include fertilizer that farmers partly divert to the traditional variety. Both points show that ATE^Y is the net effect of different farm level decisions. Such issues become important for identifying and estimating impacts using non-experimental data.

The importance of the observation that the measure of impact obtained via the binary indicator represents the net effect of several decisions can be illustrated further when we turn to yield as the outcome measure of interest: $Q = y_L$. Firstly, define aggregate yield and the yield of modern and traditional varieties as follows, where the subscript L has been ignored:

$$\begin{aligned} y &= \frac{Y}{L} \text{ if } L > 0, \text{ and } y = 0 \text{ otherwise} \\ y^j &= \frac{Y^j}{L^j} \text{ if } L^j > 0, \text{ and } y^j = 0 \text{ otherwise for } j = M, T \end{aligned}$$

That is, these outcomes are only non-zero when land is used in agriculture. Similarly, the *observed* yield $k-$factor can only be defined where it is indeed observed:

$$K^y = y^M - y^T \text{ if } L^M, L^T > 0, \text{ and } K^y = 0 \text{ otherwise}$$

Given that we are interested in the impact of moving from a non-adoption state to an adoption state, define (y_1, y_0), $\left(y_1^M, y_0^M\right)$, $\left(y_1^T, y_0^T\right)$, (α_1, α_0), (K_1^y, K_{y0}), as the counterfactual outcomes in each state for yield, yield from modern varieties, traditional yield, proportion of land devoted to modern varieties and yield $k-$factor respectively. Given that land is an essential input to production, then by definition of adoption we have the following inequalities among events: $\{D = 1\} = \left\{L^M > 0\right\} = \{\alpha_1 > 0\}$ and $\{D = 0\} = \left\{L^M = 0\right\} = \{\alpha_0 = 0\}$. Hence, $\alpha_0 = 0$, $K_0^y = 0$ and $Y_0^M = 0$. Given (4), the observed outcomes are related to the counterfactuals via switching equations of the form $w = Dw_1 + (1 - D) w_0$, where $w = \left(y^M, y^T, y, \alpha, K^y\right)$, in the following way:

$$\begin{aligned} y^M &= Dy_1^M && \text{(6a)} \\ y^T &= Dy_1^T + (1 - D) y_0^T && \text{(6b)} \\ y &= y_0^T + D\left(\alpha y_1^M + (1 - \alpha) y_1^T - y_0^T\right) && \text{(6c)} \\ \alpha &= D\alpha_1 && \text{(6d)} \\ K^y &= DK_1^y && \text{(6e)} \end{aligned}$$

These relationships allow us to define the treatment effects of interest in more detail.

4.1.2 Adoption Treatment Effects and $k-$factors for yield

For illustrative purposes we focus on defining the adoption treatment effects for yield and the yield $k-$factor. The relationships contained in equations (6) have implications for the treatment effects that can be meaningfully identified at the individual level. The treatment effects of interest include: 1) the causal effect of adoption of modern varieties on aggregate yield: $y_1 - y_0$; ii) the causal effect of the adoption of modern varieties on traditional varieties: $y_1^T - y_0^T$; 3) the yield $k-$factor *under adoption*: $K^y = y_1^M - y_1^T$; and, 4) the yield $k-$factor across adoption states or *before adoption*: $K_{10}^y = y_1^M - y_0^T$.

Equations (6) lead to the following relationships between these treatment effects and the observable outcomes:

$$K^y = DK_1^y + (1-D)\, y^T \tag{7a}$$
$$K_1^y = K_{10}^y + \left(y_1^T - y_0^T\right) \tag{7b}$$
$$y_1 - y_0 = \alpha_1 \left(y_1^M - y_1^T\right) + \left(y_1^T - y_0^T\right) \tag{7c}$$

As we have argued above in Section 3, K_1^y and AK_1^y are the most compelling measures of the intrinsic difference in yields between modern and traditional varieties in practice. Equation (7b) shows that the difference between K_1^y and K_{10}^y arises solely because of differences in the traditional yields between adoption and non-adoptions states. This difference captures changes in the inputs or techniques applied to traditional yields in the adoption state, and in this sense represents an internal spillover effect of adoption.

Individual treatment effects are not identifiable on their own, so we now turn to the identification of their associated summary statistics, in particular their average. From (7) the average treatment effects of interest are:

1. $ATE^y = E\left[y_1 - y_0\right]$: the Average Treatment Effect of adoption of modern varieties on aggregate yield;

2. $ATE^{yT} = E\left[y_1^T - y_0^T\right]$: the Average Treatment Effect of adoption on modern varieties on traditional yields;

3. $AK_1^y = E\left[y_1^M - y_1^T\right]$: the average yield $k-$factor under adoption;

4. $AK_{10}^y = E\left[y_1^M - y_0^T\right]$: the average yield $k-$factor across adoption states;

As usual, by conditioning on some well-defined subsets also define the conditional versions of these average treatment effect parameters: the average treatment effect on the treated (ATT^y and ATT^{yT}), the average treatment effect on the untreated (ATU^y and ATU^{yT}), the local average treatment ($LATE^y$ and $LATE^{yT}$) effect, the marginal treatment effect (MTE^y and MTE^{yT}). Also, conditional average yield $k-$factor parameters can also be defined similarly.

The identification and estimation of these conditional average parameters will not be pursued in this paper. Neither will we provide identification conditions for $LATE$ and MTE. Instead, we will illustrate the main points of the paper using the unconditional average parameters and only condition on some vectors of covariates X to control as required by their identification.

The treatment effects listed above are not unrelated to one another. A simple example will illustrate this. Firstly, if the D is independent of y_1 and y_0, ATE^y is given by:

$$
\begin{aligned}
ATE^y &= E[y_1 - y_0] = E\left[\alpha y_1^M + (1-\alpha) y_1^T - y_0^T\right] &\text{(8a)}\\
&= E\left[\alpha\left(y_1^M - y_1^T\right)\right] + E\left[y_1^T - y_0^T\right] &\text{(8b)}\\
&= E[\alpha]\, AK_1^y + cov\left(\alpha, y_1^M - y_1^T\right) + ATE^{yT} &\text{(8c)}
\end{aligned}
$$

Therefore ATE^y is composed of two related decisions: the decision to adopt and the intensity of adoption, as measured by the proportion α. Furthermore, (8c) shows that the magnitude of ATE^y is determined by three components: i) the intensity of adoption, α; ii) ATE^{yT}; and, iii) AK_1^y. Each of these components is interesting in its own right and can shed light on the nature of the impact of technology adoption. For instance, low levels of overall impact can arise from low α, low AK_1^y, or negative ATE^{yT}. That is, estimation of ATE^y may return low estimates of impact almost irrespective of the $k-$factor AK^y. This may be one reason for the insignificant estimates of impact frequently observed in the empirical literature. We return to this point in Section 5.

4.1.3 Identification of yield k-factors

The identification of ATE^y and ATE^{yT} is well understood using a random sample of observed $\left(y, y^M, y^T, D\right)$. Appendix A shows identification under conditional independence in a regression context. Estimation of AK_1^y and AK_{10}^y is slightly more complicated and requires different assumptions in each case. We now show that identification of AK_1^y requires more restrictive assumptions than the identification of AK_{10}^y.

Propositions 1 and 2 draw on the following assumptions:

- A1 Conditional Independence: y_1^M, y_1^T, y_0^T is independent of $D|X$
- A2 Common support: $0 < \Pr(D = 1|X) < 1$
- A3 Full common support: $\Pr(0 < \alpha < 1|X) > 0$

Proposition 1 *Direct Identification AK_{10}^y: Suppose that A1 and A2 hold, then: a) AK_{10}^y is identified from the joint distribution of $\left(y^M, y^T, D, X\right)$ with:*

$$AK_{10}^y = E_X\left(\mu_1(X) - \mu_0(X)\right)$$

where $\mu_1(X) = E\left[y^M|D = 1, X\right]$ and $\mu_0(X) = E\left[y^T|D = 0, X\right]$: or, b):

$$AK_{10}^y = E_X\left(\frac{E\left(Dy^M\right)}{P(X)} - \frac{E\left((1-D)\,y^T\right)}{(1-P(X))}\right)$$

where $P(X) = \Pr(D = 1|X)$.

Proposition 1 suggests two possible estimators for AK_{10}^y that can be implemented using data on y^M for adopters and y^T for non-adopters and conditioning variabls, X. Proposition 2 concerns the identification of AK_1^y.

Proposition 2 *Direct Identification AK_1^y : Suppose that A1 and A3 hold, the latter of which is stronger than A2. Then AK_1^y can be identified in the following ways:*

$$\begin{aligned} a) \quad AK_1^y &= E_X\left(E\left[y^M - y^T | X, 0 < \alpha < 1\right]\right) \\ b) \quad AK_1^y &= E_X\left(\frac{E\left(\alpha(y^M - y^T)|X, 0 < \alpha < 1\right)}{E\left(\alpha|X, 0 < \alpha < 1\right)}\right) \\ c) \quad AK_1^y &= E_X\left(\frac{E\left((y - y^T)|X, 0 < \alpha < 1\right)}{E\left(\alpha|X, 0 < \alpha < 1\right)}\right) \end{aligned}$$

.

Proposition 2 implies that, provided data exists for y^M and y^T for adopters (incomplete adoption is observed) then AK^y can be estimated by conditioning on sufficient X variables. Finally, Proposition 3 shows the relationship between the $k-$factor AK_1^y, ATE^y and ATE^{yT}:

Proposition 3 *Indirect Identification AK_1^y : Assuming A1 and A3, AK_1^y is related to ATE^y net of the impact of adoption on traditional production, ATE^{yT} in the following way:*

$$AK_1^y = E_X\left(\frac{ATE^y\left(X, 0 < \alpha < 1\right) - ATE^{yT}\left(X, 0 < \alpha < 1\right)}{E\left(\alpha|X, 0 < \alpha < 1\right)}\right) \tag{9}$$

and hence can be estimated via estimation of the components $ATE^y\left(X\right)$, $ATE^{yT}\left(X\right)$ and $E\left(\alpha|X\right)$.

Proof. See Appendix C ■

In sum, we have presented several alternative approaches to estimating AK^y, each relying on different identification assumptions. Identifiaction of AK_1^y is only possible under more restrictive conditions than AK_{10}^y. In a sense this is bad news since we have argued above that AK_1^y is the more interesting interpretation of the $k-$factor. In section 5 different estimators are employed to estimate the parameters of interest in each case using data from Tanzania on the adoption of new rice varieties. Before we proceed to the empirical examples, we first make a digression into an alternative interpretation of technology adoption and its use in impact evaluation. This proves to be a cautionary tale.

4.2 Proportion of land in Modern Varieties (α)

In this section we provide a cautionary tale about the interpretation of technology adoption for impact analysis. In particular we show that using proportion of land cultivated with modern varieties as a definition of technology adoption is likely to be a serious error in that theory suggests that we would expect the impact measure associated with this definition to be zero or thereabouts, or otherwise measure something unrelated to impact.

Using proportion of land cultivated with modern varieties, α, in impact analysis in principle defines a continuous measure of impact. Empirically, it defines the impact of adoption on aggregate profit, yield and gross revenue as the partial derivatives with respect to α of the respective conditional expectation functions (CEF) of aggregate yield (y), profit (Π), and gross revenue, (R). Each is a function of land and the vector of inputs X:

$$\begin{aligned}
\beta^{y} &= \frac{\partial y_L}{\partial \alpha} E\left(y_L | L, \alpha, \mathbf{X}\right) \\
\beta^{\Pi} &= \frac{\partial \Pi}{\partial \alpha} E\left(\Pi | L, \alpha, \mathbf{X}\right) \\
\beta^{R} &= \frac{\partial R}{\partial \alpha} E\left(R | L, \alpha, \mathbf{X}\right)
\end{aligned}$$

While this definition of technology adoption is quite common in the literature (see e.g. Kaguogo et al, 2012; Gemida et al., 2001; Degu et al., 1998), and usually is referred to as a measure of adoption intensity, it is not frequently used for impact analysis.[11] It is however, considered a plausible measure of adoption for impact analysis in some quarters (e.g. Shideed and Mourid, 2005). Furthermore, identification and estimation results for average derivative parameters, of which such marginal effects represent special cases, have been derived recently under very general conditions by Schennach, White and Chalak (2012).[12] We now show that in the present case, such impact parameters may well be erroneous.

The first thing to notice about this approach to estimating impact is that it is a marginal measure. Technology adoption typically involves non-marginal changes in agricultural production: e.g. large proportions of land immediately devoted towards the cultivation of modern varieties. Consequently, estimates of impact for marginal changes in land use are seldom likely to be of interest to the analyst. A more important conceptual problem with this adoption measure arises when one considers the behavioural assumptions that might apply in agricultural production. It is easy to show that optimising behaviour and profit maximisation in particular render this interpretation of adoption unusable for the estimation of impacts on yield, revenue and profit. This is shown in Proposition 4:

Proposition 4 *Suppose that the observed levels of adoption, profit, and revenue are chosen to maximise profits and that the parameters of the respective CEFs are econometrically identified. Then it follows that:*

$$\begin{aligned}
a)\ \beta^{\Pi} &= 0 \\
b)\ \ \beta^{y} &= E\left\{\frac{p^T - p^M}{p^T}\frac{\partial f^M\left(L^M, z^M\right)}{\partial L_M} - \frac{p_L^T - p_L^M}{p^T}\right\} \\
c)\ \beta^{R} &= E\left\{L\left(p_L^T - p_L^M\right)\right\}
\end{aligned}$$

.

Corollary 1 *a) If* $p_L^T = p_L^M$ *then* $\beta^R = 0$; *b) if in addition* $p^T = p^M$ *then* $\beta^y = 0$; *c) If* $p^T < p^M$ *then* β^y *could be negative.*

[11] See Doss (2006) for a discussion and further references.

[12] See Propositions 2.1 and 2.2. For example.

Proof. See Appendix E. ■

Proposition 4 states that if all farmers in the population are profit maximisers then we can expect the marginal impact of the proportion of land allocated to modern varieties (α) on the conditional expectation function for profit to be zero. The intuition is clear: β^{Π} measures the impact at the margin as land is converted from traditional to modern varieties, but profit maximisers ensure that all marginal gains from technology adoption are exhausted.

Proposition 4 also states that the marginal impact of α on the conditional expectation of yield is more or less unrelated to the impact on yield of adopting new varieties. In fact this expression represents the difference between the normalised marginal revenue product and marginal cost of modern varieties, and is a function of the differences in output and land prices between modern and traditional varieties. If, as is likely, the price of land for an individual farmer is the same regardless of whether modern or traditional varieties are grown, and if the price of the output is identical, then β^y and β^R will be identically zero.

To conclude, irrespective of the inframarginal effects on yield, revenue and profits of adopting modern varieties, theory shows that interpreting adoption as the proportion of land devoted to modern varieties leads to an impact measure which we can expect to be equal to zero. An estimator of the correctly identified empirical model will therefore provide an unbiased or consistent estimate of zero. This casts serious doubt on the usefulness of this interpretation of adoption as a means of estimating impact.

5 The Impact of Modern Varieties of Rice in Sub Saharan Africa

We retain the focus on the estimation of the impact of technology adoption on yield and undertake several estimations. Firstly, we estimate ATE^y using the estimators described in Section 4. These estimates are compared and then compared to the estimate of impact associated with the use of the proportion of land allocated to modern varieties, x in the theoretical analysis described above. As shown in Section 4.2, this measure does not have a robust theoretical interpretation since: a) it measures impact at the margin for a non-marginal change and; b) since we would expect maximisers to set marginal returns equal to zero, we would expect this measure of impact to be zero or otherwise reflect only price differences.

5.1 Data and Conditioning Variables

For Southern, Central and West Africa, household and community surveys were conducted in 2009 by Africa Rice Center (AfricaRice) under the Rice Data System project 2009-2010. Countries surveyed range geographically from Nigeria to Senegal and Guinea. The Tanzania data were collected by the International Rice Research Institute (IRRI) in Tanzania between September 2009 to January 2010. In each case data were collected at the household and village level and contain a detailed account of agricultural activity. In Tanzania the data cover the three main agro-ecological zones: the Eastern Zone, Southern Highland Zone, and Lake Zone, by sampling a representative area from each zone: Morogoro, Mbeya and

Shinyanga respectively. These areas produce nearly 40% of the rice grown in the country, with most rice grown under irrigated or rain-fed lowland conditions. In total, a stratified sample of 76 villages in 6 districts were sampled with 10 households randomly sampled from each village . The total sample size is 760 households, of which a subsample of 642 usuable records are used in the analysis below once account is taken of missing data on yields (Nakano and Kajissa, 2012).

For each estimator shown belowthe same set of conditioning variables are used. We following recent work by Wooldridge (2010) and Heckman and Vytlacil (2008) who respectively advise against conditioning on too many variables and a emphasise the need to avoid feedback effects in the estimation of treatment effects. Accordingly, our selection of conditioning variables avoids being too numerous, and avoids factors, such as inputs and technology variables, that may be affected by the adoption decision and therefore dilute the impact measured by our treatment variables. We therefore condition on regional, village level and pre-determined variables Two regional dummies are used: (Regdum1 and Regdum2) which indicate the Eastern and Southern Highland zones. Years of education of the head of household, years of experience in rice production, and distance to the capital city are the only household level variables. Village level access to credit and the presence of local credit organisations (*saccos*) together with two variables describing access to extension services: an indicator variable for access, and indicator for an extension office within 5km of the village. Descriptive statistics are shown in Appendix C.

5.2 Estimating the Average Treatment Effect: ATE^y

Column 1 of Table 2 represents the simple regression of yield on the treatment variable, and acts as a benchmark. Columns 2 and 3 show the results of the regression approaches outlined in Appendix A which assumes conditional independence conditional on the covariates, X. See (13) in Appendix A. Column 3 allows for heterogeneity in the treatment effect while the coefficient on *adopt* can be interpreted as an estimate of ATE^y. Columns 4 and 5 present the estimates of ATE^y using nearest neighbour and kernel matching methods. In all cases standard errors are in parenthesis.

Table 2 shows the results from analogous estimators using the regression based approach where the treatment variable is now the proportion of land allocated to modern varieties. The same covariates are used in order to control for selection bias under the assumption of conditional independence. In essence the treatment variable in this case is a continuous treatment variable.

Table 1 shows that the impacts measured by the adoption dummy are generally significant and positive. Yields increase by between 0.18 and $0.36t/ha$ when modern varieties are adopted. Similarly, when the proportion of land indicator, the measure of impact is also positive rather than zero as anticipated under profit maximisation. As the theory indicates, however, such measures of impact are probably more reflective of relative price changes than they are of actual impact on fdood security. If we were to take this measure seriously, it implies an increase of 0.0017t/ha for each percentage point increase in land allocated to modern varieties. This implies an impact of $0.047t/ha$, a significantly lower estimate than for the binary interpretation of technology adoption, and indicative of the theoretical point

Outcome: yield	Conditional Independence				
Treatment: adopt.	OLS	OLS	OLS	NN Match	K match
Variable	(1)	(2)	(3)	(4)	(5)
adopt	1.33***	0.367***	0.264***	0.203***	0.181**
	(0.179)	(0.229)	(0.421)	(0.322)	(0.514)
Region 1		-0.27*	-0.27*		
		(0.163)	(0.159)		
Region 2		0.81***	0.87***		
		(0.148)	(0.149)		
Educ. head (yrs)		0.023	0.011		
		(0.022)	(0.023)		
Rice exp (yrs)		-0.01	-0.01		
		(0.036)	(0.038)		
Credit access		-0.16	-0.17		
		(0.147)	(0.147)		
Dist. to capital (km)		0.008***	0.008***		
		(0.002)	(0.002)		
Saccos		0.26**	0.15		
		(0.136)	(0.142)		
Ext. Office		0.522***	0.54***		
		(0.160)	(0.165)		
Ext. Office < 5km		0.14	0.20		
		(0.178)	(0.180)		
Adopt*Region2			-2.45**		
			(1.23))		
Adopt*Saccos			1.09**		
			(0.467)		
R squared	0.12	0.51	0.53		
N	642	642	642		
* p < 0.1, ** p < 0.05, *** p < 0.01					

Table 1: Estimates of Impact on Yields of Adoption of Modern Varieties

Outcome: yield	Conditional Independence		
Treatment: Share.	OLS	OLS	OLS
Variables (X)	(1)	(2)	(3)
Share	0.0014***	0.0017***	0.0017***
	(0.002)	(0.002)	(0.004)
Region 1		-0.30**	-0.27*
		(0.159)	(0.159)
Region 2		0.81***	0.87***
		(0.148)	(0.149)
Educ. head (yrs)		0.024	0.012
		(0.022)	(0.023)
Rice exp (yrs)		-0.003	-0.012
		(0.036)	(0.038)
Credit access		-0.012	-0.17
		(0.146)	(0.148)
Dist. to capital (km)		0.008***	0.008***
		(0.002)	(0.002)
Saccos		0.24*	0.15
		(0.134)	(0.141)
Ext. Office		0.52***	0.54***
		(0.160)	(0.164)
Ext. Office < 5km		0.17	0.20
		(0.177)	(0.180)
Share*Region 2			-2.82**
			(1.53)
Share*Saccos			0.89**
			(0.438)
R squared	0.12	0.51	0.53
N	642	642	642
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$			

Table 2: Estimates of Impact on Yields using Share of Modern Varieties

outlined in Section 3.[13]

5.3 Estimating the average yield $k-$factors: AK_{10}^{y} and AK_{1}^{y}

In Section 4.1 above Propositions 1 and 2 proposed provided several identification strategies for AK_1^y and AK_{10}^y. In this section we present two estimators for each of these $k-$factors. Proposition 1a) suggested the following estimator for AK_{10}^y :

$$\hat{A}K_{10}^{ya} = \frac{1}{n}\sum_{i}^{n}\left(\hat{\mu}_1\left(X_i\right) - \hat{\mu}_0\left(X_i\right)\right)$$

where $\hat{\mu}_1\left(X_i\right) - \hat{\mu}_0\left(X_i\right)$ are estimates of the conditional expectations $E\left[Y^M|D=1,X\right] = \mu_1\left(X\right)$ and $E\left[Y^T|D=0,X\right] = \mu_0\left(X\right)$. It is possible to estimate these functions using a regression approach.

Proposition 1b suggests the following, 'inverse probability' estimator for AK_{10}^y :

$$\hat{A}K_{10}^{yb} = \frac{1}{n}\sum_{i}^{n}\left(\frac{\hat{m}_1\left(X_i\right)}{\hat{P}\left(X_i\right)} - \frac{\hat{m}_0\left(X_i\right)}{\left(1-\hat{P}\left(X_i\right)\right)}\right) \tag{10}$$

where $\hat{m}_1\left(X_i\right)$ and $\hat{m}_0\left(X_i\right)$ are estimates of the conditional expectation functions $E\left[DY^M|X\right]$ and $E\left[\left(1-D\right)Y^T|X\right]$ respectively, and $\hat{P}\left(X_i\right)$ is some estimate of the the conditional probability of adoption. The former are estimated using regression functions, the latter is estimated using a probit model.

Proposition 2 concerned the estimation of AK_1^y under the more restrictive assumptions required to identify the individual effects $K_1^y = y_1^M - y_1^T$, and hence its population average. Proposition 2a implies the following estimator for AK_1^y :

$$\hat{A}K_{1}^{ya} = \frac{1}{n}\sum_{i}^{n}\hat{\mu}_1^{\alpha}\left(X_i\right) \tag{11}$$

where $\hat{\mu}_1^{\alpha}\left(X_i\right)$ is an estimate of the conditional expectation function $E\left[y^M - y^T|X, 0<\alpha<1\right] = \mu_1^{\alpha}\left(X_i\right)$. Again, a regression approach is possible here, using the subsample of adopters for whom adoption is not complete: $0<\alpha<1$.

Proposition 2c implies an alternative estimator of the inverse probability variety:

$$\hat{A}K_{1}^{yc} = \frac{1}{n}\sum_{i}^{n}\left(\frac{\hat{\mu}_1^{\prime\alpha}\left(X_i\right)}{\hat{\alpha}\left(X_i\right)}\right) \tag{12}$$

where $\hat{\mu}_1^{\prime\alpha}\left(X_i\right)$ is an estimate of the conditional expectation function $E\left[y - y^T|X, 0<\alpha<1\right] = \mu_1^{\prime\alpha}\left(X_i\right)$ and $\hat{\alpha}\left(X_i\right)$ is an estimate of the function $E\left(\alpha|X, 0<\alpha<1\right) = \alpha\left(X_i\right)$. Both can be estimated using linear regression.

Table 3 shows the estimates of AK_1^y and AK_{10}^y using the inverse probability estimators (12) and (10) respectively.

[13] On average, the land applied to modern varieties is 3.62 ha, so a 1% increase in land cultivated with modern varieties would be 0.036ha. Multiplying the estimated marginal impact up to obtain a per hectare measure $\left(\left(0.017t/L^M/L\right)/0.036L\right)$ gives an estimated impact on yield of $0.47t/ha$.

	$k-$factors	
Country	AK^y_{10}	AK^y_1
Benin	0.495***	—
Burkina	0.552***	0.329***
Cameroon	0.342***	0.398***
Côte d'Ivoire	0.527***	0.316***
The Gambia	0.570***	0.276***
Ghana	0.505***	0.313***
Guinea	0.552***	0.312***
Kenya	0.412***	0.396***
Madagascar	0.374***	0.230***
Nigeria	0.434***	0.364***
CAR	0.427**	0.368***
DRC	0.427***	0.280***
Senegal	0.543***	0.322***
Sierra Leone	0.547***	0.312***
Tanzania	0.374***	0.336***
Togo	0.437***	0.275***
Uganda	0.451***	0.269***
All	0.457***	0.326***
*P<0.1, **P<0.05, ***p<0.01		

Table 3: Estimates of Average Yield k-Factor in SSA

$k-$factor	$\hat{A}K_1^{y3}$	
Treatment Effects	Tanzania	Togo
ATE^y	0.265***	0.752***
ATE^{yT}	0.343***	0.594***
$\alpha(X)$	0.16***	0.42***
AK_1^y	-0.48*	0.378**
N	741	426
* p < 0.1, ** p < 0.05, *** p < 0.01		

Table 4: Estimates of the Average Yield k-Factor

One striking observation from Table 3 is that the estimates of AK_{10}^y, the $k-$factor across adoption states, are always larger than the estimates of AK_1^y. Recalling that $AK_1^y = E\left[y_1^m - y_1^T\right]$ and $AK_{10}^y = E\left[y_1^m - y_0^T\right]$, the difference implies that on average the yields of traditional varieties are higher under adoption than in the absence of adoption. This implies a positive treatment effect ATE^{yT}. The following section uses the indirect estimator of Proposition 3 to disentangle these effects and presents contrasting results from Togo and Tanzania.

5.4 Indirect estimates of AK^y using ATE^y and ATE^{yT}

Proposition 3 provided an alternative identification strategy for AK_1^y which is composed of estimates of ATE^y, ATE^T and $E[\alpha|X]$ for the sub-population of partial adopters. Specifically, AK_1^y can be estimated in the following way:

$$\hat{A}K_1^{y3} = \frac{1}{n_{PA}}\sum_i^{n_{PA}} \frac{\hat{A}TE^y\left(X_i, 0<\alpha_i<1\right) - \hat{A}TE^{yT}\left(X_i, 0<\alpha_i<1\right)}{\hat{\alpha}\left(X_i\right)}$$

We employ the same regression approach as above to estimate $\hat{A}TE^y\left(X_i, 0<\alpha_i<1\right)$. $\hat{A}TE^{yT}\left(X_i, 0<\alpha_i<\right.$ can be estimated under conditional independence using regression functions to estimate $E\left[y_1^T|X, 0<\alpha<1\right]$ and $E\left[y^T|X, D=0\right]$, where $ATE^{yT}\left(X, 0<\alpha<1\right) = E\left[y_1^T|X, 0<\alpha<1\right] -$ $E\left[y_1^T|X, D=0\right]$. $\hat{\alpha}\left(X_i\right)$ is estimated using linear regression as above. We present the results of this exercise for Tanzania and Togo in Table 4.

The interesting finding here is that in Tanzania, the impact of adoption on the traditional varieties is larger than on from the modern varieties. This leads to a negative and barely significnant estimate of the $k-$factor in the adoption state.

The result in Tanzania is reminiscent of, and complementary to, the result of a randomised control trial undertaken by Bulte et al. (2012) in Tanzania. As part of this double blind RCT they gave farmers placebo seeds and found that the impact of the placebo was indistinguishable from the impact of the modern varieties. While our results are premised on actual adoption, they do indicate that adoption has a significant impact on the productivity of traditional varieties in addition to the impact of modern varieties themselves. A number of things can be learned from these results.

Firstly, when seen in light of Bulte et al (2012), it seems clear that the overall impact of technology adoption takes on many different dimensions. The Bulte et al (2012) results indicate that the idea of adoption leads to a reorganisation of cultivation which has positive spillovers for traditional varieties even in the absence of any potential k-factor. Our results for Tanzania confirm that the impact of adoption can be mostly as a result of spillovers to traditional varieties, and by comparison of AK_{10}^{y} and AK_{1}^{y} that these spillovers are probably substantial.

Secondly, the choice of impact measure is crucial. AK_{1}^{y} is essentially negative/zero for Tanzania. There is probably a good argument for using AK_{10}^{y} as the measure of the $k-$factor, which is happily easier to identify in any event.

6 Conclusion

In this paper we have shown that when it comes to measuring the impact of modern varieties on agricultural production the deeper the understanding of the impact measures the better. Researchers are faced with many possible interpretations of technology adoption and intensity of adoption when they design their impact analysis, but despite their apparent plausibility, some interpretations are definitely better than others for this purpose.

For instance, the paper provides a cautionary tale concerning the use of proportion of land allocated to modern varieties as a treatment variable in impact analysis. Theory tells us that if farmers are profit maximisers we would expect a measure of impact stemming from this interpretation to be zero, or thereabouts. This is because this is a marginal measure of impact, and profit maximisers can be expected to exhaust all gains at the margin. Otherwise, for non-zero estimates such as the estimates for Tanzania we have here, represent price differentials or departures from profit maximisation, and are unrelated to any gains in yield associated with the adoption of new varieties. The This point is illustrated using data from Tanzania, where the estimate of the ATE is far smaller when proportion of land is used as an impact variable than when the dummy variable is used.

Alternatively, the measure of impact obtained from a binary indicator for adoption has the potential to tell a very rich story of the causal path of impact. The Average Treatment Effect associated with such a dummy variable measures the net effect of three different components. In the case of yield these components are: the intensity of adoption, the impact of adoption on traditional varieties and the $k-$factor. We show that in theory where adoption of modern varieties is incomplete estimates of the ATE for yield can plausibly be zero irrespective of large and positive $k-$factors. This result arises as a consequence of the potential for negative spillovers of adoption to traditional production, and partial adoption itself. The overall message here is that the $k-$factor is often the more interesting measure of impact rather than the ATE.

The paper has two methods of empirically identifying the $k-$ factor : a direct method and an indirect. Estimates of the direct type for several sub-saharan countries show that the $k-$factor in the adoption states is more or less uniformly lower than the $k-$factor across adoption states. This implies that there are significant spillover effects from adoption to traditional varieties. Estimates of the indirect type disentangle the estimate of the $k-$factor into its subcomponents: ATE of modern varieties, the ATE on traditional varieties and the intensity of adoption. Estimates of the spillover effect are generally positive and in the case of Tanzania, larger than the impact of modern varieties themselves. This illustrates how the approach taken here allows a richer picture of adoption and impact to be identified and explains in part some of the results found in Bulte et al (2012).

One major caveat is required when interpreting the empirical results. Conditional independence is assumed throughout, which is unlikely to be a reasonable assumption. The extension of the results shown here to the selection on unobservables case is obvious deficiency of the paper. We leave this for future work.

7 References

Abadie A (2003). Semiparametric instrumental variable estimation of treatment response models. Journal of Econometrics, 113, pp231-263.

Adekambi, S.A., Diagne, A., Smite, F.P. and Biaou, G. (2009) 'The Impact of Agricultural Technology Adoption on Poverty: The Case of NERICA rice Varieties in Benin', Paper presented at the International Association of Agricultural Economists' 2009 Conference, Beijing, China, Aug 16-22, 2009.

Alston, Julian M., George W. Norten, and Philip Pardey. 1995. Science Under Scarcity: Principles and Practice for Agricultural Research Evaluation and Priority Setting, Ithaca: Cornell University Press.

Angrist, J.D. and Imbens, G.W. (1995) 'Two-Stage Least Squares Estimation of Average Causal Effects in Models with Variable Treatment Intensity', Journal of the American Statistical Association, 90:430, pp.431-442.

Bisanda, S., Mwangi, W., Verkuijl, H., Moshi, A. J., Anadajayasekeram, P., 1998. Adoption of Maize Production Technologies in Southern Highlands of Tanzania. International Maize andWheat Improvement Center (CIMMYT),The United Republic of Tanzania, and The Southern African Centre for Cooperation in Agricultural Research (SACCAR), 38 pp.

Bulte, E., Lei Pan, Joseph Hella, Gonne Beekman and Salvatore di Falco (2012). Effort Responses in Randomized Controlled Trials for Development: Evidence from a Double-Blind Field Experiment in Tanzania. Working paper, Wageningen University.

Degu, G.,Mwangi,W., Verkuijl, H.,Wondimu, A., (2000). An Assessment of the Adoption of Seed and Fertilizer Packages and the Role of Credit in Smallholder Maize Production in Sidama and North Omo Zone, Ethiopia. International Maize and Wheat Improvement Center (CIMMYT) and Ethiopian Agricultural Research Organisation (EARO), Mexico, DF, 24 pp.

Diagne, A. (2006) 'Diffusion and Adoption of NERICA Rice Varieties in Côte d'Ivoire', The Developing Economies, 44:2, pp.208-31.

Diagne, A. and Demont, M. (2007) 'Taking a new look at empirical models of adoption: average treatment effect estimation of adoption rates and their determinants', Agricultural Economics, 37, pp.201-210.

Doss C. R. (2006). Analyzing technology adoption using microstudies: limitations, challenges, and opportunities for improvement. Agricultural Economics 34, pp 207–219

Fulginiti, Lilyan E. (2008). "Estimating Griliches' k-shifts". Faculty Publications: Agricultural Economics, Paper 80. University of Nebraska. http://digitalcommons.unl.edu/ageconfacpub/80

Gemeda Abdissa, Girma Aboma, H. Verkuijl, and W. Mwangi. (2001). Farmers' Maize Seed Systems in Western Oromia, Ethiopia. Mexico, D.F.: International Maize and Wheat Improvement Center (CIMMYT) and Ethiopian Agricultural Research Organisation (EARO). p 32.

Griliches, Zvi. (1958). "Research Costs and Social Returns: Hybrid Corn and Related Innovations". Journal of Political Economy, 66(5), pp. 419-431.

Heckman, J.J. and Vytlacil, E. (2005), 'Structural Equations, Treatment Effects and Econometric Policy Evaluation', Econometrica, 73:3, pp.669-738.

Kaguongo W, Gerald Ortmann, Edilegnaw Wale, Mark Darroch and Jan Low (2012). Factors influencing adoption and intensity of adoption of orange flesh sweet potato varieties: Evidence from an extension intervention in Nyanza and Western provinces, Kenya. African Journal of Agricultural Research Vol. 7(3), pp. 493-503

Kaliba, A. R. M., Verkuijl, H., Mwangi, W., Moshi, A., Chilangane, A., Kaswende, J. S., Anadajayasekeram, P., (1998c). Adoption of Maize Production Technologies in Eastern Tanzania. International Maize and Wheat Improvement Center (CIMMYT), The United Republic of Tanzania, and The Southern African Centre for Cooperation in Agricultural Research (SACCAR), Mexico, DF, p. 40.

Katinila, R., Verkuijl, H., Mwangi, W., Anadajayasekeram, P., Moshi, A. J., (1998). Adoption ofMaize Production Technologies in Southern Tanzania. International Maize and Wheat Improvement Center (CIMMYT), The United Republic of Tanzania, and The Southern African Centre for Cooperation in Agricultural Research (SACCAR), Mexico, DF, 20 pp.

Kotu, B. H., Verkuijl, H.,Mwangi,W., Tanner, D., (2000). Adoption of Improved Wheat Technologies in Adaba and Dodola Woredas of the Bale Highlands, Ethiopia. International Maize and Wheat Improvement Center (CIMMYT) and Ethiopian Agricultural Research Organisation (EARO), Mexico, DF, 26 pp.

Mafuru, J., Kileo, R.,Verkuijl, H.,Mwangi,W., Anandajayasekeram, P., Moshi, A. J., (1999). Adoption of Maize Production Technologies in Lake zone of Tanzania. International Maize and Wheat Improvement Center (CIMMYT), the United Republic of Tanzania, and the Southern African Center for Cooperation in Agricultural Research (SACCAR), Mexico, DF, 39 pp.

Masters, William A., Bakary Coulibaly, Diakalia Sanogo, Mamadou Sidibe, and Anne Williams. (1996). The Economic Impact of Agricultural Research: A Practical Guide. Department of Agricultural Economics at Purdue University, IN.

Mussei, A., Mwanga, J., Mwangi, W., Verkuijl, H., Mongi, R., Elanga, A., (2001). Adoption of Improved Wheat Technologies by Small-Scale Farmers, Southern Highlands, Tanzania. International Maize andWheat Improvement Center (CIMMYT) and the United Republic of Tanzania, Mexico, DF, 20 pp

Nakano Y. and Kajissa K. (2012). The Determinants of Technology Adoption: A Case of the Rice Sector in Tanzania. IRRI Tanzania working paper.

Nkonya, E., Xavery, P., Akonaay, H., Mwangi, W., Anandajayasekeram, P.,Verkuijl, H., Martella, D., Moshi, A. J., (1998). Adoption of Maize Production Technologies in Northern Tanzania. International Maize and Wheat Improvement Center (CIMMYT), The United Republic of Tanzania, and The Southern African Centre for Cooperation in Agricultural Research (SACCAR), Mexico, DF, 42 pp

Shideed, Kamil H. and Mohammed El Mourid (eds). (2005). Adoption and Impact Assessment of Improved Technologies in Crop and Livestock Production Systems in the WANA Region. The Development of Integrated Crop/Livestock Production in Low Rainfall Areas of Mashreq and Maghreb Regions (Mashreq/Maghreb Project). ICARDA, Aleppo, Syria.

Suri, Tavneet (2011). Selection and Comparative Advantage in Technology Adoption, Econometrica, 79(1) pp159 - 209

Wale E (2010). How do farmers allocate land for coffee trees? Implications for on-farm conservation and seed technology adoption. Journal of Sustainable Agriculture, 34 (3): 270-291

Wooldridge, J.M. (2005) 'Violating Ignorability of Treatment by Controlling for too many Factors', Econometric Theory, 21, pp.1026-1028.

A Regression approach under conditional independence

The counter factual approach described above can be used to inform the empirical strategy to identify and estimate ATE^Q, ATT^Q, and ATU^Q. In order to illustrate the practical advantages of taking a theoretical perspective, the following exposition uses conditional mean independence and overlap for identification. That is, the treatment of technology adoption satisfies 'ignorability'.[14]

[14] Conditional mean independence is defined by:

$$E\left[Q_1|D,z\right]=E\left[Q_1|z\right] \text{ and } E\left[Q_0|D,z\right]=E\left[Q_0|z\right]$$

The overlap assumption is:

$$0<P\left(X\right)<1$$

where $P\left(X\right)$ is the conditional probability of being treated. If both assumptions hold then treatment is said to be 'ignorable'.

For any given individual Q_1 and Q_0 are not observed simultaneously since the random variable Q is realised according to the switching equation: $Q = Q_0 + D(Q_1 - Q_0)$, where D is the dummy variable indicating adoption. Define the conditional expectation functions (CEF) of the outcome variable of interest by $E[Q|D, \mathbf{z}]$, where $\mathbf{z}$ represents the observable determinants of the outcome, $\mathbf{z}$, which includes inputs and prices. Taking a regression based approach to model this CEF define:

$$Q_1 = \mu_1 + v_1, \qquad Q_0 = \mu_0 + v_0$$

where μ_i represents the population mean of potential outcome ($i = 1, 0$), and v_i represent deviations from the mean such that $E[v_1] = E[v_0] = 0$. The conditional expectation can now be written as:

$$E[Q|D, \mathbf{z}] = \mu_0 + D(\mu_1 - \mu_0) + E[v_0|\mathbf{z}] + D(E[v_1|\mathbf{z}] - E[v_0|\mathbf{z}])$$

If $E[v_0|\mathbf{z}] = \boldsymbol{\delta}_0^Q(\mathbf{z} - \bar{\mathbf{z}})$ and $E[v_1|\mathbf{z}] = \boldsymbol{\delta}_1^Q(\mathbf{z} - \bar{\mathbf{z}})$ then this can be written as:

$$E[Q|D, \mathbf{z}] = \alpha^Q + \beta^Q D + \boldsymbol{\delta}_0^Q(\mathbf{z} - \bar{\mathbf{z}}) + \boldsymbol{\delta}^Q D(\mathbf{z} - \bar{\mathbf{z}}) \tag{13}$$

where $\boldsymbol{\delta}^Q = \left(\boldsymbol{\delta}_1^Q - \boldsymbol{\delta}_0^Q\right)$ and $\alpha^Q = \mu_0$. Conditional mean independence means that $\beta^Q = (\mu_1 - \mu_0) = ATE^Q$, which can be identified provided the overlap assumption holds.[15] Ignorability identifies β^Q as ATE^Q and since no constraints are placed on $E[v_0|\mathbf{z}]$ and $E[v_1|\mathbf{z}]$, other than linearity, this specification allows treatment effects to be vary with $\mathbf{z}$. Estimation of the treatment effects is then by simple regression of Q on a constant, the treatment variable, D, observable characteristics $\mathbf{z}$ and the interactions of D and $(\mathbf{z} - \bar{\mathbf{z}})$. In particular, under ignorability of treatment:

$$E[Q|D = 1, \mathbf{z}] - E[Q|D = 0, \mathbf{z}] = ATE^Q(\mathbf{z})$$

[15] Conditional mean independence implies:

$$\begin{aligned} E[Q_1|D, \mathbf{z}] &= E[Q_1|\mathbf{z}] = \mu_1 + E[v_1|\mathbf{z}] \\ E[Q_0|D, \mathbf{z}] &= E[Q_0|\mathbf{z}] = \mu_0 + E[v_0|\mathbf{z}] \end{aligned}$$

Therefore:

$$\begin{aligned} E[Q_1|D, \mathbf{z}] - E[Q_0|D, \mathbf{z}] &= E[Q_1|\mathbf{z}] - E[Q_0|\mathbf{z}] \\ &= ATE(\mathbf{z}) \\ &= \mu_1 - \mu_0 + E[v_1|\mathbf{z}] - E[v_0|\mathbf{z}] \end{aligned}$$

Iterated expectations leads to:

$$\begin{aligned} E[ATE(\mathbf{z})] &= ATE \\ &= \mu_1 - \mu_0 \\ &= \beta \end{aligned}$$

and:

$$\begin{aligned}
ATE^Q &= E\left[ATE\left(\mathbf{z}\right)\right] \\
&= \beta^Q \\
ATT^Q &= E\left[ATE\left(\mathbf{z}\right)|D=1\right] \\
&= \beta^Q + \delta^Q\left(\bar{\mathbf{z}}_{treat} - \bar{\mathbf{z}}\right) \\
ATU^Q &= E\left[ATE\left(\mathbf{z}\right)|D=0\right] \\
&= \beta^Q + \delta^Q\left(\bar{\mathbf{z}}_{ut} - \bar{\mathbf{z}}\right)
\end{aligned}$$

where $\bar{\mathbf{z}} = E[\mathbf{z}]$, $\bar{\mathbf{z}}_{treat} = E_{treat}[\mathbf{z}]$ and $\bar{\mathbf{z}}_{ut} = E_{ut}[\mathbf{z}]$ are the expected values of $\mathbf{z}$ in the population, in the treated population and in the untreated population respectively.[16] With ignorability satisfied the treatment is randomly assigned when conditioning on observables z. If selection on observables is unrealistic, β^Q can be identified using instrumental variables for D (See e.g. Wooldridge 2006, Ch 21).[17] Maintaining the assumption of ignorability of treatment, we now describe this general identification strategy for generic outcome variable Q for outcome variables Y and y.

B Estimation of Treatment Effects ATE^y and ATE^Y

Where $Q = Y$, $Y_1 = Y_1^M + Y_1^T$ and $Y_0 = Y_0^T$. The switching equation becomes:

$$Y = Y_0^T + D\left(Y_1^M + Y_1^T - Y_0^T\right)$$

and with analogous assumptions to the generic case under conditional mean independence described above, the CEF for Y becomes:

$$E\left[Y|D,\mathbf{z}\right] = \alpha^Y + \beta^Y D + \boldsymbol{\delta}_0^Y\left(\mathbf{z} - \bar{\mathbf{z}}\right) + \boldsymbol{\delta}^Y D\left(\mathbf{z} - \bar{\mathbf{z}}\right)$$

and $ATE^Y(z)$ becomes:

$$\begin{aligned}
E\left[Y|D=1,\mathbf{z}\right] - E\left[Y|D=0,\mathbf{z}\right] &= E\left[Y_1^M + Y_1^T|\mathbf{z}\right] - E\left[Y_0^T|\mathbf{z}\right] \\
&= ATE^Y\left(\mathbf{z}\right) \\
&= \beta^Y + \boldsymbol{\delta}^Y\left(\mathbf{z} - \bar{\mathbf{z}}\right) \qquad (14)
\end{aligned}$$

From which it is easy to define ATE and the equivalent treatment effects for treated and untreated population. The parameters can be estimated with a regression of Y on a constant, the treatment variable, D, observable characteristics $\mathbf{z}$ and the interactions of D and $(\mathbf{z} - \bar{\mathbf{z}})$.

Where yield is the outcome of interest, $Q = y$, $y_1 = xy_1^M + (1-x)\,y_1^T$ and $y_0 = y_0^T$. The switching equation becomes:

[16] Typically these quantities will be estimated using the sample analogs.

[17] Although strictly speaking the impact measure that is identified is the Local Average Treatment Effect (LATE) (See Angrist and Imbens, 1994).

$$y = y_0^T + D\left(xy_1^M + (1-x)\, y_1^T - y_0^T\right)$$

In the simplified case in which $y_0^T = y_1^T$ this reduces to:

$$y = y^T + D\left(x\left(y_1^M - y^T\right)\right)$$

The CEF for yield becomes:

$$E[y|D,\mathbf{z}] = \alpha^y + \beta^y D + \boldsymbol{\delta}_0^y(\mathbf{z}-\bar{\mathbf{z}}) + \boldsymbol{\delta}^y D(\mathbf{z}-\bar{\mathbf{z}})$$

and $ATE^y(z)$ becomes:

$$\begin{aligned} E[y|D=1,\mathbf{z}] - E[y|D=0,\mathbf{z}] &= E\left[x\left(y_1^T - y^T\right)|\mathbf{z}\right] \\ &= ATE^y(\mathbf{z}) \\ &= \beta^y + \boldsymbol{\delta}^y(\mathbf{z}-\bar{\mathbf{z}}) \end{aligned} \tag{15}$$

The purpose of explicitly demonstrating the procedure for identification and estimation of treatment effects in the special case of ignorability of treatment and for y and Y is to show how theory can inform the empirical strategy. The simple theoretical model suggests that if farmers are profit maximisers, output Y and yield y are determined by inputs and prices and production technologies: $f^M(.)$ and $f^T(.)$. If selection on observables is to be a successful identification strategy then these should arguably be included among conditioning variables. Certainly, total land cultivated, H, should be included as a conditioning variables, otherwise differences in the scale of production will be attributed to the impact of adoption: neither estimate of the counterfactual Y_0^T or Y_1 would be comparable in terms of scale. Similar arguments apply when the outcome is yield.

C Proofs of Propositions 1-3:

Proposition 1. For part a), yields in modern and traditional production, y^M and y^T are observed according to:

$$\begin{aligned} y^M &= Dy_1^M + (1-D)\, y_0^M = Dy_1^M \\ y^T &= Dy_1^T + (1-D)\, y_0^T \end{aligned}$$

Under assumptions A1 we have $E\left[y^M|D=1,X\right] = E\left[y_1^M|X\right]$ and $E\left[y^T|D=0,X\right] = E\left[y_0^T|X\right]$, hence from A2 we can write $\hat{A}K_{10}^y = E_X\left(E\left[y^M|D=1,X\right] - E\left[y^T|D=0,X\right]\right)$. Part b) follows from the observation that $E\left[y^M|D=1,X\right] = E\left[Dy^M|X\right]/P(X)$ and $E\left[y^T|D=0,X\right] = E\left[(1-D)\,y^T|X\right]/(1-P(X))$. ■

Proposition 2. For part a), A1 gives $E\left[y^M|D=1,X\right] = E\left[y_1^M|X\right]$ and $E\left[y^T|D=1,X\right] = E\left[y_1^T|X\right]$. The difference yields $E\left[y_1^M|X\right] - E\left[y_1^T|X\right]$. Without further assumptions, identification of $AK_1^y = E\left[y_1^M - y_1^T\right]$ requires data on y^M and y^T for each individual. This is only true where $0 < \alpha < 1$. b) and c) follow from hence is observed for each individual over which the expectation is taken since it conditions on $0 < \alpha < 1$. Assumption A3 ensures this is possible. Proof of b) exploits the conditional independence of α and y_1^M and y_1^T; c) uses A1 and the difference in the conditional expectations of (6c) and (6b) to obtain $E[y|D=1,X] - E\left[y^T|D=0,X\right] = E[\alpha|X]\,E\left[\left(y_1^M - y_1^T\right)|X\right]$. Dividing through by $E[\alpha|X]$ and applying A3 completes the proof. ■

Proposition 3. Using A1 and conditioning on X, the conditional version of (8a) can be rearranged to obtain:

$$AK_1^y(X) = \frac{ATE^y(X) - ATE^{yT}(X)}{E(\alpha|X)}$$

since α is independent of ATE^y conditional on X, and where $AK_1^y(X) = E\left[y_1^M - y_1^T|X\right]$, $ATE^y(X) = E[y_1 - y_0|X]$ and $ATE^{yT}(X) = E\left[y_1^T - y_0^T|X\right]$. Identification of AK_1^y requires A3, which means that the expectation is only taken over partial adopters for whom $0 < \alpha < 1$. ■

D Descriptive Statistics for Tanzania

Variable	Obs	Mean	Std. Dev.	Min	Max
yield	642	2.255482	1.649791	.0211797	8.895478
regdum1	642	.3395639	.4739305	0	1
regdum2	642	.2928349	.4554181	0	1
eduhead	642	6.0919	2.892127	0	18
riceexp	642	3.587227	1.588578	0	5
creditany	642	.1635514	.3701564	0	1
distdcap	642	52.10436	38.9937	4	221
saccos	642	.2679128	.4432172	0	1
extoffice	642	.5404984	.4987458	0	1
extoffice5	642	.7772586	.4164106	0	1

Table A3a: Descriptive Statistics for whole sample.

Variable	Obs	Mean	Std. Dev.	Min	Max
yield	91	3.394758	1.830404	.5930319	8.895478
regdum1	91	.8681319	.3402219	0	1
regdum2	91	.043956	.2061331	0	1
eduhead	91	6.725275	1.944028	0	11
riceexp	91	3.692308	1.43521	1	5
creditany	91	.1318681	.3402219	0	1
distdcap	91	54.63736	29.78013	5	221
saccos	91	.3186813	.4685467	0	1
extoffice	91	.7692308	.4236593	0	1
extoffice5	91	.9230769	.2679457	0	1

Descriptive Statistics: Adopters: $D = 1$.

Variable	Obs	Mean	Std. Dev.	Min	Max
yield	551	2.067326	1.540676	.0211797	8.648381
regdum1	551	.2522686	.4347092	0	1
regdum2	551	.3339383	.4720465	0	1
eduhead	551	5.987296	3.008748	0	18
riceexp	551	3.569873	1.613049	0	5
creditany	551	.168784	.3749014	0	1
distdcap	551	51.68603	40.32028	4	221
saccos	551	.2595281	.4387741	0	1
extoffice	551	.5027223	.5004469	0	1
extoffice5	551	.753176	.4315552	0	1

Descriptive Statistics: Non-adopters: $D = 0$

E Proof of proposition 4:

Proof. The farmer's profit maximisation problem with respect to x is:

$$\begin{aligned}\max_x \Pi &= p^M Y^M + p^T Y^T - \left(C^M - C^Y\right) \\ &= p^M f^M\left(L^M, \mathbf{z}^M\right) + p^T f^T\left(L^T, \mathbf{z}^T\right) - \left(p_L^M L^M + p_L^T L^T\right) - \mathbf{p}_z \mathbf{z}\end{aligned}$$

noting that $L^M = xL$ and $L^T = (1-x)L^T$ and $L = L^M + L^T$, the first order conditions become:

$$\frac{\partial \Pi}{\partial x} = p^M f_L^M\left(xL, \mathbf{z}^M\right)L - p^T f_L^T\left((1-x)L, \mathbf{z}^T\right)L - \left(p_L^M - p_L^T\right)L = 0 \tag{16}$$

This proves Proposition 1a since if this is true for a particular farmer it will be true in expectation. From above, yield is given by $y_L = xy_L^M + (1-x)\,y_L^T$. Therefore, $\partial y/\partial x = f_L^M\left(xL, \mathbf{z}^M\right) - f_L^T\left((1-x)L, \mathbf{z}^T\right)$. Simple rearrangement of (16) to obtain this expression proves 1b. Lastly, revenue is given by $R = p^M Y^M + p^T Y^T$ hence $\partial R/\partial x = p^M f_L^M\left(xL, \mathbf{z}^M\right)L - p^T f_L^T\left((1-x)L, \mathbf{z}^T\right)L$. Again, simple rearrangement of (16) to obtain this expression proves 1c. Corollary a), b) and c) are easily proven by evaluating expression b) when $p^T = p^M$, c) when $p^T = p^M$ *and* $p_L^T = p_L^M$ and by inspection of b) when $p^T < p^M$. ■