Understanding the impact of agricultural technology adoption: $k-$factors, spillovers and pitfalls.*

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Abstract

This paper sheds light on estimating the impact of the adoption of agricultural technology. Where modern crop varieties are the technology the Average Treatment Effect on yield associated with a binary adoption indicator is shown to comprise of adoption intensity, the 'innovation effect' or '$k-$factor', and an in-farm spillover effect of adoption on traditional varieties. Hence, ATE may be zero in the presence of large $k-$factors or positive in the absence of such an innovation effect due to spillovers. Methods are developed to empirically identify these individual components and the nature of impact is shown to be heterogeneous across several Sub-Saharan countries. A potential pitfall is highlighted when adoption is defined as the continuous *proportion of land in modern varieties.* The Average Partial Derivative in such a case will be zero if farmers are profit maximising, and measure any number of deviations from profit maximisation otherwise.

JEL: C8; O3; Q12; Q16; Q55

Keywords: Technology Adoption, Treatment Effects, Spillovers, NERICAs, Africa.

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-Saharan Africa, which still lags behind other regions in terms of agricultural productivity (e.g. Evenson and Gollin, 2003, Adekambi et al, 2009). Obviously it is important

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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 (Sumberg, 2012). Put another way, why is it that the magnitude of the '$k-$factor' at the experimental level is not generally reproduced at the farm level?

There are many convincing explanations for Africa's puzzling yield-gap. Suri (2010) shows empirically that low levels of adoption and impact of adoption can be explained in part by an inverse relationship between comparative advantage and the benefits from adoption, such that many adopters have low increases in yield. Diagne et al. (2009) argue that information and awareness are central constraints to the adoption and impact of new varieties of rice in West Africa. Actual adoption is much lower than the potential adop/tion under full exposure. In Kenya, time inconsistent behaviour in the purchase and application of complementary inputs, e.g. fertilizer, represents another important stumbling block (Duflo et al., 2010), while the absence of complementary inputs, institutions (e.g. credit, social networks) and infrastructure is another oft cited explanation for the yield gap (Besley and Case, 1993). These interesting contributions speak to a simpler problem. Clearly there is no reason to expect that the experimental yields will be realised at the farm level since the experimental conditions underwhich trials are performed do not reflect the conditions prevalent in the field, so to speak, and the possibly optimising decisions that farmers make when they adopt (Sumberg 2010).

The purpose of this paper is to clarify the link between the definitions of adoption and the specific measure of impact that they identify. Two related definitions of adoption are considered, each of which is commonly used in the literature (Doss, 2003, 2006; Diagne, 2006). The first is a binary measure indicating whether a farmer has adopted any modern varieties whatsoever. Typically this measure is equal to unity when a proportion of land is allocated to modern varieties, and zero otherwise. The second definition of technology adoption is the proportion of land allocated to modern varieties. This is a continuous measure of technology adoption and commonly interpreted as a measure of 'adoption intensity' (Doss 2006; Kaguonga et. al, 2012). This measure reflects the fact that adoption of new varieties is often partial, with traditional varieties still cultivated by adopters. Definitions of modern varieties notwithstanding, the binary and the continuous measures are obviously closely related.

The merits of these two definitions of adoption are evaluated in relation to the theoretical measures of impact they identify. In the counterfactual framework of the policy evaluation literature, measures of impact in the population typically include: the Average Treatment Effect (ATE); the Average Treatment on the Treated (ATT) ; the Marginal Treatment Effect (MTE) ; and the Local Average Treatment Effect ($LATE$) (Angrist and Imbens 1994; Heckman, 2010). These averages are the natural focus of attention when treatment status is binary: e.g. adopter and non-adopter. The proportion of land allocated to modern varieties is an example of a continuous treatment. Continuous treatments have alternative measures of impact associated with them, chief among which is the Average Partial Derivative (Blundell and Powell 2004; Imbens and Newey, 2009; Schennach et al., 2012).

Of further interest in the context of the adoption of new varieties is the so called $k-$factor (Griliches, 1958; CGIAR 2010). The $k-$factor has defied a unique definition and broadly refers to the productive advantage arising from a technological change, be it through reduced cost or increased output. The yield $k-$factor is central to the analysis of the impact of modern varieties and yet several definitions are in circulation (Fulginiti 2008; Alston et al., 1995). In this paper we provide a precise definition of the $k-$factor in the counterfactual framework which reflects a straight comparison between modern and traditional varieties at the individual farm level and isolates the 'innovation' effect of technology adoption. The practical merits of different definitions of adoption for impact evaluation can then be evaluated by their ability to identify the $k-$factor.

By carefully structuring the problem of technology adoption in the context of the counterfactual framework several important results emerge. Firstly, if adoption of technology is sometimes partial, in the sense that only a proportion of land is allocated to modern varieties, the Average Treatment Effect (ATE) of technology adoption measured in the case of binary adoption states reflects the interplay of three key farm level decisions: the adoption decision; the intensity of adoption; and decisions concerning traditional varieties. For instance, if the outcome variable is yield, the Average Treatment Effect on farm yield reflects a combination of the yield $k-$factor or 'innovation effect; the intensity of adoption of modern varieties, and the impact of adoption on traditional yields. The latter is an in-farm spillover effect which may be positive or negative and captures, *inter alia*, behavioural changes arising from adoption, rather than the impact of the innovation itself (e.g. Bulte et al., 2012). This result extends to other outcome measures such as profit, revenue, cost and production.

The fact that ATE is the net effect of these underlying components: the innovation effect, the intensity of adoption, and the in-farm spillover effect, explains why ATE^y may be zero despite the potential advantage of modern varieties. Low intensity of adoption and negative in-farm spillovers could overwhelm even large $k-$factors/innovation effects. Furthermore, the decomposition allows the nature of impact to be investigated in more detail by establishing whether positive ATE^y arises because of the innovation effect of modern varieties, intensity of adoption or via the in-farm spillover, or all three in equal measure.

To the contrary, we show that caution is required when adoption is interpreted as *the proportion of land devoted to improved varieties* for the purpose of impact analysis. 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) and in some quarters this and other continous measures of adoption are considered a appropriate for impact analysis (Shideed and El Mourid, 2005; Kassie et al., 2012). A number of analysts consider this measure of adoption to be preferable since continuity provides more information on the question of impact and can measure the marginal net benefit of public policy (Heckman, 2010). Under certain circumstances continuous treatments can be used to identify marginal measures of impact, such as the Average Partial Derivative, which have clear structural interpretations via their relationship with the Average Structural Function (Blundell and Powell, 2000; Imbens and Newey 2009). However, the lens of production theory shows that the interpretation of continuous treatment effects is very different from that typically envisaged. For instance, when profit is the outcome variable, the continuous treatment effect identified by proportion of land in modern varieties is the average (across farmer) marginal profit. However, if farmers are profit maximising they will exhaust all such marginal gains. Hence, this theoretical measure of impact, and well identified empirical estimates, will be precisely zero. Subsequently, non-zero impacts are not evidence of impact per se but simply reflect differences in factor prices between modern and traditional varieties, market imperfections, transactions costs or deviations from the behavioural or other assumptions of production theory. This emphasises the need for a structural theory to underpin the interpretation of impact estimates.

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. Where partical adoption is observed it is also possible to identify and estimate the in-farm spillover effect. This altogether richer picture of the impact of technology adoption is borne out in the empirical analysis using data collected by the Africa Rice Centre for 18 Sub-Saharan African countries. The results show a heterogeneous picture of impact on yields. In short, positive and significant measures of ATE^y result from combinations of low $k-$factors and high spillovers (e.g. Tanzania), high k-factors and low spillovers (e.g. Kenya) and moderate values of each (e.g. Sierra Leone).

The empirical results provide insights for the results of a randomised control trial in Tanzania undertaken by Bulte et al. (2012). Here, 'placebo' traditional seeds produced the same impact on yields as genuine modern varieties. This speaks to a behavioural response to adoption, which is captured by the in-farm spillovers in this paper, and which are generally highly significant among partial adopters in Africa.

The paper is organised as follows. In Section 2 we outline a simple model of production which provides the structure for the ensuing analysis. Section 3 introduces and evaluates the measures of impact relevant to the adoption of modern varieties in a counterfactual framework. Binary and continuous measures are considered, a precise definition of the $k-$factor is developed in each case, and the pitfalls assocaited with the continuous measure are highlighted. The various measures or impact are identified under conditional independence in Section 4 and the new estimators are applied to data on new rice varieties from 18 Africa countries in Section 5. Section 6 discusses and 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:

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

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

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:

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

Finally, the indicator variable D is equal to unity when a farmer has adopted any modern varieties and zero otherwise. Define aggregate yield and the yield of modern and traditional varieties as follows, where the subscript L has been ignored:

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

That is, yield outcomes are only non-zero when land is used in agriculture.

3 Measures of the Impact of Technology Adoption

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 important dichotomy is between discrete, particularly binary, and continuous measures of technology adoption. Typically technology adoption is treated as binary in that adoption is considered to have place if any modern varieties whatsoever have been adopted. A continuous measure of adoption is the proportion of land cultivated with modern varieties (Doss, 2003).[4] Binary measures of programme participation or ‘treatment’ are generally more appropriate for defining average measures of impact, while continuous measures which measure intensity of adoption are more appropriate for defining marginal impacts.[5] Another measure of impact, which is specific to analysing the impact of technological change, is the so called $k-$factor.

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

[5] For clarity, the Marginal Treatment Effect is a mean evaluated at the point at which agents are indifferent between participating in a treatment and not. The Average Partial Derivative is rather the impact of a marginal change in the treatment, which is closer to a marginal effect (Heckman 2010).

3.1 The "$k-$factor"

The k-factor measures productivity increases induced by technological change and has been the focus of attention in the analysis of the impact of modern varieties since the term was coined by Griliche (1958) in his analysis of the diffusion of new corn varieties in the U.S.. Since then, however, the $k-$factor has escaped a single definition in the literature and there are several candidates in common use and regarded 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).[6] 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).[7] In each case the $k-$factor consists 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.[8] 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). Indeed, the economic surplus (ES) associated with technological change is given by:

$$ES = pqk\left(1 + \frac{1}{2}\frac{k}{\varepsilon_s + \varepsilon_D}\right)$$

where k is the proportional shift in the supply curve due to the technological change: the $k-$factor (de Janvry et al., 2010, p 40) [9] The key information required to extrapolate from micro studies to estimates of economic surplus is an estimate of the $k-$factor on yield. In practice, the non-experimental $k-$factor is typically estimated by the *observed* difference in outcomes between modern $\left(Q^M\right)$ and traditional $\left(Q^T\right)$: $Q^M - Q^T$ (ibid). For instance, the observed yield $k-$factor is given by: $K^y = y^M - y^T$, where:

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

Although this measure embodies some elements of the economically optimal yield increase, it is likely to be misleading due to selection bias. What is required is an estimate of the yield

[6] 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)

[7] 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 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)

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

[9] The economic surplus arising from a technological change is given by:

$k-$factor that can be 'causally attributed to the technological change' (ibid). In this paper we use the counterfactual framework to offer a more precise definition of the $k-$factor which can form the basis of a causal estimate.

3.2 The Impact of a Binary Treatment

3.2.1 Average Treatment Effects and $k-$factors.

A common definition of technology adoption in the context of modern varieties is the presence of modern varieties among the crops cultivated by a given farmer. The treatment variable is then an adoption dummy: $D : D = 1$ if modern varieties are cultivated and $D = 0$ otherwise. If $D = 1$ then the proportion of land allocated to modern varieties takes on some positive value: $\alpha = \alpha_1 \in (0, 1]$, where $\alpha_1 = 1$ reflects 'complete' adoption and $0 < \alpha_1 < 1$ as 'partial' adoption. Label the individual outcome variable Q and assume that Q is a function of the proportion of land, α, observables, X, and unobservables, u: $Q = \phi(\alpha, u)$, where we have suppressed the conditioning on X. Often function can be thought of as the relevant 'structural function' for the problem at hand, e.g. a production function (Blundell and Powell, 2000 p7; Imbens and Newey, 2009 p1485) The counterfactual outcomes for a given individual in the treated and untreated state are respectively:

$$Q_1 = \phi(\alpha_1, X, u_1) \quad \text{and} \quad Q_0 = \phi(0, X, u_0)$$

In attempting to measure the impact of changing between the two treatment states: $D = 0$ to $D = 1$, attention is usually focussed on the Average Treatment Effect (ATE^Q) in the population:

$$ATE^Q = E[Q_1 - Q_0]$$

with equivalent measures for the treated and untreated sub-populations or other groups.[10] In the binary treatment case the average treatment effect reflects the expected difference in the outcome variable across the treatment states: $ATE^Q = E[\phi(\alpha_1, u_1) - \phi(0, u_0)]$. The average treatment effect has structural relevance via its relationship to the Average Structural Function: $\mu(\alpha) = E_u[\phi(\alpha, u)]$.[11]

The counterfactual approach with a binary treatment provides a precise definition of the $k-$factor in the context of modern variety adoption. Define Q^M as the outcome (e.g. profit, yield, revenue) under modern production and Q^T the same under traditional production. The counterfactual quantities are (Q_1^M, Q_0^M) and (Q_1^T, Q_0^T). Two definitions of the individual $k-$factor present themselves in addition to the observed individua $k-$factor: $K^Q = Q^M - Q^T$. These are; i) the $k-$ factor in the adoption state: $K_1^Q = Q_1^M - Q_1^T$; and, ii) the $k-$factor across adoption states: $K_{10}^Q = Q_1^M - Q_0^T$. The set of possible individual impacts is completed

[10] 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).

[11] Suppose the structural function is linear and separable in the noise term $u : \phi(a, u) = \beta_0 + \beta_1\alpha + u$, then the Average Structural Function is given by: $\mu(\alpha) = \beta_0 + \beta_1\alpha$. Where α and u are independent, $\mu(\alpha)$ corresponds to $E[Q|\alpha]$. Then ATE in the binary treatment case is given by $\mu(\alpha_1) - \mu(0) = \beta_1\alpha_1$ and can be identified using, for instance, regression analysis.

by the impact across adoption states on traditional production: $Q_1^T - Q_0^T$. Together these individual level impacts lead to the following definition:

Definition 1 *: The Average $k-$factor in the adoption state $\left(AK_1^Q\right)$ and the Average $k-$factor across adoption states $\left(AK_{10}^Q\right)$ for an outcome variable Q are given respectively by:*

$$\begin{aligned} AK_1^Q &= E\left[K_1^Q\right] = E\left[Q_1^M - Q_1^T\right] \\ AK_{10}^Q &= E\left[K_{10}^Q\right] = E\left[Q_1^M - Q_0^T\right] \end{aligned}$$

The Average Treatment Effect on traditional varieties is given by:

$$ATE^{QT} = E\left[Q_1^T - Q_0^T\right]$$

The three definitions are related as follows:

$$AK_{10}^Q = AK_1^Q + ATE^{QT} \tag{5}$$

AK_1^Q is the unconditional average $k-$factor and reflects the population average of the within-farm advantage of modern varieties over traditional varieties in the adoption state. In the non-experimental context it captures the advantage of modern varieties over traditional varieties once inputs used for each technology have been optimised by each farmer. In this sense it captures the economically optimal and unconditional 'innovation effect'. This should be contrasted against the equivalent experimental $k-$factor which would condition on inputs and environmental features and therefore measure the pure 'genetic effect' of modern varieties.

AK_1^Q can also be understood by comparison to AK_{10}^Q, the impact across adoption states. Equation (5) shows the AK_{10}^Q is equal to AK_1^Q plus ATE^{QT}. The latter represents the 'in-farm spillover effect' of adoption on traditional varieties. AK_{10}^Q is greater than (less than) AK_1^Q when the spillover is positive (negative). So while AK_1^Q captures an innovation effect, AK_{10}^Q captures the sum of impacts across adoption states which may include an impact on the traditional sector due to behavioural changes associated with adoption. Adjustment of planting methods, the application of inputs complementary to modern varieties (e.g. fertilizer) in the traditional sector, or changes in the allocation of labour across sectors, are all potential causes of the spillover effect (e.g. Bulte et al., 2012).

AK_1^Q is a more appropriate measure of the intrinsic advantage that modern varieties could manifest over traditional varieties, since it is purged of the in-farm spillover effect. Yet both measures prove to be useful since they reflect different aspects of the decision to adopt and the overall ATE^Q. We now characterise the relationship between the ATE^Q, the innovation effect ($k-$ factor) and the spillover effect $\left(ATE^{QT}\right)$.

3.2.2 Average Treatment Effects and Average $k-$factors for Yield, y

Without loss of generality, but with clearer intuition, we illustrate the relationship between ATE^Q and the $k-$factors for the case where $Q = y_L$. That is, when yield is the outcome variable.

In the binary treatment case we are interested in the impact of moving from a non-adoption state to an adoption state. Defining the following counterfactual outcomes in the two adoption states: (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_0^y), for yield, yield from modern varieties, traditional yield, proportion of land devoted to modern varieties and yield $k-$factor respectively. Note that y_0^M, α_0 and K_0^y are equal to zero by definition.[12] Where yield is the outcome variable, the treatment effects of interest at the individual level include: i) 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: $y_1^T - y_0^T$; iii) the yield $k-$factor *under adoption*: $K_1^y = y_1^M - y_1^T$; and, iv) the yield $k-$factor across adoption states: $K_{10}^y = y_1^M - y_0^T$. These individual measures extend naturally to their population average counterparts. Defining the relationship between these measures of impact proves to be very instructive.

From the generalised yield in Equation (4) it folows that the individual impact on yield across adoption states is:

$$\begin{aligned} y_1 - y_0 &= \alpha_1 y_1^M + (1-\alpha_1) y_1^T - y_0^T \\ &= \alpha_1 \left(y_1^M - y_1^T\right) + y_1^T - y_0^T \end{aligned} \tag{6}$$

From definition 1 we know that the yield $k-$factors are related as follows:

$$AK_{10}^y = AK_1^y + ATE^{yT} \tag{7}$$

Given (6) and (7) ATE^y can be decomposed as follows:

$$\begin{aligned} ATE^y &= E\left[y_1 - y_0\right] \\ &= E\left[\alpha_1\left(y_1^M - y_1^T\right)\right] + E\left[\left(y_1^T - y_0^T\right)\right] \\ &= E\left[\alpha_1\right] AK_1^y + cov\left(\alpha_1, y_1^M - y_1^T\right) + ATE^{yT} \qquad (8) \\ &= E\left[\alpha_1\right] AK_{10}^y + cov\left(\alpha_1, y_1^M - y_1^T\right) + \left(1 - E\left[\alpha_1\right]\right) ATE^{yT} \qquad (9) \end{aligned}$$

Equation (8) shows that in a world of partial adoption the magnitude of ATE^y is determined by four components: i) the intensity of adoption in the adoption state, α_1; ii) The $k-$factor in the adoption state or 'innovation' effect: AK_1^y; iii) the covariance of α_1 and $y_1^M - y_1^T$: $cov\left(\alpha_1, y_1^M - y_1^T\right)$; and, iv) the in-farm spillover effect: ATE^{yT}. Equation (9) shows that if adoption is complete and $E[\alpha_1] = 1$, ATE^y collapses to AK_{10}^y, the $k-$factor across adoption states.

This relationship between ATE^y and its component parts sheds light on the nature of the impact of technology adoption in the binary treatment case. Several possibilities arise. For instance, low levels of overall impact at the centre of the yield-gap puzzle could be explained by collectively low α_1, AK_1^y, and ATE^{yT}. Furthermore, ATE^y may be small almost irrespective of the innovation effect, AK_1^y, when $E[\alpha_1]$ and ATE^{yT} are small. Negative net

[12] Since 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, $\alpha_0 = 0$ $y_0^M = 0$ and neither y_1^M nor y_1^T are observed in the no treatment case.

impacts are feasible if ATE^{yT} is sufficiently negative. Alternatively, ATE^y may be large as a consequence of positive spillovers to the traditional sector arising from adoption, even if the 'innovation effect' on yield is small.

In short, in the binary treatment case with any partial adoption, ATE^y reflects the net effect of several components. The nature of impact is conceivably very different across countries and even across crops. Variation in ATE^y can arise from differences unrelated to the yield advantage offered by modern varieties: the $k-$factor AK_1^y or innovation effect, but due to variation in intensity of adoption or in-farm spillovers. The overall nature of impact is therefore an empirical question which we address in the remainder of the paper.

Treatment Effect	Definition	
ATE^y	$E\left[y_1 - y_0\right]$	The average impact of adoption in the population
ATE^{yT}	$E\left[y_1^T - y_0^T\right]$	The average impact of adoption on traditional varieties: the in-farm spillover effect
AK_{10}^y	$E\left[y_1^M - y_0^T\right]$	The $k-$factor across adoption states
AK_1^y	$E\left[y_1^M - y_1^T\right]$	The $k-$factor within adoption: the 'innovation' effect

Table 1: Relevant Treatment Effects on Yield for the Adoption of New Varieties

3.3 The Impact of a Continuous Treatment

3.3.1 Average Partial Effects and $k-$factors.

Another common definition of technology adoption is the proportion of land allocated to modern varieties, α. 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) it is not frequently used for impact analysis.[13] It is however, considered a plausible measure of adoption for impact analysis in some quarters (e.g. Shideed and El Mourid, 2005) and similar measures such as the amount of land in modern production are used by Kassie et al. (2012) as a continuous treatment in the analysis of the impact of new varieties on food security. Like other continuous measures of treatment, proportion of land under modern cultivation measures the intensity of treatment.

The marginal effect measured by a continuous treatment variable is widely regarded as useful for the evaluation of public policy since it can measure the marginal benefit of extending an intervention (Heckman 2010). Blundell and Powell (2000) and Imbens and Newey (2009; 2002) discuss the structural relevance of marginal effects in detail. Returning to the previous framework recall that the structural function for Q is defined as:

$$Q = \phi\left(\alpha, X, u\right)$$

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

Where the treatment is continuous, and suppressing the X conditioning variables the measure of interest is usually a partial derivative treatment effect of the form: $\partial_\alpha \phi(\alpha, u)$, and the population Average Partial Effect:[14]

$$APE^Q = E\left[\delta_\alpha \phi(\alpha, u)\right]$$

This measures the average impact on the structural equation of changing the proportion of land from α to $\alpha + h$ for small h. The dependence on α shows that the marginal effect may vary with the intensity of adoption. Once again, equivalent measures can be defined for the treated and untreated sub-populations or other groups. Where the structural function is separable in the disturbance u, APE^Q coincides with the derivative of the more easily identifiable Average Structural Function: $\mu(\alpha) = E_u\left[\phi(\alpha, u)\right]$.[15] In the linear case where $\phi(\alpha, u) = \beta_0 + \beta_1 \alpha + u$, APE^Q is given by β_1, for which there exist numerous identification strategies and estimators (Imbens and Newey, 2002, p6).[16]

Focussing attention to the proportion of land allocated to modern varieties, α, continuous versions of the $k-$factors can also be derived in the case of partial adoption $(0 < \alpha < 1)$. Define $K_1^Q(\alpha) = Q_1^M(\alpha) - Q_1^T(\alpha)$ and $K_{10}^Q(\alpha) = Q_1^M(\alpha) - Q_0^T$. Together this leads to the following definition:

Definition 2 *Average Partial $k-$factors: The Average partial $k-$factor in the adoption state $\left(APK_1^Q(\alpha)\right)$ and the Average Partial $k-$factor across adoption states $\left(APK_{10}^Q(\alpha)\right)$ for an outcome variable Q are given respectively by:*

$$\begin{aligned} APK_1^Q &= E\left[\partial_\alpha K_1^Q(\alpha_1)\right] = E\left[\partial_\alpha Q_1^M(\alpha_1) - \partial_\alpha Q_1^T(\alpha_1)\right] \\ APK_{10}^Q &= E\left[\partial_\alpha K_{10}^Q\right] = E\left[\partial_\alpha Q_1^M(\alpha)\right] \end{aligned}$$

are related as follows:

$$APK_{10}^Q(\alpha) = APK_1^Q(\alpha) + APE^{QT}(\alpha) \tag{10}$$

where $APE^{QT}(\alpha) = E\left[\partial_\alpha Q_1^T(\alpha)\right]$ and is the Average Partial Effect on Q for traditional varieties.

The relationship between partial $k-$factors in (10) is entirely analogous to that of average $k-$factors in the binary case. It is also easy to show that the analogy extends to the expressions for yield. Appendix A shows that APE^y is the net effect of several effects: i) the average yield $k-$factor at α; ii) the intensity of adoption, α; ii) the partial $k-$factor in the adoption state: $K_1^y(\alpha)$; iii) the average partial in-farm spillover effect: $APE^{yT}(\alpha)$. In principle at least, a similar story can be told about the magnitude of $APE^y(\alpha)$ in the continuous treatment framework to that told about ATE^y in the binary treatment case. However, caution is needed in interpreting the results of the estimation of these continuous treatment effects. Proposition 1 explains why.

[14] Where the partial derivative is denoted: $\delta\phi(\alpha, u)/\delta\alpha = \delta_x \phi(\alpha, u)$

[15] In general $E\left[\partial_\alpha \phi(\alpha, u)\right] \neq \partial_\alpha \mu(\alpha)$.

[16] Schennach et al. (2012) have recently generalised these identification theorems. See propositions 2.1 and 2.2. of their paper for example. Florens et al. (2008) estimate the returns to education using continuous treatment for instance.

Proposition 1 *Suppose partial adopters choose intensity of adoption* (α) *to maximise profit and structural functions* $\phi^Q(\alpha, u)$ *are linear and separable in the disturbance,* $u : \phi^Q(\alpha, u) = \beta_0 + \beta^Q_\alpha \alpha + u$. *Then* β^Q_α *is the average partial effect on* Q *of variable* α *and:for* $Q \in \{\Pi, y, R\}$*:*

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

Corollary 1 *a) If* $p^T_L = p^M_L$ *then* $APE^R = 0$; *b) if in addition* $p^T = p^M$ *then* $APE^y = 0$*; c) If* $p^T < p^M$ *then* APE^y *could be negative.*

Proof. See Appendix C. ■

Proposition 1 states that if all farmers in the population are profit maximisers then we can expect $APE^\Pi(\alpha)$ to be zero. The intuition is clear: $APE^\Pi(\alpha)$ measures the marginal profit from converting land from traditional cultivation to modern, and profit maximisers ensure that all marginal gains from technology adoption are exhausted. More generally the result is related to the envelope theorem.[17] Where the treatment is a choice variable in an optimisation problem, and the outcome variable is the objective of the maximisation problem, the marginal effect of a change in the choice variable on the objective function at its optimum will be equal to zero. Hence the average partial treatment effect will be zero.

Proposition 1 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 is the same regardless of whether modern or traditional varieties are grown, and if the price of the outputs is identical, then APE^y and APE^R will also be zero.

Proposition 1 is a useful result that completely changes the interpretation of the average partial treatment effect in a continuous treatment model.[18] First and foremost, Proposition 1 illustrates the need for an underlying theory from which to interpret the theoretical measures of impact. Secondly, where it is known that farmers are profit maximisers the marginal impact of modern varieties on yield and revenue can be estimated using knowledge of the modern technology $f^M(.)$, the input and output prices and the expected amount of land under cultivation, L. Yet even if the marginal impacts on revenue and yield are positive, the impact on profit will be zero.

[17] Define the *profit function* as: $\Pi^*(\mathbf{p}) = \Pi(\mathbf{x}^*(); \mathbf{p})$. where $\mathbf{x}^*(\mathbf{p})$ is the profit maximising choice. If α is an element in $\mathbf{x}$, the envelope theorem states that:

$$\frac{\mathbf{d}\Pi^*(\mathbf{p})}{\mathbf{d}\alpha} = \frac{\partial \Pi(\mathbf{x}^*(\mathbf{p}); \mathbf{p})}{\partial \alpha} = 0$$

Since $\frac{\partial \Pi(\mathbf{x}^*(\mathbf{p});\mathbf{p})}{\partial x_i} = 0$ by definition. This is a more general proof of Proposition 1a.

[18] Florens et al. (2012) look at the returns to schooling and assume educational choices are the result of utility maximisation. Since wages are not the objective function here, the point we make in this paper does not apply.

In this light, positive estimates of the marginal impact on profit now reflect deviations from profit maximisation arising from non-separability, transaction costs or alternative behavioural models. More generally, the marginal impact measured by a continuous treatment will not capture the non-marginal impact synonymous with the adoption of modern varieties and the joint decision associated with the allocation of land and other inputs (e.g. Suri 2010). Section 5 provides an empirical illustration of this point.

4 Identification of the $k-$factor

In this section we discuss the indentification under conditional independence of the treatment effects of interest. Table 1 presents the treatment effects that we have identified as relevant in the binary treatment case. Identification requires specifying the relationship between the unobservable counterfactuals and the observable data.

Given the generalised yield in (4), the observed outcomes are related to the counterfactuals via switching equations of the form $w = w_0 + D(w_1 - w_0)$, where $w = \left(y, y^T, K^y\right)$ and $w_1 - w_0$ is the individual level impact of the treatment on w. The identification strategies are built upon the following relationships:

$$
\begin{aligned}
y &= y_0^T + D\left(\alpha_1 y_1^M + (1-\alpha_1) y_1^T - y_0^T\right) && \text{(11a)}\\
y^T &= y_0^T + D\left(y_1^T - y_0^T\right) && \text{(11b)}\\
K^y &= DK_1^y && \text{(11c)}\\
y &= y_0^T + DK_{10}^y \text{ where } \alpha_1 = 1 && \text{(11d)}
\end{aligned}
$$

Equations (11a), (11b), (11c) and (11d) can be used to identify ATE^y, ATE^{yT}, AK_1^y and AK_{10}^y respectively. Two further relationships that are exploited for identification purposes are: $y^M = Dy_1^M$, $(1-D)\,y^T = (1-D)\,y_0^T$, $\alpha = D\alpha_1$.

There are numerous methods of identifying the ATE^y and ATE^{yT} using a random sample of data $\left(y, y^M, y^T, D, \alpha\right)$ for partial and complete adopters (e.g. Heckman 2010). Estimation of AK_1^y and AK_{10}^y is more complicated and requires different assumptions in each case, with identification of AK_1^y requiring more restrictive assumptions than identification of AK_{10}^y. We now present several identification propositions.

4.1 Identification of the Average yield $k-$factors: AK_1^y and AK_{10}^y.

Identification of the $k-$factors for yield is described in Propositions 2, 3 and 4. Identification is based on the following assumptions, and the proofs can be found in Appendix B:

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 2 *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 2 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 variables, X.

Proposition 3 *Direct Identification of 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 3 concerns the identification of AK_1^y and shows three ways in which AK^y can be identified under conditional independence provided data exists for y^M and y^T for adopters (incomplete adoption is observed). Finally, Proposition 4 shows the relationship between the $k-$factor AK_1^y, ATE^y and ATE^{yT}:

Proposition 4 *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:*

$$AK_1^y = E_X\left(\frac{ATE^y(X, 0<\alpha<1) - ATE^{yT}(X, 0<\alpha<1)}{E\left(\alpha|X, 0<\alpha<1\right)}\right) \tag{12}$$

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

In sum, we have presented several alternative approaches to estimating the $k-$factor of modern varieties, each relying on different identification assumptions. Identification 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 since it represents the 'innovation effect' whereas AK_{10}^y contains a spillover effect to traditional varieties.

In the following section, two analyses are undertaken. Firstly, to illustrate the theoretical point made in proposition 1 we estimate the average treatment and average partial effect (ATE^y and APE^y) on rice yield in Tanzania using the binary and continuous treatment measures discussed above. Secondly, for a number of Sub-Saharan African countries we estimate each of the treatment effects in Table 1 using the estimators described above.

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 3. These estimates are then compared to the estimated continuous treatment effects associated with the use of the proportion of land allocated to modern varieties, α, as the interpretation of adoption. As shown in Section 3, this measure has a very specific theoretical interpretation.

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. Our selection if conditioning variables is influenced 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 conditioning variables are not overly numerous an avoid 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. The conditioning variables include age and sex of the household, number of years of residence in the village, number of cases of sickness in the village, household size, dummies for access to credit and secondary activity, main activity, marital status and ecology. Descriptive statistics are shown in Appendix B.

5.2 Estimating the Average Treatment Effect vs Average Partial Effect: ATE^y vs APE^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 simple regression assuming conditional independence conditional on the covariates, X. 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 3 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 2 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. When proportion of land is the indicator, the measure of impact is also positive and implies an increase of 0.0017t/ha for each percentage point increase in land allocated to modern varieties. Scaled up linearly to a per hectare measure, this implies an impact of $0.047t/ha$, a significantly lower estimate than for the binary interpretation of technology adoption. This is indicative of the theoretical point outlined in Section 3.[19]

5.3 Estimators for the average yield $k-$factors: AK_{10}^y and AK_1^y

In Section 4, Propositions 2 and 3 proposed 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 2a) suggests the following estimator for AK_{10}^y :

$$\hat{A}K_{10}^{ya} = \frac{1}{n}\sum_{i}^{n}\left(\hat{\mu}_1\left(X_i\right) - \hat{\mu}_0\left(X_i\right)\right) \tag{13}$$

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

Proposition 2b suggests the following, 'inverse probability' estimator for AK_{10}^y :

$$\hat{A}K_{10}^{yb} = \frac{1}{n}\sum_{i}^{n}\left(\frac{\hat{m}_1\left(X_i\right)}{\hat{P}\left(X_i\right)} - \frac{\hat{m}_0\left(X_i\right)}{\left(1-\hat{P}\left(X_i\right)\right)}\right) \tag{14}$$

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

Proposition 3 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 3a implies the following estimator for AK_1^y :

$$\hat{A}K_1^{ya} = \frac{1}{n}\sum_{i}^{n}\hat{\mu}_1^{\alpha}\left(X_i\right) \tag{15}$$

[19] On average, the land applied to modern varieties is 3.62 ha. A 1%increase in land cultivated with modern varieties is 0.036ha. Multiplying the estimated marginal impact up to obtain a per hectare measure $\left(\left(0.0017t/L^M/L\right)/0.036L\right)$ gives an estimated impact on yield of $0.047t/ha$.

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 2: 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 3: Estimates of Impact on Yields using Share of Modern Varieties

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

Proposition 3c implies an alternative estimator of the inverse probability variety:

$$\hat{A}K_1^{yc} = \frac{1}{n}\sum_{i}^{n}\left(\frac{\hat{\mu}_1'^{\alpha}(X_i)}{\hat{\alpha}(X_i)}\right) \tag{16}$$

where $\hat{\mu}_1'^{\alpha}(X_i)$ is an estimate of the conditional expectation function $E\left[y - y^T|X, 0 < \alpha < 1\right] = \mu_1'^{\alpha}(X_i)$ and $\hat{\alpha}(X_i)$ is an estimate of the function $E(\alpha|X, 0 < \alpha < 1) = \alpha(X_i)$. Both can be estimated using linear regression. We present the results of the regression approaches to the estimators in (15) and (13) in Table 4.

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

Proposition 4 provided an alternative identification strategy for AK_1^y which is composed of conditional 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:

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

where n_{PA} is the sample size of partial adopters. $\hat{A}TE^y(X_i, 0 < \alpha_i < 1)$ and $\hat{A}TE^{yT}(X_i,\ 0 < \alpha_i < 1)$ are estimated under conditional independence using a regression approach, where $ATE^{yT}(X, 0 < \alpha < 1) = E\left[y_1^T|X, 0 < \alpha < 1\right] - E\left[y_1^T|X, D = 0\right]$. $\hat{\alpha}(X_i)$ is estimated using a fractional regression approach. The results of this exercise for Tanzania and Togo are presented in Table 6.

5.5 Results

Table 4 shows the estimates of AK_1^y and AK_{10}^y using the regression based estimators (15) and (13) respectively. Column 3 of Table 4 shows the estimates of AK_{10}^y when the treatment group is the subsample of partial adopters. Column 4 of Table 4 shows the estimates of AK_{10}^y when the treatment group includes partial and complete adopters. The estimates of AK_1^y are only identified for partial adopters. Table 4 defines 'traditional varieties' as those more than 15 years old. Table 5 shows the equivalent results for the alternative cut-off points of 10 and 5 years.

The first thing to notice from Table 4 is that the estimates of AK_1^y vary considerably from 1.5t/ha in Sierra Leone, 0.9t/ha in Senegal, to essentially zero in Tanzania and Uganda. These differences can be explained by the greater prevalence of irrigation in Senegal and Sierra Leone compared to Tanzania and Uganda (Diagne et al., 2009). The striking observation from Table 4 is that the estimates of AK_{10}^y for partial adopters, the $k-$factor across adoption states, are almost always larger than the estimates of AK_1^y. Definition 1 shows that the difference between these two $k-$factors reflects the in-farm spillover effect: ATE^{yT}. The results imply that on average yields of traditional varieties are higher under adoption, $ATE^{yT} > 0$. That is, there are positive in-farm spillover effects. Neither is the magnitude of

Country	$\hat{A}K_1^y$	$\hat{A}K_{10}^y\,(0 < \alpha < 1)$	$\hat{A}K_{10}^y\,(\alpha > 0)$	α
Burkina Faso	0.572***	0.715***	0.607***	0.613***
	(0.157)	(0.195)	(0.149)	(0.027)
Cameroon	-0.366***	0.077	0.132	0.434***
	(0.137)	(0.113)	(0.106)	(0.025)
Ghana	0.487***	0.494***	0.420***	0.566***
	(0.148)	(0.164)	(0.126)	(0.026)
DRC	0.276*	0.676***	0.581***	0.538***
	(0.145)	(0.112)	(0.095)	(0.026)
Rwanda	0.352*	1.606***	1.375***	0.475***
	(0.190)	(0.236)	(0.223)	(0.035)
Senegal	0.892***	1.525***	1.581***	0.599***
	0.170)	(0.212)	(0.247)	(0.030)
Sierra Leone	1.531***	2.088***	1.641***	0.660***
	(0.178)	(0.245)	(0.187)	(0.029)
Tanzania	0.048	0.605***	0.519***	0.480***
	(0.140)	(0.099)	(0.094)	(0.026)
Uganda	0.242	0.158	0.230*	0.544***
	(0.159)	(0.154)	(0.126)	(0.029)
N	457	457	3178	457

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 4: Estimates of Average Yield k-Factor in SSA for Partial Adopter or All Adopter Treatment Groups

Country	AK_1^y >5	>10	>15	AK_{10}^y >5	>10	>15
Burkina Faso	0.513***	0.567***	0.572***	0.682***	0.709***	0.715***
	(0.156)	(0.163)	(0.157)	(0.147)	(0.202)	(0.195)
Cameroon	-0.068	-0.402***	-0.366***	0.224**	0.114	0.077
	(0.153)	(0.143)	(0.137)	(0.105)	(0.102)	(0.113)
Ghana	0.278*	0.413***	0.487***	0.288**	0.437**	0.494***
	(0.150)	(0.153)	(0.148)	(0.124)	(0.185)	(0.164)
DRC	0.667***	0.346**	0.276*	0.746***	0.679***	0.676***
	(0.163)	(0.151)	(0.145)	(0.134)	(0.101)	(0.112)
Rwanda	-0.059	0.194	0.352*	0.874***	1.377***	1.606***
	(0.193)	(0.196)	(0.190)	(0.228)	(0.207)	(0.236)
Senegal	0.001	0.744***	0.892***	0.726***	1.282***	1.525***
	(0.158)	(0.172)	(0.170)	(0.198)	(0.254)	(0.212)
Sierra Leone	-0.042	1.120***	1.531***	1.188***	1.517***	2.088***
	(0.175)	(0.184)	(0.178)	(0.245)	(0.328)	(0.245)
Tanzania	0.181	0.088	0.048	0.832***	0.737***	0.605***
	(0.153)	(0.146)	(0.140)	(0.118)	(0.102)	(0.099)
Uganda	0.362**	0.317*	0.242	0.321***	0.225	0.158
	(0.149)	(0.166)	(0.159)	(0.100)	(0.150)	(0.154)
Observations	326	424	457	326	424	457

Table 5: Estimates of Average Yield k-Factor in SSA for Partial Adopters for Different Diffusion Periods

$k-$factor	$\hat{A}K_1^{y3}$	
Treatment Effects	Tanzania	Togo
ATE^y	0.265***	0.752***
ATE^{yT}	0.343***	0.594***
$\alpha(X)$	0.48***	0.42***
AK_1^y	0.048*	0.378**
N	741	426
* p < 0.1, ** p < 0.05, *** p < 0.01		

Table 6: Estimates of the Average Yield k-Factor

these effects trivial. In Tanzania in-farm spillovers appear to be the only impact of adoption, with yields increased by around 0.6t/ha. Elsewhere, the spillover effects represent a significant additional effect over and above the innovation effect captured by AK_1^y. In Sierra Leone AK_{10}^y is estimated to be 2t/ha, 0.5t/ha of which could be attributed to in-farm spillovers. In Senegal AK_{10}^y is 1.5t/ha, 0.7t/ha of which is in-farm spillovers. In Rwanda, in-farm spillovers raise AK_{10}^y from the innovation effect of 0.36t/ha to 1.6t/ha. While these results are merely indicative, separate estimation of ATE^{yT} following a standard identification strategy for partial adopters supports this interpretation of Table 4.[20]

Column 4 of Table 4 shows the results when AK_{10}^y is estimated over the whole sample of adopters, rather than simply the partial adopters. The estimates are by and large similar in magnitude to those estimated over the partial adopter sub-sample. This provides some, albeit loose, indication of the validity of the conditional independence assumption between α and the counterfactual outcomes.

Table 4 defines traditional varieties as varieties older than 15 years. The definition includes previous releases of modern varieties and in this sense is somewhat arbitrary. Table 5 shows the results of estimating AK_1^y and AK_{10}^y for the partial adoption treatment group when varieties of less or equal to 5, 10 and 15 years old or less are compared to their respectively older counterparts in each case. The results paint a heterogeneous picture of the impact of successive releases of modern varieties. In Uganda, Tanzania and the DRC, the newer varieties ($\leq$ 5 years) have a larger impact than the older definitions of modern varieties ($\leq$ 10 and $\leq$ 15 years) as measured by AK_{10}^y. In Tanzania these effects are all down to in-farm spillovers since AK_1^y is always zero. In the DRC spillovers become less important with the newer varieties ($\leq$ 5 years). In Sierra Leone and Senegal, the impact of the modern varieties declines with as the definition of modern varieties become stricter and includes fewer years. The reason for these differences needs further investigation, and caution is needed due to sample size limitations.

Lastly, the following section uses the indirect estimator of Proposition 4 to disentangle these effects and presents contrasting results from Togo and Tanzania.

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 ran-

[20]Estimation took place under assumptions A1 and A3 and using the switching equation (11b).

domised 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, in which case there is probably a good argument for using AK_{10}^{y} as the measure of the $k-$factor, which is easier to identify in any event.

6 Conclusion

In this paper we have shown that when it comes to measuring the impact of modern varities 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, non-zero estimates such as our estimates for Tanzania, represent price differentials or departures from profit maximisation, and are should be interpreted in light of the theory. This point is illustrated using data from Tanzania, where the estimate of the impact on yield 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 innovation effect or '$k-$factor', and an in-farm spillover effect to traditional varieties. 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 is a consequence of the potential for negative spillovers of adoption to traditional production and partial adoption.

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 positive 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 an obvious deficiency of the paper. We leave this for future work.

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Appendix

A Average Partial Effects and $k-$factors for yield

Again, without loss of generality, we illustrate the relationship between APE^Q and the partial $k-$factors for the case where $Q = y$. The treatment effects of interest at the individual level include: i) the partial effect of adoption of modern varieties on aggregate yield: $\partial_\alpha \left(y_1\left(\alpha\right) - y_0\right)$; ii) the partial effect of α on traditional varieties: $\partial_\alpha \left(y_1^T\left(\alpha\right) - y_0^T\right)$; iii) the partial yield $k-$factor *under adoption*: $\partial_\alpha K_1^y\left(\alpha\right) = \partial_\alpha \left(y_1^M\left(\alpha\right) - y_1^T\left(\alpha\right)\right)$; and, iv) the partial yield $k-$factor across adoption states: $\partial_\alpha K_{10}^y\left(\alpha\right) = \partial_\alpha \left(y_1^M\left(\alpha\right) - y_0^T\right)$.[21] From Equation (4) we know that:

[21] Note that the partial derivative is not defined for the non-adoption counterfactuals: y_0 and y_0^T.

$$y(\alpha) = \alpha y_1^M(\alpha) + (1-\alpha) y_1^T(\alpha), \text{ and } y_0 = y_0^T \tag{17}$$

The average partial yield $k-$factors are given by $APK_{10}^y(\alpha) = E\left[\partial_\alpha Q_1^M(\alpha)\right]$ and $APK_1^y(\alpha) = E\left[\partial_\alpha y_1^M(\alpha) - \partial_\alpha y_1^T(\alpha)\right]$ and the Average Partial Effect on traditional varieties yield is $ATE^{yT}(\alpha) = E\left[\partial_\alpha y_1^T(\alpha)\right]$. From definition 2 we know that the yield $k-$factors are related as follows:

$$APK_{10}^y(\alpha) = APK_1^y(\alpha) + APE^{yT}(\alpha) \tag{18}$$

Together, (6) and (7) mean that $APE^y(\alpha)$ can be decomposed as follows:

$$\begin{aligned}
APE^y(\alpha) &= E\left[\partial_\alpha\left(y_1(\alpha) - y_0\right)\right] \\
&= E\left[\partial_\alpha\left(\alpha\left(y_1^M(\alpha) - y_1^T(\alpha)\right)\right) + \partial_\alpha y_1^T(\alpha)\right] \\
&= E\left[y_1^M(\alpha) - y_1^T(\alpha)\right] + E\left[\alpha.\partial_\alpha\left(y_1^M(\alpha) - y_1^T(\alpha)\right)\right] + E\left[\partial_\alpha y_1^T(\alpha)\right] \\
&= AK_1^y(\alpha) + E\left[\alpha.\partial_\alpha\left(K_1^y(\alpha)\right)\right] + APE^{yT}(\alpha)
\end{aligned} \tag{19}$$

B 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 (**??**) and (**??**) to obtain $E\left[y|D=1,X\right] - E\left[y^T|D=0,X\right] = E\left[\alpha|X\right] E\left[\left(y_1^M - y_1^T\right)|X\right]$. Dividing through by $E\left[\alpha|X\right]$ and applying A3 completes the proof. ■

Proposition 3. Using A1 and conditioning on X, the conditional version of (**??**) 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 $AK_1^y(X) = E\left[y_1^M - y_1^T|X\right]$, $ATE^y(X) = E\left[y_1 - y_0|X\right]$ 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 $0 < \alpha < 1$. ■

C 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:

$$\frac{\partial \Pi}{\partial x} = p^M f_L^M\left(xL, \mathbf{z}^M\right) L - p^T f_L^T\left((1-x)L, \mathbf{z}^T\right) L - \left(p_L^M - p_L^T\right) L = 0 \tag{20}$$

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 (20) 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 (20) 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 $p^T < p^M$. ■

D Descriptive Statistics for Tanzania

E Results for Different Definitions of Technology

	Variable	Obs	Mean	Std. Dev.	Min	Max
Full non adopters	sex	5134	0.913907	0.280528	0	1
	nbyresid	5131	35.41688	14.07367	0	50
	hhsize	5134	4.741527	4.807294	1	56
	edulevel_1	3122	0.381166	0.485751	0	1
	edulevel_2	3122	0.14542	0.35258	0	1
	ecolo	5094	2.440126	0.760197	1	4
	credit	5582	0.123612	0.329167	0	1
Partial adopters	sex	2588	0.92272	0.267086	0	1
	nbyresid	2588	35.68586	14.79691	0	50
	hhsize	2588	5.442427	4.932416	1	40
	edulevel_1	1327	0.400904	0.490266	0	1
	edulevel_2	1327	0.136398	0.34334	0	1
	ecolo	2724	2.475404	0.897082	1	4
	credit	2760	0.164493	0.370789	0	1
Full adopters	sex	4069	0.87712	0.32834	0	1
	nbyresid	4066	31.4727	15.8719	0	50
	hhsize	4069	4.629393	4.624364	1	35
	edulevel_1	2585	0.427853	0.494863	0	1
	edulevel_2	2585	0.173308	0.378586	0	1
	ecolo	4037	2.493683	0.929781	1	4
	credit	4197	0.109126	0.311834	0	1

Table 7: Descriptive Statistics for Conditioning Variables

Country	$\hat{A}K_1^y$	$\hat{A}K_{10}^y$	α
Burkina Faso	0.567***	0.709***	0.592***
	(0.163)	(0.202)	(0.028)
Cameroun	-0.402***	0.114	0.427***
	(0.143)	(0.102)	(0.025)
Ghana	0.413***	0.437**	0.551***
	(0.153)	(0.185)	(0.027)
DRC	0.346**	0.679***	0.525***
	(0.151)	(0.101)	(0.027)
Rwanda	0.194	1.377***	0.435***
	(0.196)	(0.207)	(0.035)
Senegal	0.744***	1.282***	0.577***
	(0.172)	(0.254)	(0.030)
Sierra Leone	1.120***	1.517***	0.635***
	(0.184)	(0.328)	(0.031)
Tanzania	0.088	0.737***	0.458***
	(0.146)	(0.102)	(0.026)
Uganda	0.317*	0.225	0.520***
	(0.166)	(0.150)	(0.030)
Observations	424	424	424

Table 8: Average Yield k-Factor: Partial Adopters, Traditional = >10 years

Country	$\hat{A}K_1^y$	$\hat{A}K_{10}^y$	α
Burkina Faso	0.567***	0.680***	0.592***
	(0.163)	(0.138)	(0.028)
Cameroun	-0.402***	0.139	0.427***
	(0.143)	(0.100)	(0.025)
Ghana	0.413***	0.442***	0.551***
	(0.153)	(0.126)	(0.027)
DRC	0.346**	0.644***	0.525***
	(0.151)	(0.087)	(0.027)
Rwanda	0.194	1.173***	0.435***
	(0.196)	(0.191)	(0.035)
Senegal	0.744***	1.131***	0.577***
	(0.172)	(0.330)	(0.030)
Sierra Leone	1.120***	1.229***	0.635***
	(0.184)	(0.229)	(0.031)
Tanzania	0.088	0.528***	0.458***
	(0.146)	(0.093)	(0.026)
Uganda	0.317*	0.259**	0.520***
	(0.166)	(0.127)	(0.030)
Observations	424	3,178	424

Table 9: Average Yield k-Factor: All adopters, Traditional = >10 years

Country	$\hat{A}K_1^y$	$\hat{A}K_{10}^y$	α
Burkina Faso	0.513***	0.682***	0.520***
	(0.156)	(0.147)	(0.031)
Cameroun	-0.068	0.224**	0.417***
	(0.153)	(0.105)	(0.029)
Ghana	0.278*	0.288**	0.474***
	(0.150)	(0.124)	(0.030)
DRC	0.667***	0.746***	0.487***
	(0.163)	(0.134)	(0.033)
Rwanda	-0.059	0.874***	0.327***
	(0.193)	(0.228)	(0.036)
Senegal	0.001	0.726***	0.442***
	(0.158)	(0.198)	(0.032)
Sierra Leone	-0.042	1.188***	0.407***
	(0.175)	(0.245)	(0.034)
Tanzania	0.181	0.832***	0.379***
	(0.153)	(0.118)	(0.029)
Uganda	0.362**	0.321***	0.473***
	(0.149)	(0.100)	(0.029)
Observations	346	346	346

Table 10: Average Yield k-Factor: Partial adopters, Traditional = >5 years

Country	$\hat{A}K_1^y$	$\hat{A}K_{10}^y$	α
Burkina Faso	0.513***	0.501***	0.520***
	(0.156)	(0.116)	(0.031)
Cameroun	-0.068	0.328***	0.417***
	(0.153)	(0.096)	(0.029)
Ghana	0.278*	0.290***	0.474***
	(0.150)	(0.101)	(0.030)
DRC	0.667***	0.577***	0.487***
	(0.163)	(0.091)	(0.033)
Rwanda	-0.059	0.801***	0.327***
	(0.193)	(0.203)	(0.036)
Senegal	0.001	0.876***	0.442***
	(0.158)	(0.234)	(0.032)
Sierra Leone	-0.042	1.033***	0.407***
	(0.175)	(0.195)	(0.034)
Tanzania	0.181	0.517***	0.379***
	(0.153)	(0.090)	(0.029)
Uganda	0.362**	0.232**	0.473***
	(0.149)	(0.112)	(0.029)
Observations	346	3178	346

Table 11: Average Yield k-Factor: All Adopters Traditional = >5 years