Productivity effects of sustainable intensification: The case of urea deep placement for rice production in Niger State, Nigeria

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Abstract

This paper uses household data to explore the yield effects of an intensification practice called urea deep placement (UDP) in Nigeria. The propensity score matching and instrumental variables methods provide consistent evidence of a positive and significant effect of UDP on rice yields. The Rosenbaum sensitivity analysis reveals that these results are not likely driven by unobservable factors. The paper also finds that farmers' yields are further enhanced by adhering to several prescribed practices, confirming the potential for UDP to significantly improve rice yields.

Key words: productivity; sustainable development; urea deep placement (UDP); rice, Nigeria

1. Introduction

Sustainable intensification has gained prominence as a response to the challenges of the increasing global demand for food alongside the limited supply of land, water, energy and other inputs (The Montpellier Panel 2013). Due to this interest in increasing food production in a sustainable manner, methods that increase the efficiency of fertiliser use in a manner that minimises the potentially negative effects of its use on the environment are a top research and policy concern. Developing countries like Nigeria (where expanded fertiliser use is being promoted to improve agricultural productivity) are in a position to take advantage of opportunities that can increase fertiliser use in a sustainable manner, particularly when such environmental benefits occur alongside potential productivity and profitability gains.

Despite the agronomic advantages of many input-intensification strategies, a long-standing puzzle is why farmers' adoption of such technologies remains low. One likely reason is the difference between agronomic potential and on-farm productivity. Other factors include the profitability of these technologies, given the structure and accessibility of input and output markets, the complementarity of many inputs (such as fertiliser and improved seeds), the importance of management practices, and several other constraints faced by farmers in developing countries (Duflo *et al*. 2008).

In the light of this dearth of information, this article evaluates the productivity effects of an input-intensification strategy (deep placement of urea fertiliser) among rice producers in one of Nigeria's key rice-producing states: Niger. As the returns to inputs vary across farmers and their practices, this study investigates how returns vary according to farmer characteristics and adherence to the prescribed practices for urea deep placement (UDP) in rice production. Although widely promoted in Sub-Saharan Africa in recent past, there have been no empirical assessments of the effect of UDP on rice production using survey data. Consequently, this study begins to fill this research gap. Apart from adoption (the usual focus of impact assessment studies), this article also explores the effect of adherence to prescribed practices on the extent of productivity gains.

UDP involves the use of briquetted urea (application of pressure to the urea to produce oval compacted pellets of 1.8 to 2.7 grams) buried several inches deep between four rice stands. These pellets, called urea super granules (USG), are considered to be a possible solution to the problem of nutrient wastage in rice production. The USG are said to increase nitrogen-use efficiency because more urea nitrogen stays in the soil, close to the plant roots, where it is absorbed more effectively. UDP could potentially increase crop yields by 25%, while reducing nitrogen losses by 40%. Compared to the traditional application of urea by broadcasting, done two or three times in a planting cycle, the urea super granules are applied only once. Because they are placed deep, the fertiliser nutrients are beyond the reach of weeds, thus reducing weed incidence. Consequently, UDP potentially is profitable for farmers because it increases crops yield, reduces the number of fertiliser applications necessary, as well as lowers weeding costs, while being competitively priced relative to other fertilisers.

The productivity effect of UDP adoption was estimated using quasi-experimental and instrumental variable techniques. First, propensity score matching (PSM) was used to estimate average treatment effects of UDP adoption. Since propensity score estimates rely on observable characteristics, it is still possible that there may be unobserved characteristics that drive UDP adoption that also drive productivity. Consequently, the Rosenbaum sensitivity analysis for matched data was run. This provides a method to assess how robust the PSM results are to hidden bias due to an unobserved confounder. The PSM results are then supplemented with those in an instrumental variables (IV) regression analysis.

The study finds consistent and positive yield effects of UDP on rice production in Niger State. These yield effects are partly driven by the adherence to certain prescribed planting methods and management practices. As many governments and development practitioners pursue sustainable input-intensification strategies alongside increased agricultural productivity, this study provides some empirical evidence on the potential yield and income effects of one of these technologies (UDP) alongside factors likely to enhance these yield benefits.

Given Nigeria's complexity and the heterogeneity of its agro-ecology and farming systems, this study on Niger State provides some evidence that can be applied in similar environments or that can be contextualised appropriately for environments that might differ in significant ways. Finally, the study provides information to guide government extension services, farmers and private sector farm service providers about the importance of certain management practices associated with UDP for the successful adoption of this more targeted fertiliser application method for rice production.

The remainder of this paper is organised as follows. The empirical framework used is described in Section 2 and the data described in Section 3. This is followed by a presentation and discussion of the results in Sections 4 and 5 respectively. Section 6 concludes.

2. Empirical framework

2.1 Propensity score matching

This study used a quasi-experimental and an instrumental variables approach to estimate the effect of UDP on rice yields in Niger State. First, propensity score-matching techniques were used to capture productivity measured by the Average Treatment effect on the Treated (ATT). As laid out in Takahashi and Barrett (2014), ATT computes the average difference in outcomes of rice farmers using UDP for their rice production and those using traditional practices.

$$ATT = E(y_{1i} - y_{0i} \mid D_i = 1) = E(y_{1i} \mid D_i = 1) - E(y_{0i} \mid D_i = 1), \qquad (1)$$

where $E(\cdot)$ denotes an expectation operator, y_{1i} is an outcome of interest of farmer i who used urea super granules (USG) in rice production in the main agricultural season, 2012, y_{0i} is the outcome of the same farmer had he/she not used USG in rice production, and D is a treatment indicator equal to 1 if the farmer actually used USG and 0 otherwise. The fundamental problem in estimating equation (1) is that it is impossible to observe the outcome of farmers who used UDP had they not used it, i.e. $(y_{0i} \mid D_i = 1)$. While one may be inclined to simply compare outcomes between farmers who used UDP and those who did not, such an analysis will likely result in biased estimates, expressed by

$$[E(y_{1i} \mid D_i = 1) - E(y_{0i} \mid D_i = 0)] = ATT + [E(y_{0i} \mid D_i = 1) - E(y_{0i} \mid D_i = 0)]. \qquad (2)$$

The left-hand side of equation (2) measures the average difference in outcome between actual farmers who used UDP for rice production and those who did not, while the last term of the right-hand side indicates the magnitude of bias from the true ATT due to the fact that outcomes between the same group of farmers would still be different even in the absence of using UDP.

PSM, introduced by Rosenbaum and Rubin (1983), was used to try to eliminate the bias due to the bracketed term on the right-hand side of equation (2). PSM relies on an assumption of conditional independence where, conditional on being treated and given certain characteristics, the outcome of interest in the absence of treatment and being treated are statistically independent. In this case, conditional on the probability of using UDP, given observable covariates, rice yields in the absence of UDP use, y_{0i}, and the use of UDP for rice production, D_i, are statistically independent. This leads to:

$$E(y_{0i} \mid D_i = 1, p(x_i)) = E(y_{0i} \mid D_i = 0, p(x_i)), \qquad (3)$$

where $p(x_i)$ denotes the probability of being a farmer who used UDP for rice production given characteristic x, which is defined as:

$$\Pr(D_i = 1 \mid x_i) \equiv p(x_i). \qquad (4)$$

Consequently, PSM eliminates bias that might otherwise result from selection on observed characteristics. The propensity score generated here estimates the probability of a farmer using UDP, conditional on observable characteristics. Another important assumption of PSM is the common support condition, which requires substantial overlap in covariates between farmers who used UDP in the main agricultural season in 2012 and farmers who did not, so that the farmers being compared have a common probability of using UDP, such that $0 < p(x_i) < 1$.

If these two assumptions are fulfilled, then the PSM estimator for ATT can be specified as the mean difference of the farmers using UDP matched with those not using the technology who are balanced on the propensity scores and lie within the region of common support, expressed as:

$$ATT^{PSM} = E[y_{1i} \mid D_i = 1, p(x_i)] - E[y_{0i} \mid D_i = 0, p(x_i)] . \qquad (5)$$

The above PSM estimator yields consistent estimates of the ATT if covariates x properly characterise the probability of being an adopter of UDP.

While it is possible to eliminate the impact of unobservable characteristics by using an instrumental variable (IV) estimator or a Heckman selection model instead of PSM, it is difficult to find good instruments. Furthermore, an IV estimator imposes a linear functional form assumption that is more restrictive than PSM, which is invariant to functional form assumptions (Takahashi & Barrett 2014). In addition, selection models such as Heckman also rely on rather strong distributional assumptions, where the unobserved characteristics of technology adoption and outcomes are jointly normally distributed with zero mean, constant variance and a covariance term (Mendola 2007; Takahashi & Barrett 2014). Consequently, the selection of X is an important issue. It is recommended that all factors affecting farmers' decision to adopt the technology in question are included (Heckman *et al*. 1997; Caliendo & Kopeinig 2008).

A key limitation of the PSM method is that, if unobservable factors affect the farmers' decisions to adopt UDP, the estimated ATT may be biased by selection on those factors (Smith & Todd 2003). In this study, while it is recognised that this is a possibility, we attempt to address this with a rich set of observable farmer characteristics. These include farmers' age, gender, years of farming experience, membership in farmer groups, exposure to information about the technology at hand, use of other technologies and past rice yields, which are likely to capture unobserved characteristics – such as ability – that likely are to be correlated with adoption and also productivity. It is virtually impossible, however, to control for all relevant unobservable factors. Therefore, the sensitivity test proposed by Rosenbaum (2002) is used to test whether unobservable factors might affect the estimated results.

There are different matching algorithms that can be used to estimate average treatment effects on the treated, each with positive and negative attributes (Caliendo & Kopeinig 2008). For this paper, three different matching procedures were applied to ensure that the results are not driven by estimation procedure and for comparison. Nearest-neighbour matching ensures that each treated observation is matched and compares individuals from the control group to a matching partner closest in propensity score (Caliendo & Kopeinig 2005). Nearest-neighbour matching could be affected by poor matches in which the distribution of scores across treated and control individuals are very different. Thus radius matching was also used. This matching procedure specifies a calliper, or maximum propensity score distance, by which matches can be made, thus increasing the quality of matching. Finally, a nonparametric Kernel matching[1] was used. Kernel matching tends to have a lower variance because more information is used (Caliendo & Kopeinig 2005; Heinrich *et al*. 2010). As alluded to earlier, in order to address the possibility of bad matches, this study used only observations that lie within the common support and compared the results to those of other matching procedures. Furthermore, bootstrapping was also used to generate all standard errors, given that the propensity score used for matching is based on a separate regression.

2.2 The Rosenbaum sensitivity analysis

[1]Kernel matching operates as a weighted regression of the counterfactual outcome on an intercept with weights given by the kernel weights. Weights depend on the distance between each individual and the control group and the participant observation for which the counterfactual is estimated (Caliendo & Kopeinig 2005).

Although propensity score matching satisfies the balancing property and only observations that lie within the common support are used in the analysis, it is still possible that there is some unobserved characteristic that drives UDP adoption that is also driving productivity. Thus, the Rosenbaum sensitivity analysis for matched data was applied to assess how robust these findings are to hidden bias due to an unobserved confounder.

Given two individuals, *i* and *j*, with the same observed characteristics (x_i an x_j), they should have the same probability of adopting UDP for rice production,

$$P(X_i) = P(T_i=1/x_i) = P(X_j) = P(T_j=1/x_j) = F[(\beta(x)], \tag{6}$$

where $x = \{x_i , x_j\}$.

In the presence of an unobserved characteristic u_i, which could drive the adoption of UDP, the probability of adoption of UDP can be expressed as: $P (X_i) = F (\beta (x_i) + \gamma u_j)$, and two individuals with the same observable characteristics may not have the same probability of adopting the technology.

A logistic regression model linking the odds of assignment to these two covariates can be written as

$$Log\left(\frac{p(x_i)}{1-p(x_i)}\right) = F(\beta(x_i)+\gamma u_i), \tag{7}$$

with a constraint on u_i of $0 \leq u_i \leq 1$, and where F ( ) is some function and γ is an unobserved parameter. If units *i* and *j* have the same values on x, then $x_i = x_j$, and the odds ratio of treatment for these two units can be written as

$$\left(\frac{p(x_i)/1-p(x_i)}{p(x_j)/1-p(x_j)} = \frac{p(x_i)}{1-p(x_i)}\frac{(1-p(x_j)}{p(x_j)} = \exp\{\gamma(u_j-u_i)\right) \tag{8}$$

Here, two individuals with the same x values differ in their odds of adopting UDP by a factor of γ and the difference in the unobserved covariate. If the unobservable characteristics of the two individuals are the same $(u_j = u_i)$, or if they do not affect the probability of using UDP $(\gamma = 0)$, UDP adoption is truly driven by the observables, the matching based on these observables is sufficient, and it would then not be expected that the treatment estimates are biased due to selection. However, if $(u_j \neq u_i)$ or $(\gamma \neq 0)$, then the treatment estimates are likely to be biased (Rosenbaum 2002; Keele 2010).

Gamma is the size of the log of the coefficient for the unobserved covariate *u.* Rosenbaum (2002) shows that it can also be thought of as a sensitivity parameter that measures the degree of departure from the random assignment of a treatment. Here, two subjects with the same observed characteristics may differ in their odds of adopting UDP use for rice production by a factor of gamma.[2] The sensitivity analysis uses several values of gamma to show how inferences might change if a hidden bias were present.

2.3 Instrumental variables

[2] Thus, if gamma = 2, the two units that have the same values of x could differ in their odds of receiving treatment by as much as a factor of 2.

Following the Rosenbaum sensitivity test, the PSM analysis was supplemented with an instrumental variable (IV) analysis, recognising the limitations inherent in both approaches. Although neither is perfect, using multiple approaches is the best option to provide statistical evidence of the causal effects of UDP on farmer productivity with a cross-sectional dataset.

A two- step, continuously updated generalised method of moments (GMM) estimation approach was used. First, the factors that determine UDP adoption were estimated with appropriate instruments that are correlated with UDP adoption but not with rice yields (except through their effect on UDP adoption). Following Wooldridge (2010), the probability that a farmer will use UDP as a function of these set of correlates (x, z) is estimated and the predicted probability is then included as an instrument.[3] The excluded instruments (z) used in this study are the distance of a farmer's home to the demonstration plot established in the village and the distance of a farmer's home from his plot. It is expected that farmers in close proximity to the demonstration plot are likely to have been more exposed to information about UDP and its potential effect on rice yields than those further away. Farmers in close proximity to the demonstration plot are likely to have seen when the village promoter[4], extension agents and development agency promoting UDP were engaged in the different activities on the demonstration plot. They also would have been more likely to have seen the various stages of the process of rice production with UDP. Similarly, given that the location of the demonstration plot was central to the village, it is expected that farmers whose plots are located close to their homes would have been more able to attend the various demonstration activities than those whose plots are further away.

3. Data

Data for this study was collected from a census survey conducted in two villages (Washe and Sheshi in Bida local government area) in Niger State, where UDP for rice production was promoted actively in 2011. Niger State is the second largest producer of rice in Nigeria, after Kaduna State. Between 2007 and 2010, the state produced an average of five hundred thousand metric tons of rice (Cadoni & Angelucci, 2013).

Data collected for the study included farmer and farmer household characteristics, the characteristics of their social networks and their agricultural practices. The propensity score for the PSM was estimated using a nonlinear logit regression from a set of observable characteristics that were expected to affect both the probability that a farmer adopted UDP and their yields. Ideally, the variables used for the propensity score should not be affected by the farmers' use of UDP (Becker & Ichino 2002; Caliendo 2006; Heinrich *et al*. 2010). In this study, the propensity scores were based on either farmer characteristics that do not change much over time or characteristics that were not expected to be affected by their use of UDP in 2012. These include the plot manager's age, sex, marital status, experience in farming, education, distance of the plot to the home, area planted to rice and yields in 2011[5] (prior to the programme), whether the respondent used improved seed in 2011 (before the programme started), whether the respondent is a member of a farmers' organisation and whether the farmer attended the training by the private fertiliser company, which also happened prior to the decision to use UDP or not. All observations with propensity scores out of common support

[3] The details of the setup are available from the authors upon request.

[4] The village promoter is usually an entrepreneurial farmer (selected by the community) who is trained in the importance and use of various technologies by input suppliers and who also serves as a sales agent for the input suppliers in the community. This private sector-led model provides an opportunity for farmers to avoid the high transportation costs associated with securing inputs like fertiliser by making the product available in their community.

[5] To capture farmers' unobserved but differential ability, motivation and/or likely strength, independent of exposure to UDP, information on farmers' yields in the main agricultural season prior to the promotion of the technology and demonstrations was used. Information on whether farmers used improved varieties of rice seed in the year prior to the programme was also collected and used in the generation of the propensity score.

were dropped. To address extreme values, the yield per hectare variable was winsorised at 95%. Furthermore, land size in hectares was imputed for all respondents who reported their land size in non-conventional units (other than hectare, acre or metres squared).

Table 1 describes the study sample. Overall, the UDP technology was used on 52.32% of the plots in the study sample in the main planting season of 2012. This follows one year of intense experimentation on a demonstration plot within the boundaries of the study area and widespread promotion of the technology in the study villages. The typical plot manager was a 32-year-old male (92%) farmer who had spent most of his life in the village, regardless of whether he was an adopter or not. Most of the plot managers were married (80.31 %) with some formal education (85.63%), and were likely to be members of a farmer organisation (78%). The average wealth of UDP adopters and non-adopters was not significantly different, while the likelihood of being in a farmer organisation (though common among all) was higher for plot managers using UDP than for those who did not. Most plot managers (96% overall) participated in the training organised by the private sector fertiliser supply company (Notore), which promoted the technology in the study area.[6]

Although most plots are owned by their plot manager (95%), tenure status differed between adopters (98%) and non-adopters (91%). Irrigation practices (likely dependent on the availability of water sources in the vicinity) were not very common in the study area. Only 13.40% of the plots analysed were irrigated, and this did not vary significantly across UDP adopters and non-adopters. Monocropping was common for rice production, and over 90% of plot managers used hired labour for rice production. However, the proportion of plot managers who used UDP and hired labour was significantly higher than their counterparts not using the technology. This might reflect the additional labour requirement for UDP application compared to the traditional broadcasting of urea.

[6] This was a joint partnership between the private fertiliser company and a development agency called IFDC.

Table 1: The characteristics of rice farmers in Niger State

		Mean/percentage			
Variables		**Plots using UDP**	**Plots not using UDP**	**Total**	**T test**
Have heard of UDP (1/0)		100%	90.64%	93.79%	-5.8299***
Use UDP (1/0)		100%	0%	52.32%	
Gender	Male	91.30%	94.16%	91.55%	
	Female	8.70%	5.84%	8.45%	-1.3938
Age (years)		37.95 (14.43)	36.59 (13.28)	37.17 (14.01)	-1.2373
Number of years of residence in the village (years)		37.83 (14.57)	35.99 (13.73)	36.84 (14.34)	-1.6581*
Experience in agriculture (years)		27.60 (14.16)	25.79 (13.74)	26.67 (14.16)	-1.6423
Marital status	Married	80.86%	80.56%	80.31 %	-0.0958
	Single	19.14%	19.44%	19.69%	
Schooled		88.29%	83.70%	85.63%	-1.7139
Size of plots cultivated (ha)		1.53 (0.10)	6.65 (5.01)	3.97 (2.39)	1.0711
Asset index		.055 (1.21)	-.014 (1.19)	-.0065 (1.24)	-0.7406
Member of farmer association		83.58%	74.92%	78.79%	-2.7092***
Attended the Notore training		96.86%	93.90%	96.10%	-1.5408
Ownership of cultivated plot		98.22%	91.80%	95.39%	-3.8330***
Irrigation practice		14.37%	12.94%	13.40%	-0.5169
Only rice on the plot		92.01%	89.74%	89.95%	-0.8743
Use of hired labour		97.92%	94.41%	95.73%	-2.3395**
Yield in 2011 (kg/ha)		2993.21 (170.93)	2266.79 (172.73)	2720.62 (125.81)	-2.8153***
Use of improved seeds in 2011		73.03%	46.81%	59.14%	-6.5590***
Distance from plot to home (km)		1.89 (5.52)	2.30 (5.13)	1.97 (4.91)	0.9433
Area of rice plots (ha)		1.50 (0.12)	1.29 (0.05)	1.42 (0.07)	- 1.3327 ***
Yield 2012 (kg/ha)		3314.79 (188.96)	2222.45 (172.44)	2898.34 (136.19)	-3.9547***

4. Estimation results

4.1 Results for propensity score matching

The results from the nonlinear logit estimation of the propensity score are displayed in Table 2. They reveal that farmers who owned their rice plots were more likely to adopt the use of UDP. Plot managers were likely to use UDP on plots that were in closer proximity to the homestead and on plots that were monocropped. As expected, farmers who used complementary inputs such as irrigation and improved rice varieties were also more likely to adopt UDP. Interestingly, female plot managers were more likely to adopt UDP for rice production than male plot managers. The propensity score estimation satisfied the balancing property, indicating that conditional on the observable characteristics included in the propensity score estimation, the treatment and control groups were similar. For the treatment effects, only respondents whose propensity score fell within the common support region were included, since a substantial overlap in covariates is required between farmers who used UDP in the main agricultural season in 2012 and farmers who did not so that the farmers being compared have a common probability of both using UDP.

Table 2: Logit model for estimating rice farmers' propensity for adopting UDP technology

Variables	**coefficient**	**p value**
Area of rice cultivated (in ha)	-0.088	0.683
Squared area of rice cultivated	0.034	0.163
Owned land (0/1)	1.228**	0.052
Irrigation (0/1)	0.532*	0.093
Only rice cultivated on the plot (0/1)	1.333***	0.000
Hired labour is used (0/1)	1.284**	0.039
Improved seed used in 2011(0/1)	1.003***	0.000
Age of plot manager (in years)	0.003	0.960
Squared age of plot manager	0.000	0.284
Female plot manager (0/1)	0.950**	0.051
Plot manager is married (0/1)	-0.185	0.576
Plot manager is educated (0/1)	0.408	0.204
Plot manager experience in agriculture (in years)	0.005	0.771
Plot manager is member of a farmer's association (0/1)	0.423	0.135
Number of years of residency in the area (in years)	0.047	0.182
Plot manager has attended Notore training (0/1)	0.372	0.614
Distance to home (in km	-0.173***	0.011
Constant	-5.615***	0.000
Number of observations	507	

Source: Estimated by the authors using STATA
Note: * = significant at 10%, ** = significant at 5%, and *** = significant at 1%.

The results for propensity score matching are displayed in Table 3. There is evidence of positive and significant treatment effects of UDP on rice yields. The ATT effects range between about 620 and 780 kilograms per hectare and are consistently significant at 1%, irrespective of the matching method used. The results from the radius matching method have the highest treatment effect, supported by the most robust results regarding the presence of unobservable characteristics that could affect UDP adoption (see Table 4).

Table 3: Average treatment effects on the treated (ATT)

Kilograms of rice per hectare	**Nearest-neighbour matching**	**Radius matching**	**Kernel density**
ATT	697.94***	778.25***	617.963***
Bootstrapped standard error	192.58	205.58	90.08
T statistic	3.62	3.79	3.25
Number of observations	385	385	385

Source: Estimated by the authors using STATA
Note: * = significant at 10%, ** = significant at 5%, and *** = significant at 1%.

Table 4 below indicates the robustness of the PSM results. When using radius matching, the higher yield from using UDP would still be significant at 10% or less, unless unobservable characteristics increased the likelihood of UDP adoption by a factor of 2.5 or more. For the kernel and nearest-neighbour matching, the results are robust up to a factor of 1.5 and 1.3 respectively. Confidence in the radius-matching results is strengthened by the confidence interval results from the radius matching not bracketing zero up to a factor of 2. These results indicate that it is not likely that the yield effects of UDP adoption are driven by unobservable characteristics that determine adoption and productivity, which the propensity score matching does not address.

Table 4: Rosenbaum sensitivity results for treatment effects

	Nearest-neighbour matching			Radius matching			Kernel matching		
Gamma	*UB sig level*	*Confidence interval*		*UB sig level*	*Confidence interval*		*UB sig level*	*Confidence interval*	
1	0.00	273.76	788.16	0.00	453.70	918.31	0.00	139.38	674.03
1.5	0.05	-34.90	1 227.45	0.00	144.89	1 271.85	0.34	-156.54	1 205.01
2	0.59	-227.64	1 531.33	0.09	-72.16	1 563.85	0.94	-338.53	1 469.70
2.5	0.95	-372.20	1 743.88	0.51	-245.95	1 822.92	1.00	-474.77	1 643.70

Source: Generated by authors using STATA. UB sig = upper-bound significance.

4.2 Instrumental variables analysis

The results from the instrumental variables estimation are shown in Table 5. The estimates are efficient for arbitrary heteroskedasticity, and standard errors are clustered at the household level to account for the fact that one household might have several plots. The instrumental variables results are compared to a traditional OLS model, and the productivity effects of adoption are much higher in the IV model.

Table 5: Productivity estimates of UDP use

	OLS			IV	
Kilograms per hectare	Coefficient	P > t		Coefficient	P > z
UDP use (0/1)	430.781***	0.005		1848.169*	0.077
Primary work Activity	-74.978***	0.008		-103.542***	0.005
Tenure (1/0)	-146.593	0.586		-873.797	0.200
Plot manager experience in agriculture (in years)	4.474	0.713		4.993	0.721
Plot manager has attended Notore training (0/1)	-165.680	0.703		-344.539	0.486
Area of rice cultivated (in ha)	-623.617***	0.000		-628.780***	0.000
Squared area of rice cultivated	18.062***	0.000		17.555***	0.000
irrigation (0/1)	-307.514*	0.068		-493.408	0.138
Used improved rice seed (1/0)	42.757	0.808		-234.855	0.347
only rice cultivated on the plot (0/1)	-49.717	0.859		-206.443	0.505
Female plot manager (0/1)	-240.150	0.437		-213.177	0.537
Plot manager is married (0/1)	615.144***	0.003		792.658***	0.001
Plot manager is educated (0/1)	-268.919	0.318		-300.140	0.261
Age of plot manager (in years)	11.659	0.320		3.691	0.797
Use of chemicals	165.657	0.403		1094.525	0.513
Sheshi Village	918.286***	0.000		604.160*	0.074
Constant	901.359	0.218		1588.109	0.394
Number of observations	425			371	

Source: Estimated by the authors using STATA
Note: * = significant at 10%, ** = significant at 5%, and *** = significant at 1%.

The F statistic of the instrument in the first-stage regression is 11.75 ($p > F = 0.0007$), which surpasses the value of 10 that normally is an indication of the presence of a weak instrument (Staiger & Stock 1997). With an Anderson canonical correlation likelihood ratio statistic of 11.92, (p-value = 0.000) and a Cragg–Donald statistic of 12.31 (p-value = 0.000), the null hypothesis that the model is under-identified and that the instruments are irrelevant is rejected. With an F-statistic F (1, 354) = 3.51 (p-value = 0.06) and Chi-sq (1) = 3.68 (p-value = 0.055) for the Anderson–Rubin Wald test of joint significance of endogenous variables, the null hypothesis that the endogenous variables are inappropriately included in the main equation is also rejected.

However, with a Kleibergen-Paap rk LM statistic of 11.750, it appears that the size distortion is potentially large (more than 10% rejection rate with a 5% alpha (Stock & Yogo 2005) and the model does not convincingly pass the weak identification test. Weak identification arises when the excluded instruments are correlated with the endogenous regressors, but only weakly. Given that estimators can perform poorly when instruments are weak, caution must be exercised with the claims on the IV estimates. However, given that they also are significant and even larger than the OLS estimates, the OLS estimates are considered as a lower bound on the likely effect of UDP use on farmers' rice yields.

Generally, the results from the OLS and IV models confirm the strong and positive yield effects of UDP use for rice production found in the quasi-experimental approach, and improve confidence in the fact that this is significantly different from zero. These yield effects are relatively large in magnitude. Improvements in yields that range between about 430 (from the OLS results) and 780 kilograms per hectare (from the most robust propensity score-matching results) amount to between 15% and 27% improvements in average yields.

5. The effect of good practices

Finally, the effect of prescribed UDP practices on the extent of yield effects enjoyed by the adopters of the technology was estimated. As discussed earlier, the adoption of UDP is expected to occur alongside a set of prescribed practices for rice production. These include the establishment of a nursery, and the application of UDP one week after transplanting from the nursery to the main plot (at a depth of 7 to 10 cm). The main plot should be well watered and each USG should be applied to four rice plants. Table 6 reveals that farmers who used UDP and actually adhered to the required application rate had significantly higher yields than those who did not. When comparing the differential effect of the depth at which the granules were inserted, those who inserted at a depth of 3 to 6 cm had about 525 kg higher yields per hectare than those farmers who inserted at a depth of 0 to 3 cm. Inserting at a depth greater than 6 cm is not significantly different from zero. This indicates that inserting at a depth of 3 to 6 cm is likely deep enough to reach the roots of the plant while avoiding the roots of weeds. This is an important finding, as it indicates a likely reduction in the drudgery associated with the task of fertiliser application to the required depth of 7 to 10 cm in the UDP process.

There also is evidence that, while the use of herbicides does not appear to have an effect on yields, USG users who applied pesticides on their rice fields tended to have lower yields. This result might reflect the fact that farmers who had been adversely affected by pests had lower yields than their counterparts who had not been affected by pests, but possibly better off than they would have been without applying the pesticides.

These results suggest that just by adopting USG, farmers can expect some yield increases, and that using the correct application rate for USG (one granule for four rice plants), and inserting the USG at a depth of 3 to 6 cm, further improve the benefits of UDP use. The fact that UDP users who hired labour had significantly higher yields also indicates the additional labour requirement for UDP use if farmers are expected to engage in additional practices (such as nursery establishment, transplanting of seedlings, flooding of fields, USG application) and also be able to harvest higher yields. There were no significant effects of a farmer's knowledge about the practices associated with UDP for rice production on their yields.[7] This confirms the importance of distinguishing between what farmers know and what they do. While many farmers correctly indicated that they should place the USG at a depth of 7 to 10 cm, almost 60% of those who used USG applied it at a depth of 3 to 6 cm, with only about 25% actually placing it at a depth of 7 to 10 cm.

[7] Farmers were asked questions about the procedure for using USG on rice and asked to describe the process from land preparation to harvesting.

Table 6: The effects of good practices on rice yields among UDP adopters

	Coefficient	P > t
Female plot manager (0/1)	-29.765	0.927
Plot manager is married (0/1)	816.559***	0.001
Plot manager is formally educated (0/1)	-278.204	0.422
Age of plot manager (in years)	24.826***	0.002
On what percentage of rice planted was USG applied?	-0.776	0.818
Area of rice cultivated (in ha)	-689.704***	0.000
Squared area of rice cultivated	21.091***	0.000
Did you use improved rice seeds in rainy season 2012?	65.732	0.810
Irrigation of the plot (0/1)	-114.879	0.651
Granules inserted 3 – 6 cm deep	522.706**	0.042
Granules inserted greater than 6 cm deep	-64.728	0.831
Hired labour is used (0/1)	999.496***	0.000
Number of household members working on the plot	-45.731	0.447
Correct number of USG used (1/0)	403.240*	0.086
Did you use pesticides in rainy season 2012	-779.760***	0.000
Did you use herbicides in rainy season 2012	695.621	0.460
Knowledge score of UDP practice	-73.317	0.127
Sheshi Village	1 383.234***	0.000
Asset index	207.360**	0.017
Constant	-111.318	0.923

Source: Estimated by the authors using STATA
Note: *= significant at 10%, **= significant at 5%, and ***= significant at 1%.

6. Conclusion

This article explored the effects of the use of urea super granules on rice yields in Niger State, Nigeria. Using the propensity score-matching and instrumental variables techniques, consistent evidence was found of the significance of USG use on rice yields. The most conservative estimates indicate that the use of USG increases farmers' yields by at least 430 kilograms per hectare, which is a 15% increase in yield. The effect of good practices on yields among UDP users also indicates that farmers' yields are further enhanced by adopting several prescribed practices (such as the recommended application rate of one USG per four rice plants and the placement of the granules at a depth of 3 to 6 cm). The results indicate that farmers who have access to extra labour are better able to benefit from UDP use. This likely reflects the higher labour demand of UDP use and necessitates further attention to see how this labour requirement can be met, for example with an easier mechanism for USG application. This also indicates the importance of understanding the labour allocation decisions that are likely to occur in UDP-adopting households and their consequent effect on the profitability of UDP use and on household welfare.

The results indicate that there is a definite potential for UDP to significantly improve farmers' rice yields. However, a properly designed social experiment on the impact of UDP would be useful to provide additional information about the mechanisms through which the adoption process and yield effects occur, and the likely effects of different practices and farmer characteristics.

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