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THE EFFECTS OF KENYA'S 'SMARTER' INPUT SUBSIDY PROGRAM ON SMALLHOLDER BEHAVIOR AND INCOMES: DO DIFFERENT QUASI-EXPERIMENTAL APPROACHES LEAD TO THE SAME CONCLUSIONS?

By

Nicole M. Mason, Ayala Wineman, Lilian Kirimi, and David Mather

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EXECUTIVE SUMMARY

Kenya joined the ranks of sub-Saharan African (SSA) countries implementing targeted input subsidy programs (ISPs) for inorganic fertilizer and improved seed in 2007 with the establishment of the National Accelerated Agricultural Inputs Access Program (NAAIAP). While several features of NAAIAP were 'smarter' than other ISPs in the region, some aspects were less 'smart'. However, the efficacy of this program, and the relationship between its design and effectiveness, have been little studied. This article uses nationwide survey data to estimate the effects of NAAIAP participation on Kenyan smallholders' cropping patterns, incomes, and poverty status. Unlike most previous studies of ISPs, a range of panel data- and propensity score-based methods are used to estimate the effects of NAAIAP. The article then compares these estimated effects across estimators and to the effects of other ISPs in SSA, and discusses the likely links between differences in program designs and impacts. The results are robust to the choice of estimator and suggest that, despite substantial crowding out of commercial fertilizer demand, NAAIAP had sizable impacts on maize production and poverty severity. NAAIAP's success in targeting resource-poor farmers and implementation through vouchers redeemable at private agro-dealer shops likely contributed to its more favorable impacts than those of ISPs in Malawi and Zambia.

Keywords: input subsidy programs, fertilizer, hybrid seed, poverty, welfare, smallholder farmers, Kenya, sub-Saharan Africa

JEL Classification: I3, I32, I38, Q12, Q18

ACRONYMS

AEZ	Agro-Ecological Zone
ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
CF	Control Function
DID	Difference-in-Differences
FE	Fixed Effects
ISP	Input Subsidy Program
IV	Instrumental Variables
NAAIAP	National Accelerated Agricultural Inputs Access Program
NCPB	National Cereals and Produce Board
OLS	Ordinary Least Squares
PSM-DID	Propensity Score Matching Difference in Difference
PSW-DID	Propensity Score Weighting Difference in Difference
SSA	Sub-Saharan Africa
TAPRA	Tegemeo Agricultural Policy Research and Analysis

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1. INTRODUCTION

Often cited as a prime example of successful private sector-led fertilizer market development in sub-Saharan Africa (SSA), Kenya has joined the ranks of SSA countries implementing targeted input subsidy programs (ISPs) for inorganic fertilizer and improved seed (Ariga and Jayne, 2009). Common during the post-independence period of the 1960s and 1970s, then scaled back during structural adjustment in the 1980s and 1990s, ISPs have made a comeback since the early 2000s, and SSA governments currently spend more than US$1 billion on the programs each year (Jayne and Rashid, 2013). Although the literature on ISPs in SSA has proliferated in recent years,[1] most previous research on the programs has focused on Malawi, Zambia, and Nigeria. There is a dearth of empirical evidence on the effects of Kenya's targeted ISP, the National Accelerated Agricultural Inputs Access Program (NAAIAP).[2] For example, while Sheahan *et al.* (2014) have analyzed the targeting of NAAIAP, and Jayne *et al.* (2013) and Mather and Jayne (2015) have estimated its effects on smallholder farmers' demand for fertilizer at commercial market prices, little is known about the effects of the program on other dimensions of farmer behavior or welfare. This article begins to fill that gap by using household panel survey data from Kenya to answer the question, what are the effects of Kenya's NAAIAP on smallholder crop production, incomes, and poverty? In the course of this investigation, we also ask, do different quasi-experimental methods lead to the same conclusions about the effects of NAAIAP on smallholder behavior and welfare?

To address the second research question, we employ several different methods, namely: difference-in-differences (DID) and fixed effects (FE) approaches; propensity score matchingDID (PSM-DID) and calculation of associated Rosenbaum bounds to assess the sensitivity of the results to unobserved heterogeneity; and propensity score weighting-DID (PSW-DID). NAAIAP participants are not randomly selected, so correlation between NAAIAP participation and observed and unobserved factors affecting smallholder behavior and economic well-being must be controlled for in order to obtain unbiased estimates of NAAIAP impacts. Each of the aforementioned approaches deals with the self-selection or endogeneity problem in a different way and relies on different assumptions. Our use of multiple methods allows us to test the robustness of our findings to the choice of estimation approach. It also sets this article apart from previous non-experimental studies of the impacts of government ISPs in SSA, which rely on either panel data and instrumental variables (IV) or control function (CF) methods (e.g., most of the articles reviewed in the 2013 special issue of *Agricultural Economics*), or PSM (e.g., Chirwa, 2010, and Liverpool-Tasie, 2014b).[3] While IV/CF methods have the potential to control for endogeneity related to unobservables including those that are time invariant, it is extremely difficult to find relevant and valid IVs.[4] Using multiple methods gives us more confidence in our estimates of NAAIAP impacts; it can also provide an indication of whether the estimated impacts of ISPs in other SSA countries might be

[1] For a review of this literature through mid-2013, see the November 2013 special issue of *Agricultural Economics*.
[2] NAAIAP actually consisted of two sub-programs, *Kilimo Plus* and *Kilimo Biashara*, both of which are described in detail below. This paper focuses on the Kilimo Plus sub-program, which was the only one to provide subsidized inputs. Moreover, most Kenyans refer to Kilimo Plus simply as "NAAIAP" as it is the better known and larger, more visible of the two NAAIAP sub- programs. For these reasons, we use the terms NAAIAP and Kilimo Plus interchangeably throughout the paper and unless otherwise specified.
[3] To our knowledge, to date the only experimental (randomized-controlled trial, RCT) evaluation of a *national* or *government-piloted* ISP in SSA is Carter *et al.* (2013, 2014).
[4] We also explored using IV/CF methods in this article but were unable to identify a sufficiently strong and plausibly exogenous IV for NAAIAP.

sensitive to the methods employed. To our knowledge, no previous study on the effects of ISPs in SSA has investigated whether different quasi-experimental approaches lead to the same conclusions.

The quantitative results of our analysis are then applied to a broader discussion focused on two additional questions. First, how do the effects of NAAIAP compare to those of other ISPs in SSA? Second, how might differences in program context, design, and implementation explain differences in program effects? Beyond an imperative to improve the effectiveness of targeted ISPs in Kenya, understanding the behavioral and welfare effects of NAAIAP is important because the program's context, design, and implementation differ substantially from those of other ISPs in SSA. Thus one might expect the impacts of NAAIAP to differ also. Estimating and comparing the effects of NAAIAP to the outcomes of other ISPs in SSA can shed light on how program context, design, and implementation affect program outcomes. For example, private input markets are much better developed in Kenya than in many other parts of SSA, and most Kenyan maize farmers in high potential areas purchased fertilizer at commercial prices prior to the subsidy program (Ariga and Jayne, 2009; Sheahan *et al.*, 2014). As a result, subsidized fertilizer 'crowds out' or 'displaces' commercial fertilizer demand at a much higher rate in Kenya than it does in Malawi and Zambia, where private fertilizer markets are less developed. Specifically, while a one-kilogram increase in subsidized fertilizer raises a household's fertilizer use by 0.87 kg in Zambia and 0.82 kg in Malawi, the increase in fertilizer use in Kenya is only 0.57 kg (Ricker-Gilbert *et al.*, 2011;

Mason and Jayne, 2013; Jayne *et al.*, 2013; Mather and Jayne, 2015).[5] One might expect Kenya's ISP to have more muted effects on household production, incomes, and poverty given its relatively modest effect on total fertilizer use. On the other hand, while Malawi's and Zambia's ISPs allocated more subsidized fertilizer to smallholders with greater land and asset wealth (Jayne *et al.*, 2013), participants in Kenya's NAAIAP tended to be relatively 'resource-poor' farmers with less land or asset wealth (Sheahan *et al.*, 2014). Thus one might expect larger NAAIAP impacts on poverty than have been found for the Malawi and Zambia ISPs (Mason and Tembo, 2015; Ricker-Gilbert and Jayne, 2012; Arndt *et al.*, 2014).

Finally, NAAIAP was implemented through a system of voucher coupons that beneficiary farmers could redeem at accredited agro-dealers for one 50-kg bag of basal dressing fertilizer, one 50-kg bag of top dressing fertilizer, and 10 kg of improved maize seed for free. This input distribution system differs markedly from the systems for Zambia's and Malawi's ISPs during the periods of analysis for the afore- and below-mentioned studies.[6] While the Malawi program uses a voucher system, until recently only the seed vouchers have been redeemable at private agro-dealers' shops; the fertilizer vouchers had to be redeemed at government depots (Lunduka *et al.*, 2013). Until 2015/16 when it started to pilot an electronic voucher system in selected districts, the Zambia program did not use vouchers at all, and subsidized fertilizer and seed were distributed through a dedicated ISP system that operated parallel to, rather than through, private agro-dealers (Mason *et al.*, 2013). NAAIAP's private sector-oriented voucher program may have improved the timely availability of inputs to program beneficiaries relative to Malawi's and Zambia's late-deliveryplagued government distribution systems, thereby increasing NAAIAP's impacts (Mason *et al.*, 2013; Lunduka *et al.*, 2013). In general, Kenya's NAAIAP is 'smarter' than ISPs in Zambia and Malawi given its successful

[5] There have also been studies of crowding out for Nigeria's ISPs (Takeshima *et al.*, 2012; Liverpool-Tasie, 2014a). Throughout the article, we mainly draw comparisons between the effects of Kenya's ISP and those in Malawi and Zambia because extensive work has been done on the effects of the latter two countries' ISPs on smallholder behavior and welfare – the main focus of this article. To our knowledge, such analyses have not been done for Nigeria's government-run ISPs.

[6] Zambia and Malawi have since started piloting voucher programs with greater private sector agro-dealer participation.

targeting of resource-poor farmers and greater engagement of private sector agro-dealers (Morris *et al.*, 2007).[7] However, NAAIAP is less 'smart' because the rationale for any ISP is much weaker in Kenya than most other countries in SSA due to Kenya's better developed fertilizer markets and strong pre-existing demand for fertilizer (Ariga and Jayne, 2009; Jayne *et al.*, 2013).

In what follows, we begin by outlining the key features of NAAIAP. We then describe the data and methods used in analysis, present results, discuss these results with a cross-country comparison of the characteristics and outcomes of several ISPs, and close with a summary of conclusions and policy implications.

[7] See Morris *et al.* (2007) for their ten guiding principles of (market-) 'smart' subsidies.

2. KENYA'S NATIONAL ACCELERATED AGRICULTURAL INPUTS ACCESS PROGRAM (NAAIAP)

First implemented in 2007/08 and running to date, NAAIAP marked the return of fertilizer subsidies to Kenya's input marketing landscape after 17 fertilizer subsidy-free years (1990-2007) (Ariga and Jayne, 2009). The overall goal of NAAIAP is "to improve farm input (fertilizer and seeds) access and affordability of smallholder farmers to enhance food security/availability at the household level and generate income from the sale of surplus produce" (MOA, 2007, p. 7). NAAIAP also sought to raise productivity and output, and eradicate poverty among smallholder farmers (MOA, 2007, 2010). The program consisted of two components: (i) *Kilimo Plus* fully subsidized input packs targeted at resource-poor farmers; and (ii) *Kilimo Biashara* subsidized credit for relatively better off (but credit-constrained) farmers. Kilimo Plus is the main component of NAAIAP and the focus of this article. We henceforth use the term NAAIAP to refer to Kilimo Plus only.

NAAIAP beneficiaries received vouchers redeemable at participating accredited agro-dealers for free inputs: 50 kg each of basal dressing and top dressing fertilizer, and 10 kg of improved maize seed. The input pack was intended for one acre of maize cultivation. Key eligibility criteria for beneficiary farmers included: (1) being unable to afford farm inputs at unsubsidized prices; (2) growing maize and having at least one acre but less than 2.5 acres of land; (3) being "vulnerable members of society", with preference given to female- and child-headed households; and (4) not having received government support in the past (MOA, 2007, p. 19). Participation in NAAIAP was to be a one-time opportunity for beneficiary households. Districts were selected to participate in the program based mainly on the district poverty level and its agro-ecological suitability for maize production (MOA, 2007). Stakeholder forums composed of representatives from the Ministry of Agriculture and the Ministry of Livestock and Fisheries Development, as well as farmer representatives and other community members, selected beneficiary farmers in targeted districts (MOA, 2007). Table 1 summarizes the number of vouchers distributed through the program each year from 2007/08 through 2011/12, as well as the vouchers' value and the number of districts included in the program. The scale of the program peaked at nearly 176,000 beneficiaries in 2009/10, the year captured in the last wave of the household panel survey data used in this article. The program is estimated to have cost Ksh1.05 billion (approximately US$14 million) and reached roughly 5% of Kenyan smallholders that year (MOA, 2013). The NAAIAP participation rate in our sample is similar at 4.6%.

Table 1: NAAIAP (Kilimo Plus) coverage and value of vouchers, 2007/08-2011/12a

	2007/08	2008/09	2009/10	2010/11	2011/12	Total
Total number of beneficiaries	36,000	92,876	175,973	125,883	63,737	494,469
Number of districts covered	40	70	131	95	63	
Voucher value (nominal Ksh)	6,500	7,300	5,687[b]	6,500	8,000	
Nominal exchange rate (Ksh/US$)[c]	62.7	77.7	74.8	80.0	83.6	
Voucher value (nominal US$)	103.67	93.95	76.03	81.25	95.69	

Notes: [a]We have requested but been unable to obtain this information for 2012/13 to date from the Kenya Ministry of Agriculture, Livestock, and Fisheries. [b]Voucher value for 2009/10 is the average value of the vouchers distributed, as vouchers that year had different values (Ksh 5,600 or Ksh 6,100) depending on the type of fertilizer. [c]Exchange rates are for Jan. 1, 2008, 2009, 2010, 2011, and 2012, respectively, and are from Oanda.com. Source: MOA (2013).

3. DATA

The data are mainly from the Tegemeo Agricultural Policy Research and Analysis (TAPRA) Rural Household survey, a nationwide, five-wave longitudinal survey of Kenyan farm households conducted by the Tegemeo Institute of Agricultural Policy and Development of Egerton University and Michigan State University in 1997, 2000, 2004, 2007, and 2010. This sample covered 22 districts and 107 villages across eight agro-ecological zones (AEZs), and sampling was based on probability proportional to size, with reference to census data. (See Argwings-Kodhek *et al.* (1998) for further details on the sampling frame, and Sheahan *et al.* (2013, Figure 1) for a map of districts and villages covered in the TAPRA survey)[8]. A total of 1,500 sedentary agricultural households were interviewed in the first wave of the survey and 1,243 (82.9%) households were interviewed in all five waves of the panel. While this is a high re-interview rate given the length of the panel (13 years), attrition bias is still a potential concern. However, we fail to reject ($p>0.10$) the null hypothesis of no attrition bias for all outcome variables in the study based on regression-based tests recommended by Wooldridge (2010, p. 837).

The five TAPRA survey waves cover the 1996/97, 1999/2000, 2003/04, 2006/07 and 2009/10 agricultural years. Recall that NAAIAP was initiated in 2007/08. In the analysis, we use data from the last three waves of the survey, which gives us two pre-NAAIAP waves (the 2003/04 and 2006/07 agricultural years) and one during-NAAIAP wave (2009/10). NAAIAP focused on maize-growing households and districts (MOA, 2012). We therefore limit our analytical sample to the balanced panel of 1,064 smallholder maize-growing households in the six maize-suitable AEZs.[9]

The TAPRA surveys collect detailed information on respondent households' crop and livestock production and sales, off-farm income-generating activities, demographic characteristics, asset holdings, and recent morbidity and mortality. The 2010 wave of the survey also collected data on households' receipt of subsidized fertilizer through NAAIAP, which we henceforth refer to as

'NAAIAP participation'. We complement the TAPRA data with wholesale price data from the Kenya Ministry of Agriculture, Livestock and Fisheries, and historical rainfall estimates from the Climate Prediction Center of the National Oceanic and Atmospheric Administration.

[8] The random sampling of households in the original 1997 sample ensures that future NAAIAP participation was independent of a household's inclusion in the survey. That said, by reinterviewing the same households included in earlier panel waves, the 2010 wave is not a stratified random sample of NAAIAP participants and non-participants. Quasi-experimental approaches are used to address this issue.

[9] These are Eastern Lowlands, Western Lowlands, Western Transitional, High Potential Maize Zone, Western Highlands, and Central Highlands. The Coastal Lowlands and Marginal Rain Shadow are covered by the TAPRA data but excluded from our analytical sample.

4. METHODS

4.1. Outcome Variables and Potential Impact Pathways

Previous studies (Jayne *et al.*, 2013; Mather and Jayne, 2015) have estimated the impacts of NAAIAP on household demand for inorganic fertilizer at commercial (unsubsidized) prices and on total household fertilizer use. In this article, we consider higher-level impacts of NAAIAP on crop production (total area cultivated, maize quantity harvested and output per acre, value of both maize and non-maize crop production, number of field crops grown, and net crop income), net total household income, and Foster-Greer-Thorbecke (FGT, 1984) poverty metrics. See Table 2 for a complete list of outcome variables and associated summary statistics.[10] We single out maize production from other crops because NAAIAP provided beneficiaries with improved maize seed and inorganic fertilizer to be used for maize production. However, we also check for potential NAAIAP effects on the production of other crops, as it is possible that households applied the fertilizer to other crops and/or adjusted their crop portfolio or use of other inputs on other crops upon receipt of NAAIAP. As will be discussed in section 5, results seem to confirm that fertilizer received through NAAIAP was applied predominantly to maize. Maize is also the most important staple crop produced by Kenyan smallholders.

[10] Intercropping of maize with other crops is very common in Kenya but the surveys do not apportion intercropped area among crops. Therefore, instead of using the terms 'maize area planted' and 'maize yield' we use, respectively, 'acres planted with maize' (to refer to acres under mono- or inter-cropped maize), and 'maize output/acre' (in kilograms (kg) of maize harvested per acre planted with maize).

Table 2: Summary statistics for outcome variables

Variables	Mean	Std. dev.	25th percentile	50th percentile	75th percentile	N
Net total income (2010 Ksh)	304.783.00	(362,331.00)	(100,133.30)	203,459.80	380,223.40	3,192
Net total income per capita per day (2010 Ksh)	181.97	(257.32)	52.63	110.26	218.64	3,192
Poverty incidence (1=poor)	0.47	(0.50)	0	0	1	3,192
Poverty gap	0.23	(0.33)	0	0	0.47	3,192
Poverty severity	0.16	(0.53)	0	0	0.22	3,192
Net crop income – both seasons (2010 Ksh)	120,089.40	(158,532.40)	33,959.71	70,038.29	149,975.30	3,192
Net crop income – main season (2010 Ksh)	95,637.31	(151,535.50)	19,816.23	50,360.86	120,221.00	3,192
Net crop income/acre – main season (2010 Ksh)	34,081.32	(37,694.27)	11,113.78	22,917.49	46,590.13	3,189
Value of maize production – main season (2010 Ksh)	27,838.89	(51,177.64)	6,244.22	12,366.89	26,595.74	3,192
Value of non-maize crop production – main season (2010 Ksh)	91,463.48	(150,223.40)	16,678.95	42,147.83	107,937.40	3,192
Maize kgs produced – both seasons	1,549.27	(2,433.53)	450.19	833.66	1,620.28	3,192
Maize kgs produced – main season	1,334.33	(2,437.05)	315.05	596.32	1,260.19	3,192
Maize proportion of total crop value – both seasons	0.32	(0.23)	0.12	0.27	0.48	3,189
Number of different field crops grown	4.76	(1.56)	4	5	6	3,192
Total acres cultivated – main season	3.21	(3.25)	1.25	2.26	4.00	3,192
Acres cultivated with maize – main season	1.53	(1.78)	0.50	1.00	2.00	3,192
Maize output/acre – main season (kg maize/acre with maize)	1,241.12	(4,022.56)	416.32	721.31	1,260.98	3,169

Note: 'Both seasons' means both the main and short cropping seasons.

Source: Authors' calculations based on the 2004, 2007, and 2010 TAPRA data.

Similar to previous studies for Kenya using the TAPRA data (e.g., Mathenge *et al.*, 2014), net crop income is defined as the gross value of crop production minus fertilizer and land preparation costs. Net total household income is net crop income plus net livestock income (gross livestock income minus feed, salaried labor, and veterinary costs) and off-farm income (income from salaried/wage employment, pensions, and remittances received and net income from formal and informal business activities). Costs other than those mentioned above were not collected in all of the TAPRA panel survey waves and so cannot be netted out. To compute the FGT poverty metrics, we use net total household income relative to the US$1.25/capita/day extreme poverty line. Poverty incidence is equal to one for households with net total income below this poverty line, and equal to zero otherwise. The FGT poverty gap at the household level is equal to zero for households above the poverty line, and equal to the proportion difference between household income and the poverty line for households below the poverty line. FGT poverty severity at the household level is the poverty gap squared (FGT, 1984).

Receipt of free fertilizer through NAAIAP could affect the outcome variables through several potential pathways. The most direct pathways are through its impacts on fertilizer use and fertilizer expenditures. Jayne *et al.* (2013) and Mather and Jayne (2015) find that an additional kg of subsidized fertilizer raises Kenyan smallholders' total fertilizer use by 0.57 kg on average, *ceteris paribus*; this is less than 1 kg due to crowding out of the household's fertilizer purchases at unsubsidized prices. Even if NAAIAP completely crowded out commercial purchases (such that it had no impact on total fertilizer use), the household would have received the NAAIAP fertilizer for free and hence experienced a reduction in its fertilizer expenditures. Given previous results that NAAIAP does increase fertilizer use (Jayne *et al.,* 2013, Mather and Jayne, 2015), holding other factors constant and assuming the fertilizer is applied to maize we would expect to see an increase in household maize production as a result of NAAIAP participation. This could come through an increase in maize yields and/or through an increase in maize area planted.

If other crop activities and prices are unaffected by NAAIAP, then we would expect an increase in total net crop income equal to the increase in net maize income. On the other hand, NAAIAP participation could negatively affect the land, labor, or other resources devoted to non-maize crops, so it is possible that increases in net maize income could be offset by decreases in the production of other crops, resulting in no change in net crop income overall. Similar arguments could be made for positive or no effects on net total income (crop + livestock + off-farm). Alternatively, households might choose to apply some of the NAAIAP fertilizer to crops other than maize, which could positively affect the production of and income from those crops.

An increase in net total income (in per capita terms) resulting from NAAIAP would translate into a reduction in poverty incidence if, for example, the change in income were sufficient to alter a household's poverty status from poor without NAAIAP to non-poor with NAAIAP. However, given the high rate of poverty in rural Kenya (e.g., the official rural poverty rate was 49% in 2006 (Republic of Kenya, 2007)) and in our sample (47% of the sample is poor per Table 2), and given that the mean poverty gap among poor households in our sample is 50%, the increase in income resulting from NAAIAP would have to be quite large to substantively affect poverty incidence. Smaller income increases among the poor would reduce the poverty gap and poverty severity. Other impact pathways may also be possible.[11] In the next several sections, we outline how we use the TAPRA data to estimate the impacts of NAAIAP on the various outcome variables considered in the article.

[11] We acknowledge that there may be spillover effects associated with the NAAIAP program, whereby non-direct recipients of NAAIAP may benefit from the sharing of Kilimo Plus packs. Unfortunately, the data are insufficient for a robust analysis of such spillover effects. This is an important area for future research.

4.2. Framework for Impact Evaluation of NAAIAP: The Rubin Causal Model[12]

The main objective of this article is to estimate the impacts of NAAIAP participation on various dimensions of smallholder behavior and economic well-being. Let Y_{1i} be the value of a given outcome variable for household *i* with participation in NAAIAP (i.e., with treatment), and let Y_{0i} be the household's outcome without participation in NAAIAP (i.e., without treatment). At a given point in time, a household either participates in NAAIAP ($W_i = 1$) or does not ($W_i = 0$). Thus the observed outcome, Y_i, is:

$$Y_i = W_i Y_{1i} + (1 - W_i) Y_{0i}$$

(1) The treatment effect of NAAIAP for household *i* is:

$$\tau_i = Y_{1i} - Y_{0i} \qquad (2)$$

but this effect is not directly observable because the household can only be in one state of nature (treated or untreated) at a given time. The population parameters we seek to estimate are the average treatment effect (ATE) or the average treatment effect on the treated (ATT) of NAAIAP, where:

$$\tau_{ATE} = E(Y_1 - Y_0)$$

(3)

$$\tau_{ATT} = E(Y_1 - Y_0 \mid W = 1)$$

(4)

If NAAIAP participation were randomly assigned, then the potential outcomes would be independent of treatment (i.e., $(Y_1, Y_0) \perp W$, $E(Y_1 \mid W = 1) = E(Y_1 \mid W = 0)$,

$E(Y_0 \mid W = 1) = E(Y_0 \mid W = 0)$), $\tau_{ATE} = \tau_{ATT}$, and we could estimate τ_{ATE} by comparing the mean outcomes of NAAIAP participants and non-participants. In practice, NAAIAP participation was not randomly assigned, so selection bias/endogeneity is a major concern. This may arise due to program placement effects (e.g., NAAIAP targeted poorer districts) or self-selection (e.g., a household's decision to participate in NAAIAP could be related to unobserved factors that affect the outcomes of interest in this article). We employ various econometric and quasi-experimental approaches (DID, FE, PSM-DID, and PSW-DID) to address these selection bias/endogeneity issues and obtain unbiased and/or consistent estimates of the ATT of NAAIAP. These approaches and their key assumptions are discussed next.

4.3. The Difference-in-Differences Estimator (DID)

The data cover periods before and during NAAIAP implementation; thus, one estimator at our disposal is DID. With a household-level treatment indicator, the DID estimate of the ATT is the ordinary least squares (OLS) estimate of the parameter $\tau_{ATT,DID}$ from the following regression:

[12] This section draws on Rosenbaum and Rubin (1983), Holland (1986), Imbens and Wooldridge (2009), and Guo and Fraser (2015).

$$Y_{i,t} = \beta_0 + \beta_1 dNAAIAP_i + \beta_2 d2007_t + \beta_3 d2010_t + \tau_{ATT,DID} dNAAIAP_i \times d2010_t + \varepsilon_{i,t},$$

(5) $t = 2004, 2007, 2010$ where t indexes the year; $dNAAIAP_i$=1 for NAAIAP participants and zero otherwise; $d2010_t$=1 for the 2010 survey wave and zero otherwise (recall that NAAIAP was not implemented as of the earlier survey waves); $d2007_t$ =1 for the 2007 survey wave and zero otherwise; $\varepsilon_{i,t}$ is the

idiosyncratic error term; and the β's are the other parameters to be estimated.[13]

The key assumption for the DID estimator is parallel trends in $Y_{i,t}$ for NAAIAP participants and non-participants in the absence of NAAIAP. While this assumption cannot be directly tested, we use information from the pre-2010 TAPRA survey waves to check for parallel trends prior to NAAIAP. Table A1 in the Appendix shows the mean changes in the various outcome variables between the 2004 and 2007 survey waves for households that were NAAIAP recipients versus non-recipients as of the 2010 wave, and tests for differences in these means. The differences are not statistically significant ($p>0.10$) for the vast majority of outcome variables; the only significant differences are for main season net crop income/acre, number of different field crops grown, and main season land cultivated. Thus the data are generally consistent with the key assumption of the DID estimator.

4.4. The Fixed Effects Estimator (FE)

Although DID regressions are typically set up as in equation (5), note that with household-level panel data and a household-level variable indicating participation in NAAIAP, $\tau_{ATT,DID}$ could be obtained by estimating the following equation via FE:

$$Y_{i,t} = \alpha_0 + \alpha_1 d2007_t + \alpha_2 d2010_t + \tau_{ATT,DID} NAAIAP_{i,t} + c_i + u_{i,t}, \quad t = 2004, 2007, 2010$$

(6)

where $NAAIAP_{i,t}$ =1 if household i participated in NAAIAP in year t, and equals zero otherwise;

c_i is time-invariant unobserved heterogeneity; and $u_{i,t}$ is time-varying unobserved heterogeneity (Imbens and Wooldridge, 2007). Framed this way, the key assumption for FE to produce unbiased and consistent estimates of $\tau_{ATT,DID}$ is that $NAAIAP_{i,t}$ be strictly exogenous conditional on c_i (Wooldridge, 2010). This assumption becomes more plausible if we also control for observable (and exogenous) time-varying variables ($X_{i,t}$) that could be correlated with $NAAIAP_{i,t}$:

[13] Note that $dNAAIAP_i$ in equation (5) is household-level participation in NAAIAP, not a more aggregate 'exposure-to-NAAIAP' indicator, such as whether NAAIAP targeted a household's division or district. We have requested, but been unable to acquire, administrative data on the divisions or districts included in NAAIAP each year. One typically uses this type of exposure variable in DID models, but there is precedent for using household-level participation in a DID framework (e.g., Michelson (2013) and Imbens and Wooldridge (2007)).

$$Y_{i,t} = \gamma_0 + \gamma_1 d2007_t + \gamma_2 d2010 + \tau_{ATT,FE} NAAIAP_{i,t} + X_{i,t}\gamma_3 + c_i + u_{i,t}, \quad t = 2004,\ 2007,\ 2010 \tag{7}$$

$X_{i,t}$ includes a rich set of household, village, and regional characteristics such as prices of key agricultural inputs, lagged prices of key crops (as proxies for expected prices), distances to various markets and services, rainfall- and temperature-related variables, landholding size, lagged productive assets (livestock and equipment), demographic characteristics of the household head, household composition, and recent morbidity and mortality shocks. See Table A2 in the Appendix for summary statistics for all variables in $X_{i,t}$.

Estimating equation (7) via FE to remove c_i gives an estimate of the ATT, $\tau_{ATT,FE}$. Having controlled for potential correlation between NAAIAP and c_i, the main threat to internal validity is if NAAIAP is correlated with time-varying unobserved factors affecting the outcome ($u_{i,t}$).

4.5. Propensity Score Matching-DID (PSM-DID) and Rosenbaum Bounds

An alternative approach to controlling for differences between NAAIAP participants and nonparticipants to obtain unbiased estimates of the ATT is PSM-DID. PSM matches NAAIAP participants with non-participants of similar propensity scores, i.e., similar probabilities of participating in NAAIAP. For PSM, the first key assumption is 'ignorability of treatment' or 'unconfoundedness', i.e., that conditional on observed covariates (X), NAAIAP participation (W) and the potential outcomes are independent: $(Y_1, Y_0) \perp W \mid X$ (Rosenbaum and Rubin, 1983). The second key PSM assumption is that there is overlap: $0 < P(W = 1 \mid X) < 1$, i.e., households with the same covariates have positive probabilities of both participation and non-participation in NAAIAP. We estimate a probit model of participation in NAAIAP in the 2010 survey wave as a function of household, village, and regional characteristics as of the 2007 survey wave ($X_{i,2007}$).

The characteristics included in the probit model used to generate the estimated propensity score (Table A3 in the Appendix) are selected from a larger pool of candidate characteristics (Table A2 in the Appendix) following the iterative procedure recommended in Imbens (2014). There is adequate overlap in these propensity scores, and balancing tests per Dehejia and Wahba (2002) suggest that the balancing property is satisfied (i.e., NAAIAP participants and non-participants have similar propensity scores within blocks in the region of common support).[14]

We next match NAAIAP participants and non-participants using two different matching estimators: radius and caliper matching. Rather than using PSM alone to obtain ATTs, we take advantage of the panel nature of the data and use PSM-DID, which controls for differences in both observed and time-invariant unobserved factors between NAAIAP participants and nonparticipants (Heckman *et al.*, 1997, 1998). The PSM-DID estimator of the ATT is:

$$\hat{\tau}_{ATT,PSM-DID} = \frac{1}{N_1} \sum_{i \in I_1 \cap S_p} \left[(Y_{1i,t} - Y_{1i,t-1}) - \sum_{j \in I_0 \cap S_p} \omega(i,j)(Y_{0i,t} - Y_{0i,t-1}) \right] \tag{8}$$

[14] The optimal number of blocks was nine. Each household, village, and regional characteristic used in the probit to generate the propensity score is also balanced between NAAIAP participants and non-participants within each block of the propensity score in the region of common support. [16] We compute the Rosenbaum bounds for our estimates using the <rbounds> command in Stata (DiPrete and Gangl, 2004).

where the subscripts refer to NAAIAP participants (1) and non-participants (0); N_1 is the number of NAAIAP participants; I_1 and I_0 are the observations for NAAIAP participants and nonparticipants, respectively; S_p is the common support; and φ (.)is a weight that depends on the matching estimator.

Although we have controlled for a rich set of observables as well as time-constant unobservables to obtain $\hat{\tau}_{ATT,PSM-DID}$, there may still be differences in time-varying unobservables between NAAIAP participants and non-participants that are correlated with NAAIAP participation and affect the outcome variables of interest. This 'hidden bias' would influence $\hat{\tau}_{ATT,PSM-DID}$ (Rosenbaum, 2002). In the PSM-DID context, we can compute Rosenbaum bounds to test the sensitivity of our estimates to time-varying unobserved heterogeneity (Rosenbaum, 2002; personal communication with M. Gangl, April 2015).[16] Among other things, Rosenbaum bounds can be used to calculate upper bound significance levels (p-values) for PSM (and PSM-DID) ATT estimates assuming no hidden bias ($\Gamma = 1$, which indicates that matched households have the same probability of participating in NAAIAP), and at various levels of hidden bias ($\Gamma > 1$) (Rosenbaum, 2002; Becker and Caliendo, 2007). For example, $\Gamma = 1.1$ suggests that households that have similar observed covariates (and hence propensity scores) could differ in their odds of participating in NAAIAP by up to 10% due to differences in unobservables (Becker and Caliendo, 2007). As discussed in Dillon (2011) and the references therein, $\Gamma = 2$ is generally considered a high level of unobservable differences, and if the upper bound significance level of a given ATT is still below 0.10 when $\Gamma = 2$, the statistical significance of the ATT is considered quite robust to hidden bias.[15]

4.6. Propensity Score Weighting-DID (PSW-DID)

The fourth and final approach taken to estimate the effects of NAAIAP is PSW-DID. The PSWDID estimator of the ATT is given by:

$$\hat{\tau}_{ATT,PSW-DID} = \frac{1}{N}\sum_{i=1}^{N}\frac{\left[dNAAIAP_i - \hat{\Pr}(\boldsymbol{X}_{i,2007})(Y_{i,t} - Y_{i,t-1})\right]}{\hat{\rho}\left[1 - \hat{\Pr}(\boldsymbol{X}_{i,2007})\right]} \tag{9}$$

where N is the total number of observations; $\hat{\Pr}(\boldsymbol{X}_{i,2007})$ is the estimated propensity score; $\hat{\rho}$ is the proportion of treated observations in the sample; and all other variables are defined as above (Wooldridge, 2010). This approach is equivalent to using the estimated propensity scores as weights in a simple DID regression.

[15] Throughout the remainder of the article and unless otherwise specified, we use the 10% level as our cutoff for statistical significance.

5. RESULTS

To what extent did NAAIAP achieve its goals of raising productivity, output, and incomes, and reducing poverty among Kenyan smallholders? The ATT estimates for NAAIAP participation summarized in Table 3 generally suggest that, other factors constant, NAAIAP boosted maize production by increasing maize output per acre (as opposed to expanding the area cultivated with maize). The lack of significant effect seen for the value of non-maize crop production seems to confirm that recipients did apply the fertilizer sourced through NAAIAP predominantly to maize.

In addition, NAAIAP seems to have increased the maize share of households' total value of crop production. The results further indicate that NAAIAP reduced the poverty gap and poverty severity. At the same time, although we find statistically significant, positive effects on net total income for one of the five estimation approaches in Table 3 (DID), we find no evidence of statistically significant NAAIAP impacts on net crop income or poverty incidence. The Rosenbaum bounds results in Table 4 suggest that the PSM-DID radius matching-based estimates of the ATT are quite robust to time-varying unobserved heterogeneity (hidden bias).

Among the statistically significant ATT point estimates for this approach, only for the maize share of the total value of crop production does the upper bound significance level exceed 0.10 for a Γ value of less than 2. In other words, the inferences drawn about the direction and statistical significance of NAAIAP impacts on poverty severity, maize production, and maize output per acre based on PSM-DID with radius matching would still stand if households with similar observed covariates differed in their odds of participating in NAAIAP by 100% due to differences in unobservables. The caliper matching-based PSM-DID ATT estimates are more sensitive to hidden bias, with the upper bound significance levels exceeding 0.10 before $\Gamma=2$ for both statistically significant ATT point estimates.

The title of the article poses the question; do different quasi-experimental approaches lead to the same conclusions? The results in Table 3 suggest that DID, FE, PSW-DID, and PSM-DID with radius matching lead to similar conclusions regarding the direction and statistical significance of NAAIAP effects on the outcome variables. (An exception is the estimated ATT on the poverty gap for PSM-DID with radius matching, but with a p-value of 0.126, this result is marginally statistically significant. Other exceptions are that, of these four estimators, only DID suggests statistically significant NAAIAP impacts on net total income overall and per capita.) The main difference across these four estimators is the magnitude of the ATT estimates. PSW-DID generally produces the most conservative point estimates of the ATT. It is only the PSM-DID approach with caliper matching that leads to substantially different inferences. This may be because the matches are relatively poor for caliper matching, which is a one-to-one matching algorithm. Radius matching, in contrast, is a one-to-many matching approach and produces results that are generally similar to DID, FE, and PSW-DID.

Table 3: ATT estimates for participation in NAAIAP

Estimator:	DID	FE	PSW-DID	PSM-DID	PSM-DID
Matching algorithm for PSM-DID:				Radius	Caliper
Outcome variable	(A)	(B)	(C)	(D)	(E)
Net total income (Ksh)	56,866.43	32,491.63	22,060.41	53,618.88	55,214.60
	(0.088)	(0.298)	(0.393)	(0.183)	(0.334)
Net total income per capita per day (Ksh)	22.74*	6.93	8.77	7.21	24.98
	(0.071)	(0.755)	(0.483)	(0.684)	(0.586)
Poverty incidence (1=poor)	-0.04	-0.05	-0.05	0.00	-0.06
	(0.526)	(0.387)	(0.443)	(0.971)	(0.497)
Poverty gap	-0.08***	-0.10***	-0.04*	-0.07	-0.08
	(0.007)	(0.006)	(0.096)	(0.165)	(0.373)
Poverty severity	-0.08**	-0.11***	-0.04**	-0.09*	-0.08
	(0.014)	(0.004)	(0.020)	(0.096)	(0.352)
Net crop income – both seasons (Ksh)	10,317.39	16,419.99	9,009.93	-8,613.94	-23,953.64
	(0.236)	(0.203)	(0.217)	(0.412)	(0.190)
Net crop income – main season (Ksh)	11,917.25	8,999.15	6,955.99	-4,669.87	-25,539.89
	(0.149)	(0.448)	(0.305)	(0.618)	(0.137)
Net crop income/acre – main season (Ksh)	5,806.26	1,510.37	4,052.83	-1,752.51	-7,758.64
	(0.164)	(0.727)	(0.231)	(0.712)	(0.280)
Value of maize production – main season (Ksh)	10,935.71***	9,131.57***	5,215.23***	7,748.34***	4,273.31
	(0.000)	(0.001)	(0.000)	(0.005)	(0.301)
Value of non-maize crop production – main season (Ksh)	1,940.91	-1,361.56	2,380.35	-11,318.82	-27,022.03*
	(0.805)	(0.902)	(0.717)	(0.239)	(0.095)
Maize kgs produced – both seasons	462.17***	430.20***	200.68***	470.73***	276.60
	(0.000)	(0.002)	(0.000)	(0.007)	(0.240)
Maize kgs produced – main season	520.60***	361.11***	191.23***	533.37***	242.45
	(0.000)	(0.009)	(0.000)	(0.002)	(0.264)
Maize proportion of total crop value – both seasons	0.04**	0.04*	0.02*	0.04**	0.04
	(0.010)	(0.069)	(0.093)	(0.038)	(0.325)
Number of different field crops grown	0.10	-0.08	0.12	0.32	0.40
	(0.534)	(0.646)	(0.339)	(0.270)	(0.213)
Total acres cultivated – main season	-0.41	-0.08	-0.35	0.15	0.43
	(0.472)	(0.899)	(0.419)	(0.623)	(0.349)
Acres cultivated with maize – main season	-0.07	0.41*	-0.15	-0.02	0.64*
	(0.736)	(0.056)	(0.352)	(0.914)	(0.066)
Maize output/acre – main season (kg maize/acre with maize)	721.36***	556.42**	303.11***	684.46**	59.82
	(0.000)	(0.024)	(0.000)	(0.010)	(0.961)

Notes: ***p<0.01. **p<0.05. *p<0.10. p-values in parentheses (based on robust standard errors clustered at the household level for DID, FE, and PSW-DID; bootstrapped standard errors for PSM-DID). All Ksh values are in real 2010 terms. See Table A4 in the Appendix for the full FE regression results for income per capita per day, maize kg produced (both seasons), area cultivated with maize, and maize output/acre. Full regression results for the other ATT estimates above are excluded due to space considerations but are available from the authors upon request. Source: Authors' calculations.

Table 4: Rosenbaum bounds sensitivity analysis of PSM-DID ATT estimates to unobserved heterogeneity

	Panel A: Upper bound significance levels (p-values) for statistically significant ATTs in Table 3 – Radius Matching					
Γ	Poverty severity	Value of maize production – main season	Maize kgs produced – both seasons	Maize kgs produced – main season	Maize proportion of total crop value – both seasons	Maize output/ha – main season
1	0.00	0.00	0.00	0.00	0.00	0.00
1.1	0.00	0.00	0.00	0.00	0.01	0.00
1.2	0.00	0.00	0.00	0.00	0.02	0.00
1.3	0.00	0.00	0.00	0.00	0.03	0.00
1.4	0.00	0.00	0.00	0.00	0.04	0.00
1.5	0.00	0.00	0.00	0.00	0.06	0.00
1.6	0.01	0.00	0.01	0.00	0.09	0.00
1.7	0.01	0.00	0.01	0.00	**0.12**	0.00
1.8	0.01	0.01	0.01	0.00	0.15	0.00
1.9	0.02	0.01	0.02	0.00	0.19	0.00
2	0.03	0.02	0.02	0.01	0.23	0.00

	Panel B: Upper bound significance levels (p-values) for statistically significant ATTs in Table 3 – calliper matching	
Γ	Gross value of non-maize production – main season	Area cultivated with maize – main season
1	0.08	0.05
1.1	**0.13**	0.09
1.2	0.20	**0.14**
1.3	0.27	0.20
1.4	0.35	0.26
1.5	0.42	0.33
1.6	0.50	0.40
1.7	0.57	0.47
1.8	0.63	0.53
1.9	0.69	0.59
2	0.74	0.65

Note: Bold text indicates that value of Γ at which the upper bound significance level (p-value) exceeds 0.10.
Source: Authors' calculations.

The title of the article poses the question; do different quasi-experimental approaches lead to the same conclusions? The results in Table 3 suggest that DID, FE, PSW-DID, and PSM-DID with radius matching lead to similar conclusions regarding the direction and statistical significance of NAAIAP effects on the outcome variables. (An exception is the estimated ATT on the poverty gap for PSM-DID with radius matching, but with a p-value of 0.126, this result is marginally statistically significant. Other exceptions are that, of these four estimators, only DID suggests statistically significant NAAIAP impacts on net total income overall and per capita.) The main difference across these four estimators is the magnitude of the ATT estimates. PSW-DID generally produces the most conservative point estimates of the ATT. It is only the PSM-DID approach with caliper matching that leads to substantially different inferences. This may be because the matches are relatively poor for caliper matching, which is a one-to-one matching algorithm. Radius matching, in contrast, is a one-to-many matching approach and produces results that are generally similar to DID, FE, and PSW-DID.

The fact that DID, FE, PSW-DID and PSM-DID with radius matching generate similar estimates of the ATT of NAAIAP (at least in terms of sign and statistical significance) is important because most previous non-experimental studies on the impacts of ISPs employ only one or two approaches (typically PSM or panel data methods, but not both in the same paper). While there is no guarantee that these previous studies' findings would also be robust across estimation approaches, our findings increase confidence that their conclusions would still stand even if other methods had been used. The similarity between our FE and PSM-DID with radius matching inferences, as well as the Rosenbaum bounds results indicating that the latter are not sensitive to time-varying unobserved heterogeneity, also increases our confidence in the FE estimates. That is, even though we were unable to identify a suitable IV for NAAIAP participation and thus did not estimate FEIV models, these results suggest that time-varying unobserved heterogeneity is also unlikely to be a major threat to internal validity in the case of our FE estimates.

6. DISCUSSION

This section discusses the magnitudes of the estimated effects of NAAIAP vis-à-vis the analogous effects of Malawi's and Zambia's ISPs. It also discusses the likely reasons for observed differences in the effects of the ISPs across countries including differences in program designs and implementation modalities. We thereby situate our quantitative results within the wider literature on ISPs in order to better understand the policy implications of the findings.

First we ask, how do the estimated effects of NAAIAP on smallholder crop production, incomes, and poverty compare to those of other ISPs in SSA? The estimated NAAIAP ATTs on annual maize production range from a low of 201 kg for PSW-DID to a high of 471 kg for PSM-DID with radius matching. This is a large increase (13-30%) relative to mean household maize production in our sample (1,549 kg). While economically significant in magnitude, these production increases are fairly modest given that a NAAIAP package consisted of 100 kg of fertilizer and 10 kg of improved maize seed. If we attribute all of the maize production increase to fertilizer (which is unlikely), the results suggest a 2.01 to 4.70 kg of maize per kg of subsidized fertilizer response rate. This is higher than the estimated impacts of a 1 kg increase in subsidized fertilizer on maize production in Malawi (1.65 kg/kg per Ricker-Gilbert and Jayne (2011)) and Zambia (1.88 kg/kg per Mason *et al.* (2013)).[16] The finding is also consistent with a generally higher estimated yield response to fertilizer in Kenya (approximately 6-7 kg of maize per kg of fertilizer) than in Malawi and Zambia (approximately 3-4 kg/kg), which could be due to better soil conditions or greater familiarity with fertilizer use in Kenya (Jayne *et al.*, 2013). Table 3 also indicates that NAAIAP increases the maize share of households' total value of crop production by 2-4 percentage points. This suggests that NAAIAP may be making Kenyan smallholder crop production more maizecentric.

Moving beyond the impacts of NAAIAP on maize, the results in Table 3 imply that NAAIAP has not incentivized Kenyan smallholders to expand their area under cultivation. Given the often binding land constraints in Kenya, the lack of NAAIAP impact on total area cultivated is not surprising. In relatively land-abundant Zambia, the country's main ISP (the Farmer Input Support Program) incentivizes both an area expansion and an increase in the area devoted to maize; however, the additional area brought under maize comes at the expense of fallow land, and not at the expense of the area devoted to other crops (Mason *et al.*, 2013). There is also evidence that

Malawi's ISP incentivizes farmers to devote a larger share of their area cultivated to maize (Chibwana *et al.*, 2012). We find no evidence of NAAIAP impacts on the number of different field crops grown by Kenyan smallholders (a crude measure of crop diversification).[17] We are not aware of results from other SSA countries on the effects of ISPs on crop diversification.

Beyond the effects of NAAIAP on crop production, the estimated reductions in Kenyan farmers' depth and severity of poverty attributable to NAAIAP are also sizeable in magnitude. The results in Table 3 suggest that participation in NAAIAP reduced the poverty gap by an average of 4 to 10 percentage points, and poverty severity by an average of 4 to 11 percentage points. This is against mean poverty gap and severity levels in our sample of 23.4% and 16.1%,

16 Note that these studies do not control for the quantity of subsidized seed received when estimating the effects of subsidized fertilizer on maize production or other outcomes, so these estimates also essentially attribute all increases in maize production to subsidized fertilizer.

17 Because we cannot measure the area devoted to each crop using the TAPRA data, we cannot compute more sophisticated diversification indexes such as a Simpson's index.

respectively. Although these reductions in the poverty gap and poverty severity were insufficient to reduce poverty incidence, coupled with the findings that NAAIAP did not increase income per capita overall, these results suggest that NAAIAP did significantly raise per capita incomes *among the poor*. (Note that reductions in the poverty gap and poverty severity imply per capita income increases among households below the poverty line.) Results from Zambia also suggest that the country's main ISP reduced the severity of poverty but not poverty incidence among smallholder farmers, using the same US$1.25 per capita per day poverty line as we have here (Mason and Tembo, 2015).

A 100 kg increase in subsidized fertilizer acquired through Zambia's ISP is estimated to reduce smallholder poverty severity by approximately 2 percentage points (ibid.), far less than the estimated impacts of NAAIAP participation on poverty severity (Table 3). Moreover, at 54.1%, mean poverty severity is much worse in Zambia, so the ISP-related reduction in poverty severity there is even smaller than the associated NAAIAP impact when considered in percentage (and not percentage point) terms.[18] In contrast to our finding that NAAIAP has no statistically significant effect on net crop income, results from Malawi and Zambia do suggest that those countries' ISPs raised net crop income; however, of the three countries, only in Zambia did this translate into significant increases in total household income (Ricker-Gilbert and Jayne, 2011; Mason and Tembo, 2015).

What might explain differences in ISP effects on maize production and poverty severity in Kenya versus Malawi and Zambia? To a certain extent, the larger impacts of NAAIAP on maize production relative to Malawi's and Zambia's ISPs are surprising because Kenyan smallholders were using significantly more fertilizer without subsidies than were Malawian and Zambian smallholders; relatedly, NAAIAP crowds out more commercial fertilizer demand than the Malawian or Zambian ISPs and thus raises total fertilizer use less than those programs (Ariga and Jayne, 2009; Sheahan *et al.*, 2014; Jayne *et al.*, 2013; Mather and Jayne, 2015). But the 'smarter' features of NAAIAP relative to Malawi's and Zambia's ISPs, particularly NAAIAP's ***effective targeting of relatively land- and asset-poor farmers*** (Sheahan *et al.*, 2014) and its ***implementation through voucher coupons redeemable at private agro-dealers' shops***, may have compensated for these shortcomings and contributed to NAAIAP's greater impacts on maize production and poverty severity.

Unlike NAAIAP, Malawi's and Zambia's ISPs effectively target relatively land- and asset-*rich* smallholders (Ricker-Gilbert *et al.*, 2011; Jayne *et al.*, 2013; Mason *et al.*, 2013), and both deliver subsidized fertilizer (and in the case of Zambia, subsidized seed) to beneficiaries through government distribution systems that largely sideline rather than directly engage and build the capacity of private sector agro-dealers.[19] Within the ISPs of Malawi and Zambia, government distribution systems for subsidized inputs have also been plagued by late delivery, resulting in delayed planting and/or fertilizer application (Lunduka *et al.*, 2013; Mason *et al.*, 2013), whereas inputs obtained with NAAIAP vouchers appear to have been available sufficiently early to enable early planting. For example, based on the 2010 TAPRA data, 96% of the NAAIAP recipients in our sample report having planted their largest maize field 'on time'. Better soil quality and greater familiarity with fertilizer use in Kenya may have also contributed to the more favorable

[18] Mason and Tembo (2015) did not estimate the effects of Zambia's ISP on the poverty gap. Also, to our knowledge, no previous studies have estimated the effects of Malawi's ISP on poverty incidence, gap, or severity using household survey data. Arndt *et al.* (2014) use a CGE model to estimate the economy-wide effects of Malawi's ISP including its effects on the rural poverty rate, but these estimates are not comparable to our estimates of the household-level poverty effects of NAAIAP.

[19] By 'effective' targeting, we mean targeting in practice as revealed by household survey data as opposed to the 'official' targeting criteria based on program implementation guidelines.

impacts of NAAIAP vis-à-vis Malawi's and Zambia's ISPs. While we cannot determine which of these differences in country context or ISP design and implementation are most important, it is likely that each of them contributed in some way to the greater impacts of NAAIAP on maize production and poverty severity than Malawi's and Zambia's ISPs. Future work could endeavor to quantitatively attribute differences in program effects to differences in specific aspects of ISP design and implementation.

7. CONCLUSIONS AND POLICY IMPLICATIONS

This article sought to answer two main questions: (i) what are the effects of Kenya's NAAIAP on smallholder crop production, incomes, and poverty? and (ii) do different quasi-experimental methods lead to the same conclusions about these effects? The article also explored the implications of its quantitative findings by further asking, how do the effects of NAAIAP compare to those of other ISPs in SSA, particularly Malawi's and Zambia's for which comparable estimates are available? And how might differences in program context, design, and implementation explain differences in ISP effects in Kenya versus Malawi and Zambia? For question (i), estimation results based on nationwide panel survey data from Kenyan smallholder farmers suggest that participation in NAAIAP significantly increased maize production by an average of 201-471 kg, *ceteris paribus*, mainly by raising maize output/acre (as opposed to expanding the area planted with maize).

NAAIAP also increased the maize share of farmers' total value of crop production but did not affect total area cultivated. Moreover, while the program did not significantly affect net crop income, net total household income, or poverty incidence, it did substantially reduce the poverty gap and severity of poverty (by 4-10 and 4-11 percentage points, respectively). For question (ii), the results are largely robust to the choice of method, with DID, FE, PSW-DID, and PSM-DID with radius matching-based estimates generally leading to same conclusions. Only the PSM-DID with caliper matching-based estimates lead to substantively different conclusions, but this is likely due to the poorer matches achieved with this one-to-one matching algorithm.

A comparison of our results with those seen elsewhere in the literature suggests that NAAIAP had generally larger impacts on maize production than did Malawi's or Zambia's ISPs; moreover, NAAIAP reduced the severity of poverty to a greater extent than did Zambia's ISP. The reasons for this are likely due (at least in part) to NAAIAP's more effective targeting of relatively land- and asset-poor farmers (Sheahan et al., 2014) and its implementation through the private sector, rather than the parallel distribution system found in Malawi and Zambia.

Beginning in the 2014/15 crop year, some Kenyan counties started implementing their own ISPs to complement the national government-run NAAIAP. So what are the implications of these findings for Kenyan counties?[20] First, like the national-level NAAIAP, county-level ISPs should strive to target resource-poor farmers (to improve program impacts on poverty reduction), and target those that cannot afford fertilizer at commercial prices (to reduce crowding out and increase program impacts on total fertilizer use and maize production). Second, county-level ISPs should continue to use vouchers redeemable at private agro-dealers' shops to crowd in private sector participation and improve timely availability of inputs. Third, as our results suggest that the maizefocused NAAIAP may have led to more maize-centric production systems, county-level ISPs might consider allowing the vouchers to be used for seed for crops other than maize and even other crop inputs (e.g., crop protectants, lime, etc.), farm equipment, and livestock or fisheries inputs to put farmers in the driver's seat and promote diversification – an innovation that is being piloted in Zambia in 2015/16. Ultimately, however, Kenyan counties should carefully weigh the (potentially region-specific) costs and benefits of ISPs, and compare these to other possible measures aimed at assisting smallholder farmers to raise their productivity and incomes. More broadly, it is important that ISPs be viewed not as a silver bullet but as one potential element of a more holistic strategy for promoting sustainable agricultural intensification and rural poverty reduction (Jayne and Rashid, 2013; Jayne et al., 2015).

[20] The national government can also apply these lessons to the activities of its National Cereal and Produce Board (NCPB), which is a universal input subsidy program that operates in parallel to NAAIAP.

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9. APPENDIX

Table A1: Tests for parallel trends in outcome variables prior to NAAIAP (mean difference in outcomes between the 2007 and 2004 survey waves)

Outcome variable	Mean: NAAIAP recipients (A)	Mean: NAAIAP non-recipients (B)	Difference (A) - (B)	p-value H_0: (A) = (B) H_1: (A) ≠(B)
Net total income (2010 Ksh)	-37,324.87	-43,059.34	5,734.47	0.92
Net total income per capita per day (2010 Ksh)	20.28	-7.45	27.73	0.55
Poverty incidence (1=poor)	0.00	0.03	-0.03	0.70
Poverty gap	-0.01	-0.01	-0.00	0.93
Poverty severity	-0.01	-0.03	0.02	0.83
Net crop income – both seasons (2010 Ksh)	1,270.77	-33,286.56	34,557.33	0.13
Net crop income – main season (2010 Ksh)	-9,574.33	-40,099.51	30,525.18	0.16
Net crop income/acre – main season (2010 Ksh)	3,743.34	-8,894.77	12,638.11	**0.03
Value of maize production – main season (Ksh)	-2,424.16	-8,457.65	-6,033.49	0.35
Value of non-maize production – main season (Ksh)	-2,161.69	-25,582.34	-23,420.65	0.25
Maize kgs produced – both seasons	161.24	195.35	-34.11	0.91
Maize kgs produced – main season	92.13	142.25	-50.12	0.87
Proportion of crop value comprised of maize	0.03	0.02	0.01	0.73
Number of different field crops grown	-0.41	0.09	-0.49	**0.04
Total acres cultivated – main season	-1.44	-0.31	-1.13	**0.02
Acres cultivated with maize – main season	-0.11	-0.06	-0.04	0.87
Maize output/acre – main season (kg maize/acre with maize)	135.21	126.04	9.16	0.99

Notes: ***p<0.01. **p<0.05. *p<0.10. N=1,064 (49 NAAIAP participants and 1,015 non-participants).
Source: Authors' calculations.

Table A2: Control variables and summary statistics

Variable	Mean	Std. dev.	25th percentile	50th percentile	75th percentile
HH participated in NAAIAP (=1) (summary stats for 2010 only)	0.05	(0.21)	0	0	0
Maize wholesale price (2010 Ksh/kg, t-1)	22.86	(2.87)	20.94	22.25	24.96
Beans wholesale price (2010 Ksh/kg, t-1)	7,002.62	(1,747.84)	4,870.00	7,368.99	8,379.10
Cowpeas wholesale price (2010 Ksh/kg, t-1)	5,382.31	(1,296.26)	4,592.93	5,010.46	5,800.00
Sweet potato wholesale price (2010 Ksh/kg, t-1)	2,217.42	(869.42)	1,474.00	1,850.14	3,160.00
Irish potatoes wholesale price (2010 Ksh/kg, t-1)	3,482.05	(1,504.46)	2,139.38	2,850.00	4,502.27
Cassava wholesale price (2010 Ksh/kg, t-1)	1,905.06	(834.17)	1,100.00	1,920.68	2,004.32
District median cost of DAP fertilizer (2010 Ksh/kg)	54.87	(3.99)	52.42	55.00	57.41
District median cost of hybrid seeds (2010 Ksh/kg)	157.27	(36.39)	130.00	140.92	192.72
Agricultural wage (2010 Ksh/hour)	23.31	(7.11)	17.99	21.84	26.10
Land rental price (2010 Ksh/acre/year)	4,657.78	(2,155.51)	3,083.56	4,175.39	6,167.13
Km to nearest tarmac road	6.98	(6.54)	2	6	10
Km to nearest motorable road	0.62	(1.00)	0.10	0.20	0.70
Km to nearest fertilizer seller	3.11	(3.24)	1	2	4
Km to nearest maize seed seller	3.27	(3.62)	1	2	4
Km to nearest extension advice	4.74	(4.38)	2	4	6
Km to nearest piped water	4.74	(7.08)	0.20	2	6
Km to nearest health center	2.94	(2.70)	1	2	4
Proportion of village respondents that have received any credit	0.49	(0.31)	0.21	0.46	0.75
Main season rainfall (mm)	600.90	(253.05)	428.94	613.89	778.60
Main season rainfall (squared)	425,092.70	(301,176.40)	183,989.50	376,860.90	606,217.90
Moisture stress (main season % of 20-day periods with <40 mm rainfall)	30.30	(24.64)	7.69	25.00	53.85
Long-run average main season rainfall (mm, last 10 years)	551.15	(168.44)	425.62	589.96	705.72
Long-run average moisture stress (%, last 10 years)	30.06	(20.82)	10.77	23.54	51.67
Average temperature over main growing season (°C)	22.06	(4.37)	21.60	23.17	25.66
Elevation (meters above sea level)	1,667.46	(339.35)	1,463.92	1,647.45	1,910.84
1=Rift Valley Province	0.23	(0.42)	0	0	0
1=Eastern Province	0.19	(0.39)	0	0	0
1=Nyanza Province	0.20	(0.40)	0	0	0
1=Western Province	0.22	(0.42)	0	0	0
1=Central Province	0.15	(0.36)	0	0	0
Value of productive assets excluding land & TLU (2010 Ksh, previous survey)	107,173.20	(550,047.7)	4,893.96	19,032.08	64,074.64
Land owned (acres)	5.22	(6.62)	1.80	3	6

Variable	Mean	Std. dev.	25th percentile	50th percentile	75th percenti
Tropical livestock units (TLU, for cattle, sheep, goats, and pigs, previous year)	2.34	(4.04)	0.80	1.50	2.90
1=Female head	0.24	(0.43)	0	0	0
Age of head	58.77	(13.25)	49	59	68
Number of children age 4 and under	0.40	(0.69)	0	0	1
Number of children age 5 to 14	1.47	(1.54)	0	1	2
Number of prime age adults (age 15 to 59)	3.04	(1.81)	2	3	4.08
Number of adults age 60 and above	0.68	(0.75)	0	0.75	1
1=Head has lower primary education	0.19	(0.39)	0	0	0
1=Head has upper primary education	0.35	(0.48)	0	0	1
1=Head has secondary education	0.21	(0.41)	0	0	0
1=Head has post-secondary education	0.08	(0.27)	0	0	0
1=HH experienced post-election violence after 2007 (summary stats for 2010 only)	0.59	(0.49)	0	1	1
1=Max education in HH is lower primary	0.02	(0.14)	0	0	0
1=Max education in HH is upper primary education	0.25	(0.43)	0	0	0
1=Max education in HH is secondary education	0.49	(0.50)	0	0	1
1=Max education in HH is post-secondary education	0.23	(0.42)	0	0	0
1=Experienced death of male head/spouse in past 3 years	0.01	(0.08)	0	0	0
1=Experienced death of female head/spouse in past 3 years	0.01	(0.11)	0	0	0
1=Experienced death other prime-age death in past 3 years	0.04	(0.20)	0	0	0
1=Male head/spouse has been chronically ill	0.06	(0.23)	0	0	0
1=Female head/spouse has been chronically ill	0.06	(0.24)	0	0	0
1=Other prime-age member has been chronically ill	0.07	(0.25)	0	0	0
1=HH belongs to any group or farmer organization	0.77	(0.42)	1	1	1

Note: N=3,192.

Source: TAPRA surveys, 2004, 2007, and 2010.

Table A3: Probit model results used to obtain estimated propensity scores (dependent variable=1 if household participated in NAAIAP)

HH and other characteristics (as of 2007 survey wave)	Coef.	APE	p-value
1=Female head	-0.06	-0.00	(0.78)
Age of head	-0.00	-0.00	(0.65)
Number of children age 4 and under	0.05	0.00	(0.67)
Number of children age 5 to 14	0.02	0.00	(0.71)
Number of prime age adults (age 15 to 59)	-0.05	-0.00	(0.39)
Number of adults age 60 and above	-0.00	-0.00	(0.97)
1=Head has lower primary education	-0.36	-0.03	(0.24)
1=Head has upper primary education	-0.07	-0.01	(0.81)
1=Head has secondary education	-0.12	-0.01	(0.72)
1=Head has post-secondary education	-0.11	-0.01	(0.84)
Value of productive assets excluding land and TLU (2010 Ksh)	0.00	0.00	(0.84)
Land owned (acres)	-0.03	-0.00	(0.19)
Tropical livestock units (TLU, for cattle, sheep, goats, and pigs)	-0.10*	-0.01*	(0.06)
1=HH head belongs to group or farmer organization	-0.09	0.25***	(0.65)
Km to nearest fertilizer seller	-0.01	-0.00	(0.89)
Km to nearest maize seed seller	-0.01	-0.00	(0.92)
Km to nearest tarmac road	-0.04***	-0.00***	(0.00)
1=Eastern Province	-4.60***	-0.32***	(0.00)
1=Nyanza Province	-1.01**	-0.07**	(0.01)
1=Western Province	-0.71	-0.05	(0.21)
1=Central Province	-0.24	-0.02	(0.57)
1=Rift Valley Province (base category)	-		
Long-run average main season rainfall	-0.01**	-0.00**	(0.04)
Long-run average moisture stress	-0.05	-0.00	(0.14)
Controls for the tribe of the household head included?	Yes	Yes	

Notes: ***p<0.01. **p<0.05. *p<0.10. APE=average partial effect. N=1,064. Source: Authors' calculations.

Table A4: Fixed effects regression results for selected outcome variables

	(1) Net total income per capita per day (Ksh)		(2) Poverty gap		(3) Maize kgs produced – both seasons		(4) Maize output/acre – main season (kg maize/acre with maize)	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
1=HH participated in NAAIAP	6.93	(0.755)	-0.10***	(0.006)	430.20***	(0.002)	556.42**	(0.024)
1=Year is 2010	-376.48***	(0.008)	0.90***	(0.000)	-7,651.83***	(0.000)	-4,713.87	(0.257)
1=Year is 2007	-153.29***	(0.001)	0.37***	(0.000)	-2,853.72***	(0.000)	-1,981.90	(0.106)
Maize wholesale price (2010 Ksh/kg, t-1)	-4.06	(0.367)	0.01	(0.205)	-68.67	(0.308)	165.96*	(0.071)
Beans wholesale price (2010 Ksh/kg, t-1)	-0.06	(0.109)	0.00***	(0.009)	-1.63***	(0.000)	-0.48	(0.456)
Cowpeas wholesale price (2010 Ksh/kg, t-1)	0.02	(0.155)	-0.00**	(0.039)	0.34***	(0.001)	0.09	(0.564)
Sweet potato wholesale price (2010 Ksh/kg, t-1)	-0.06	(0.202)	0.00	(0.420)	-1.12**	(0.017)	1.60*	(0.095)
Irish potatoes wholesale price (2010 Ksh/kg, t-1)	-0.01	(0.337)	0.00***	(0.001)	-0.09	(0.219)	-0.24	(0.112)
Cassava wholesale price (2010 Ksh/kg, t-1)	-0.01	(0.742)	0.00*	(0.065)	0.13	(0.728)	-0.93	(0.285)
District median cost of DAP fertilizer (2010 Ksh/kg)	-1.46	(0.463)	0.00	(0.198)	-22.94	(0.104)	-6.90	(0.805)
District median cost of hybrid seeds (2010 Ksh/kg)	0.12	(0.779)	-0.00	(0.312)	4.43	(0.201)	4.74	(0.379)
Agricultural wage (2010 Ksh/hour)	0.75	(0.347)	-0.00**	(0.024)	-14.49	(0.104)	-1.61	(0.926)
Land rental price (2010 Ksh/acre/year)	0.01	(0.113)	0.00	(0.255)	0.03	(0.184)	0.06	(0.445)
Km to nearest tarmac road	-1.03	(0.501)	-0.00	(0.936)	-4.53	(0.642)	-32.06*	(0.085)
Km to nearest motorable road	0.80	(0.831)	0.00	(0.825)	44.99	(0.203)	-53.17	(0.501)
Km to nearest fertilizer seller	0.34	(0.794)	0.00	(0.466)	18.21	(0.308)	34.72	(0.465)
Km to nearest maize seed seller	-0.38	(0.666)	-0.00	(0.767)	-12.96	(0.279)	18.60	(0.380)
Km to nearest extension advice	0.02	(0.985)	-0.00	(0.664)	16.07	(0.139)	36.41	(0.261)
Km to nearest piped water	0.33	(0.597)	-0.00*	(0.052)	9.43	(0.315)	28.55	(0.121)
Km to nearest health center	-0.13	(0.939)	-0.00	(0.942)	1.70	(0.928)	0.05	(0.999)
Proportion of village respondents that received any credit	79.06	(0.184)	-0.01	(0.846)	759.12***	(0.002)	251.32	(0.609)
Main season rainfall (mm)	0.07	(0.713)	-0.00***	(0.002)	2.26	(0.171)	1.45	(0.743)
Main season rainfall (squared)	-0.00	(0.256)	0.00***	(0.000)	-0.00***	(0.004)	-0.00	(0.507)
Moisture stress	-0.71	(0.367)	0.00	(0.407)	-17.20*	(0.084)	-2.14	(0.891)

Long-run average main season rainfall (mm, last 10 years)	0.15	(0.513)	-0.00	(0.598)	-1.76	(0.385)	-6.15**	(0.048)
Long-run average moisture stress (%, last 10 years)	-4.04*	(0.070)	0.01***	(0.005)	-65.28***	(0.003)	-73.53	(0.237)
Average temperature over main growing season (°C)	-14.38	(0.218)	0.02	(0.219)	-216.20	(0.113)	-66.01	(0.760)
Value of productive assets (2010 Ksh, previous survey)	0.00	(0.124)	0.00	(0.864)	0.00	(0.370)	-0.00	(0.193)
Land owned (acres)	3.70**	(0.016)	-0.00	(0.102)	66.52**	(0.040)	11.78	(0.815)
Tropical livestock units (TLU)	0.23	(0.848)	0.01**	(0.011)	45.56	(0.313)	-49.72	(0.126)
1=Female head	-44.71**	(0.023)	0.08**	(0.029)	-385.29**	(0.046)	89.91	(0.594)
Age of head	0.95	(0.188)	-0.00	(0.351)	-6.22	(0.219)	-15.62*	(0.075)
Number of children age 4 and under	-18.46***	(0.000)	0.02*	(0.073)	103.67	(0.330)	329.29	(0.108)
Number of children age 5 to 14	-22.88***	(0.000)	0.03***	(0.000)	83.09	(0.281)	29.55	(0.838)
Number of prime age adults (age 15 to 59)	-27.10***	(0.000)	0.04***	(0.000)	34.71	(0.334)	41.01	(0.561)
Number of adults age 60 and above	-37.01***	(0.000)	0.03**	(0.021)	130.26	(0.136)	-24.36	(0.905)
1=Head has lower primary education	-36.77**	(0.014)	0.01	(0.774)	-56.04	(0.682)	-568.43	(0.124)
1=Head has upper primary education	7.05	(0.723)	-0.02	(0.592)	-120.41	(0.401)	-612.63*	(0.079)
1=Head has secondary education	1.09	(0.962)	-0.03	(0.458)	-303.80	(0.158)	-586.43*	(0.080)
1=Head has post-secondary education	45.36	(0.208)	-0.02	(0.741)	-231.29	(0.404)	-1,175.39**	(0.012)
1=HH experienced post-election violence after 2007	0.73	(0.959)	0.01	(0.816)	26.80	(0.875)	-194.05	(0.334)
1=Max education in HH is lower primary	-10.60	(0.784)	0.12	(0.255)	-17.02	(0.958)	507.45	(0.560)
1=Max education in HH is upper primary education	-18.09	(0.582)	-0.04	(0.613)	-159.50	(0.612)	-341.81	(0.272)
1=Max education in HH is secondary education	-9.38	(0.781)	-0.05	(0.524)	-102.94	(0.748)	-498.07	(0.208)
1=Max education in HH is post-secondary education	-5.06	(0.889)	-0.04	(0.609)	-250.34	(0.457)	-183.86	(0.629)
1=Experienced death of male head/spouse in past 3 years	78.94*	(0.075)	-0.07	(0.334)	264.27	(0.482)	-397.10	(0.147)
1=Experienced death of female head/spouse in past 3 years	-13.02	(0.702)	0.07	(0.267)	-76.76	(0.720)	-5.45	(0.978)
1=Experienced death other prime-age death in past 3 years	4.55	(0.783)	-0.02	(0.608)	167.07	(0.389)	-309.24*	(0.093)
1=Male head/spouse has been chronically ill	-8.86	(0.531)	-0.04	(0.110)	-166.40	(0.278)	-400.19	(0.256)
1=Female head/spouse has been chronically ill	12.29	(0.336)	-0.01	(0.714)	55.89	(0.693)	-113.49	(0.520)
1=Other prime-age member has been chronically ill	-4.22	(0.647)	-0.02	(0.418)	298.69	(0.152)	197.21	(0.589)
1=HH belongs to any group or farmer organization	-1.27	(0.893)	-0.02	(0.208)	114.61	(0.305)	498.15*	(0.052)
Constant	1,460.25***	(0.000)	-2.46***	(0.000)	26,973.46***	(0.000)	9,008.19	(0.352)
Controls for the tribe of the household head included?	Yes		Yes		Yes		Yes	
Observations	3,192		3,192		3,192		3,169	

Notes: ***p<0.01. **p<0.05. *p<0.10. p-values are based on robust standard errors clustered at the household level. Source: Authors' calculations.