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By
Martin Limbikani Mwale
Department of Economics, University of Stellenbosch, Cape Town
martinresearch4@gmail.com

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Abstract

Non-classical measurement errors produce biased and inconsistent estimates in estimations. Previous studies have examined the effects of farm production on crop productivity without accounting for non-classical measurement errors. Using satellite data, which is free from neo-classical errors, this study sought to establish whether the effects of Malawi's farm input subsidy on crop productivity are biased. The study compared results generated using satellite yields to those generated using yields reported by farmers through a survey. The study tested the sensitivity of the satellite estimates by changing the possible yields to fertilizer response rates, and the results remained consistent with the main findings. The findings revealed that the effect of farm input subsidies on crop productivity generated through survey data are upward biased. Farmers over-report yields to demonstrate that they are productive and retain their status as subsidy beneficiaries. Studies on farm input subsidies, therefore, need to pay attention to non-classical measurement errors to provide reliable results and policy advice on farm input subsidies. Furthermore, policy on farm input subsidies needs to strengthen the targeting of beneficiaries to evade inclusion and exclusion errors of productive farmers.

Keywords: Maize yields; Farm input Subsidy Program; Satellite data; Strategic Bias; Malawi

1. Introduction

Despite food security being a top agenda item for Sustainable Development Goals (SDGs) (Colglazier, 2015), most countries still struggle to meet their food requirements due to low productivity (Nyagumbo et al., 2020). Low crop productivity is critical in Sub-Saharan Africa (SSA), where the majority of farmers are credit-constrained and rely on subsistence farming (Eriksson et al., 2018). These farmers barely afford market-priced farm inputs, leading to market failure in food supply (Dillon & Barrett, 2017). Reducing market failures through subsidizing farm inputs is a popular strategy SSA countries use to improve crop productivity (Sheahan & Barrett, 2017). However, whether these agriculture subsidy programs effectively increase the crop productivity remains contentious. Evaluations reveal discrepancies in the reported impacts of the subsidy programs on crop productivity variations in reported crop yields (Jayne et al., 2018).

The main objective of this study, therefore, is to understand whether non-classical misreporting errors influence the observed impacts of the subsidies on maize productivity. To date, this subject remains non-investigated within the SSA's subsidy literature (As can also be seen in a systematic review of this literature by Jayne et al. (2018) and Hemming et al. (2018)). Hence, this is the main contribution of this study. The study uses data obtained from Malawi. Malawi is an interesting case because it pioneered the implementation of the agricultural subsidy programs, yet the impacts of the Malawi Farm Input Subsidy Program (FISP) on maize productivity, remain contentious.

While some studies showed that the FISP increased maize yields (S. T. Holden & Fisher, 2015; Karamba & Winters, 2015), others revealed that the impacts of the program on maize yields were limited (Jayne et al., 2018; Messina et al., 2017). However, each of these literature strands relies on measuring yields using data that is reported by farmers through surveys. This data is prone to two forms of measurement error. The first form of measurement error is classical and involves random misreporting of harvests among subsistence farmers due to poor record-keeping (Abay et al., 2019). Subsistence farmers often use non-standard units when reporting the harvests (Lobell et al., 2020). Because this form of measurement is random, it only affects estimation precision but not bias coefficients (Abay et al., 2019).

The second form of measurement error is non-classical and involves a group of farmers with similar attributes systematically misreporting yields (Abay et al., 2019). The Non-Classical Measurement Error (NCME) is critical because it biases coefficients in evaluations (Kosmowski et al., 2021). NCME can be more applicable to agricultural subsidy implementation. One reason for this is political pressure to demonstrate that the programs are enhancing food security even when the de facto impacts of the programs are limited (Jerven, 2014). Politics plays a clientele role by rewarding areas that support this course with large numbers of beneficiaries for the programs (Chinsinga & Poulton, 2014). Another reason for NCME is that beneficiaries over-report yields to demonstrate that they are efficient users of the subsidies (Basurto et al., 2020). This productivity signaling likely assists them to protect their beneficiaries' status and continue receiving the subsidy.

Without using alternative maize yields data that is free from NCME, evaluating the objective impacts of the subsidy programs on maize productivity therefore remains difficult. Particularly, due to the scarcity of this alternative data, the debate on the impacts of the agriculture subsidy programs on crop productivity remains under-informed. Yields calculated using satellite data provide this alternative. Because space products used in predicting satellite yields are independent of farmers' reports, NCME can be eliminated. Messina et al. (2017) made the first attempt to use satellite data in evaluating the effects of agricultural subsidies on maize yields. However, their study remains in inadequate guide to the productivity debate due to several reasons.

Firstly, Messina et al. (2017) compare national yields aggregate to Food and Agricultural Organization (FAO) estimates, yet the subsidy-productivity debate grounds in studies that use micro-survey data (for instance see systematic reviews by Jayne et al. (2018) and Hemming et al. (2018)); Secondly, they do not establish the presence of the subsidies' strategic bias in reporting yields, hence their results cannot be disentangled from the impacts of other yield determinants beyond the programs. In addition, they do not account for the potential endogenous selection of beneficiaries into subsidy programs. Therefore, Messina et al. (2017) results are not comparable to the previous literature on the subject, which used micro-survey data.

Therefore, this paper estimates the effects of agriculture subsidies on maize yields by comparing micro-level results from yields data that are provided by farmers through surveys, and results from yields data that are generated using satellite products. It first establishes the presence of strategic bias in maize yield misreporting, before estimating the effects of the subsidies on maize yields. Furthermore, it accounts for the potential non-random selection of beneficiaries into the subsidy programs using instrumental variables. It investigates whether the yields misreporting resulted from resulted production or land area, by creating four scenarios of yield: in their first scenario it generates yields using farmers' production and GPS land area; in the third scenario it generates yields using satellite production and farmers' land area; and in the last scenario, it uses satellite production and satellite land area.

This paper makes several contributions to the scholarly work on farm input subsidies. Firstly, it informs the debate on whether SSA agriculture subsidies improved maize productivity. While studies (including Lunduka et al. (2013); Hemming et al. (2018); Jayne et al. (2018)) agree that total maize production increased under the subsidies, they disagree on whether this was achieved through increased productivity. A strand of literature (Mason et al., 2013; Seleka & Mmopelwa, 2020) shows that increase in total maize production were attained through allocating more land maize production. While this paper does not estimate the NCME-free impacts of subsidies on land under maize cultivate, its results provide an explanatory basis to suggest so, because it does not find the effects of the subsidies on maize productivity.

Secondly, the paper contributes to the literature about the targeting efficiency of the farm input subsidies. While previous evidence from Kilic et al. (2015) and (Asfaw et al., 2017) only shows that FISP mistargets beneficiaries through inclusion errors, it adds that this mistargeting has far-reaching consequences. Particularly, the results suggest that mistargeting distorts assessments of value for money in the FISP investment. This is because the true impacts of the program on maize yields are distorted by NCME from unintended beneficiaries who seek alignment to the political narrative of a successful program and also wish to safeguard their beneficiary status.

In addition, the paper contributes to the debate about whether subsidies should be made universal or remain targeted. While targeted subsidies can be seen to promote misreporting bias, we argue that they remain a lesser evil compared to universal subsidies. This is because, under universal subsidies, the mistargeting effects observed here would be amplified. Thus, many farmers who do not need the subsidy to improve maize productivity would access it and dampen the overall productivity gains from the program. They would, in the end, only substitute market-accessed inputs for the subsidized inputs (Ricker-Gilbert et al., 2011; Ricker-Gilbert & Jayne, 2017). This would also stall the development of the agriculture inputs market (Mason & Ricker-Gilbert, 2013).

In addition to these empirical contributions, this study also tests the economic theory of second best (Abay et al., 2019; Lipsey & Lancaster, 1973). This theory states that when two or more economic items are in equilibrium, efforts to correct distortions of one may drive the outcomes away from Pareto efficiency. The effects of FISP on crop productivity could be biased because of the mismeasured independent variable (FISP beneficiary status) and the dependent variable (productivity). Yet previous studies have spent much effort correcting only FISP beneficiary status measurement errors using instrumental variables techniques. This study addresses errors in both the independent and dependent variables (using instrumental variables and satellite data, respectively) and confirms the theory.

2. The Malawi Farm Input Subsidy Program

With the aim of increasing food production, agriculture subsidies were introduced in Sub-Saharan Africa during the 1960s and 1970s (Crawford et al., 2003). These earlier subsidies were universal and mainly boosted fertilizer usage(Jayne et al., 2018). However, it became apparent that universal subsidies were a fiscal burden to the implementing countries, that could not be satisfied over time due to increase in the cost of inputs(Jayne et al., 2018). Through Structural Adjustment Programs (SAPs), the universal subsidies were therefore abolished in the late 1980s and early 1990s (Jayne et al., 2018). After abolishing the subsidies, the SSA experienced declines in food productions, and increases in food insecurity (Harou, 2018). In response to the rising food insecurity, SSA countries began to reintroduce subsidy program in the 2000s.

Unlike the earlier universal subsidies, the second-generation farm input subsidies were targeted, here coined “smart subsidies” or “targeted subsidies” (Jayne & Rashid, 2013). They aimed to increase input usage, and ultimately crop productivity, among poor smallholder farmers. These were farmers who could not manage to purchase the inputs at market prices but stood to benefit the most if they were to access the inputs (Harou, 2018). This generation of subsidies also aimed to induce market development (Morris, 2007). Beneficiaries received vouchers that could be used to redeem inputs at the subsidized price from selected agro-dealers (Chibwana et al., 2010). The dealers obtained full reimbursement of the vouchers from designated government agencies, hence the targeted subsidy programs increased market participation (Morris, 2007). Malawi pioneered the targeted subsidy program, and several other countries including Nigeria, Zambia, Tanzania. Kenya, and Ghana, followed.

Malawi introduce its Farm Input Subsidy Program, popularly known as FISP, in 2005. This was to offset a prolonged severe food shortage that hit the country in the early 2000s. In this period, Malawi required food aid for about 38 percent of its population to become food secure (Denning et al., 2009). At its inception, FISP targeted 50 percent of farmers(S. Holden & Lunduka, 2012). Beneficiaries received four vouchers that could be used to redeem inputs. Two of these vouchers could redeem a bag of 50 kilograms of fertilizer each, used for basal and top dressing, respectively (Lunduka et al., 2013). The subsidy covered 64 to 91 percent of the fertilizer cost between 2005 and 2010 (Harou, 2018). The remaining two vouchers could redeem maize seeds (Holden & Lunduka, 2012). Government statistics reported dramatic increase in maize productions in the early years of FISP implementation. For instance, it was reported that in 2007 the country attained a 53 percent maize surplus, overturning the pre-FISP food deficit of 43 percent recorded in 2005 (Denning et al., 2009; Lunduka et al., 2013). However, these high levels of maize production have been contested. For instance, (Jerven, 2014) revealed that FISP's maize production was over-reported, and the over reporting resulted from a collusion between agricultural extension workers and smallholder farmers, who intended to maintain high FISP concentration in their areas (Jerven, 2014). The concerns about the accuracy of these estimates further increased following the 2007 government claim of 1.5 million metric tons of surplus maize that was exported to Zimbabwe, but never fully materialized(Chinsinga & Poulton, 2014). The exportation was stopped after sending 302, 000 metric tons to Zimbabwe (Chinsinga & Poulton, 2014). In the following months, maize prices dramatically increased, and the Ministry of Agriculture banned maize exports (Chinsinga & Poulton, 2014).

The paradox of non-existent maize surpluses attracted academic attention that put into question the impacts of the FISP on maize productivity. While a consensus is reached that FISP increased maize production (Hemming et al., 2018), disagreements remain on the extent of these impacts(Jayne et al., 2018), and importantly on whether increases in total maize production resulted from rising productivity; high yields. While (Karamba & Winters, 2015) show that this was the case, (Jayne et al., 2018) argue that maize volumes increased, but at low productivity. This is because even land which was not suitable for maize growing was used for maize cultivation to leverage the available subsidized inputs (Chibwana et al., 2012).

Besides the contentious productivity effects of FISP on maize yields, the targeting of beneficiaries has also been a point of controversy. Particularly, the targeting of FISP has remained loosely defined, leading to inclusion errors

(Kilic et al., 2015). The documented beneficiary selection criteria stipulated that primarily, recipients must be Productive poor (Basurto et al., 2020), without defining the threshold of poverty and productivity required for a household to enter into the program. Secondary attributes for the selection also remained blunt. For instance, FISP required that recipients be permanent members of their communities(Karamba & Winters, 2015) without defining the number of years since immigration into a community, required for a household to be deemed permanent. The loosely defined attributes are however not the only loopholes in the mistargeting of FISP. Even the more clearly defined secondary criteria have not been followed. From 2008 FISP changed from targeting areas with more farmland to areas with high population density (Lunduka et al., 2013). Malawi's densely populated areas also contained many poor farmers (National Statistics Office, 2005). Therefore, beyond 2008 FISP emphasized vulnerability as key selection attribute. This stance aimed to increase targeting towards female-headed households, child-headed households, households taking care of the elderly, and households taking care of the HIV/AIDS infected (Chinsinga & Poulton, 2014). However, empirical evidence (Kilic et al., 2015) reveals that FISP's vulnerability targeting was not well achieved.

Poor definition and enforcement of targeting criteria allowed tradition leaders and villagers who managed selection process to define the final selection attributes un their context (Holden & Lunduka, 2013). This opened up avenues for the inclusion of unintended beneficiaries. Indeed, Holden & Lunduka (2013) found that FISP benefited male headed households more than female-headed households, while Kilic et al. (2015) found that FISP ended up in the hands of the relatively wealthier farmers. Wealthier farmers did not need the program to impve their productivity, as they could afford market-priced inputs (Ricker-Gilbert & Jayne, 2017). Therefore, productivity effects of FISP were limited, when the wealthier dominated (Ricker-Gilbert & Jayne, 2017). Nevertheless, to remain beneficiaries, these wealthier farmers needed to show that receiving FISP improved their productivity (Basurto et al., 2020), even though this may not have been the case. Over-reported productivity could manifest either by over-reporting production (the numerator for yield measurement) or under-reporting land areas (the denominator for yield measurement).

Therefore, weak targeting of FISP that maintained inclusion errors through misreporting yields, in addition to the political demand to demonstrate that FISP increased production, might have led to over-reporting of the impacts of the program on maize yields. However, previous evaluations of the program lacked alternative means to cross-check results produced using government administrative data of farmer-reported survey data. Therefore, this study cross-examined the impacts of FISP on maize yields, using yields provided by farmers (prone to NCME) against yields generated by satellite data (free from NCME).

3. Data

To study how the impacts of FISP on maize productivity differ when accounting for strategic misreporting of yields, data were obtained from two sources. The first was from a survey that collected information concerning maize production and land areas from Malawian farmers. The second was from retrospect satellite products that were used in predicting yields that a specific maize field, that the survey reports on, should have produced at the time of harvest. They linked the survey and satellite data by the geographical coordinates that each of these data sources provided. After linking the data from the two sources, there were farmer-reported and satellite-generated yields for the same farms, that could be used interchangeably in the FISP analysis. The study describes these data sources in detail in the following subsections.

Survey data

Survey data was from the fourth Malawi Integrated Households Survey (IHS) conducted by the Malawi National Statistical Office in 2016, with technical support from the World Bank. HIS forms part of the series of Living Standards Measurement Studies for Integrated Surveys in Agriculture (LMS-ISA) that the Bank coordinates in several SSA countries. The HIS aimed to monitor the poverty and welfare of Malawi Households. It interviewed 12, 447 randomly selected households that resided in 779 enumeration areas, also called clusters. Each cluster had approximately 16 households. The HIS is nationally representative at rural, urban, district and regional levels. The HIS provided geographical locations that were however offset at household level by 10 km, but accurate at cluster level. Therefore, the study aggregated all household information at the cluster level. This was necessary to enable accurate linking of survey data and satellite data.

The HIS survey included four questionnaires. The first focused on household characteristics and included geographical files that collected spatial information including the distance between farms and households, cluster slope, elevation, rainfall, and type of agro ecological zones. These files also classified the data into Malawi's three regions, the northern, the central and the southern. The second questionnaire concentrated on the agricultural characteristics. The agricultural questionnaire asked farmers to report on crop production and land area dedicated to each crop in the most recent growing season. The study limited its sample to information about maize. It then generated maize yields by dividing production by land under maize cultivation. The questionnaire also asked the households whether they benefited whether from FISP in the same reference growing season. This is the main treatment variable for the study. The third questionnaire asked about community characteristics, while the last questionnaire asked questions on fisheries, for communities that practiced fish farming.

Because the interest was clusters that had an equal probability of participating in the FISP program, the study concentrated only on those that reported having at least one farmer who cultivated maize in reference growing season. This exercise gave a working sample of 694 survey clusters that had average figure of maize yields and FISP participation. The study then extracted satellite data, used to calculate satellite-generated maize yields from maize yields of the same 694 survey clusters. This was to allow comparisons between the survey and the satellite yields.

Satellite data

Satellite yields were generated using Net-Primary Productivity (NPP), a spatial product from Moderate Resolution Imaging Spectroradiometer (MODIS) data. NPP is the difference between Gross Primary Productivity (GPP) and plant respiratory carbon. It captures what is left in the plant once respiration nutrients are excluded. NPP is an input into maize yield generation model that was formulated by Reeves et al. (2005). The model provides maize yields inkilograms per hectare and was first used on Malawian data by Messina et al. (2017). The model can be presented as follows:

$$Maize\ yields\left(\frac{kg}{ha}\right) = \sum_{DOY}^{\alpha} \frac{NNP_{DOY} \times HI \times AGR \times AC \times SF}{HA} \quad (1)$$

The model in equation 1 predicts maize yields by capturing the changes in photosynthesis cover across Malawi. NNP_{DOY} captures daily net photosynthesis, HI is the fertilizer substitution primary change, AGR above-ground biomass ratio, CB a carbon-to-biomass conversion, AC is areas conversion, and SF is a scale factor to fit a trend lune. HA is hectares obtained by the satellite as an area under maize NPP. The study obtained NNP_{DOY} from each of the IHS cluster locations. The rest of the parameters for calibrating

Equation 1 were obtained from Messina et al. (2017) and Reeves et al. (2005): HI was 0.4, CB 2, AGR 0.86, and SF 0.27. The final product from Equation 1 was the average maize yields in kilograms per hectare from farms of every IHS cluster. These yields are particularly for maize crop that was harvested in the year 2016, a period that matched the survey data.

It is worth noting that the study obtained NNP_{DOY} only from fields that were identified as being under maize crops within the survey clusters. Identification of maize crops, also known as maize crop classification, involved creating a machine-learning algorithm that separated images of maize crops from other crops, and images of maize crops from non-crop land use, using Landsat 7 and 8 images[1].

Furthermore, the algorithm unmasked cloud cover whenever NPP was collected on a cloudy day, to ensure accurate prediction of satellite-generated maize yields. My maize crop classification algorithm achieved an accuracy of 76 percent.

4. Methodology

Empirical Specifications

The empirical application of the research question demanded modelling yields as a function of the FISP for four separate equations that had varying forms of measurement errors. However, the first step involved establishing the presence of the NCME to justify the usage of satellite images. Therefore, the study began by estimating the correlates of measurement errors that included FISP as one of the independent variables as follows:

$$Error_c = \alpha_1 + \alpha_2 FISP_c + \alpha_3 X_{ic} + \epsilon_c \qquad (2)$$

$Error_c$ represents either production or land mismeasurement calculated as the lagged ratio of farmer-reported land area under maize cultivation of farmer-reported production, divided by satellite-calculated land areas under maize cultivation or satellite production[2] in some IHS clusters c. $FISP_c$ captures

[1] The Landsat Program is a series of Earth-observing satellite missions jointly managed by NASA and the U.S. Geological Survey. Landsat satellites have the optimal ground resolution and spectral bands to efficiently track land use and to document land change due to climate, urbanization, drought, wildfire, biomass changes (carbon assessments) and a host of other natural and human-caused changes. (https://www.usgs.gov/faqs/what-landsat-satellite-program-and-why-it-important?)

[2] Because these quantities are cluster averages, and hence no zeros or negative values, logging did not drop any observations. Furthermore, the study used an alternative method that does not

the proportion of program beneficiaries in an IHS survey cluster. X_{ic} contains control variables including average distance from households and their farms, land slope and elevation, average annual rainfall, agro-ecological zones dummies, and regional dummies (including central and south, with the north as the omitted category). α_1 is a constant, α_2 is the NCME coefficient, and α_3 captures the relationship between each of the independent variables and the measurement errors. An α_2 that is significant entails that NCME exists: FISP beneficiaries systematically misreport the measured quantity. An insignificant α_2 entails that misreporting errors are idiosyncratic: they average to zero and, hence cannot bias FISP coefficients. ϵ_c captures all other factors that affect Errors, but might have been omitted from the model.

Establishing NCME in Equation 2 justifies estimating the relationship between FISP and maize yields using both survey and satellite yields as follows:

$$Yields_c = \rho_1 + \rho_2 FISP_c + \rho_3 X_{ic} + \mu_c \qquad (3)$$

In Equation 3 the study presents average yields in a cluster c as a function of FISP, and the same control variables used in Equation 2. ρ_1 is a constant, while ρ_2 is the effect of FISP on maize yields. The study created for scenarios of maize yields to understand whether it is production or mismeasurement that distorts FISP evaluations the most. The first scenario did not correct for any measurement error, the second corrected only for land measurement errors, while the third corrected for production measurement errors. The last scenario corrected for both production and land measurement errors. μ_c is an error term that is assumed to be independent and identically distributed. Nevertheless, this assumption is often violated in observation data. I therefore identified my effects of interest using instrumental variables as explained in the next subsection.

Identification

The main empirical challenge faced by studies that estimate the impacts of FISP on maize productivity is that the selection of beneficiary households into the program is non-random. Whether *de jure* beneficiary targeting criteria, *productive-poor*, were followed religiously, or the *de facto* targeting of wealthier farmers dominated, FISP ended up with farmers that are systematically similar. These groups of farmers could have attributes that relate to their maize production ability and capability, but that are unobserved to the researcher. Therefore, estimating the relationship between the FISP and

drop zero (if they existed) and negative valued observations, the hyperbolic sine transformation, and the results remained the same with those from logging.

maize yields by Ordinary Least Squares (OLS) likely leads to biased coefficients in this setting. The study controlled for this potential endogeneity by instrumenting the proportion of vouchers received in a cluster using two-stage least squares.

The study considered two instrumental variables (IV) : whether the ruling party, the Democratic Progressive Party (DPP), won the district in which a cluster was found, during the 2014 general elections; and the proportion of farmers who received FISP vouchers in the respective district of the cluster in 2016.Mason & Ricker-Gilbert (2013) used these two instruments to examine the effects of FISP on commercial purchases of seeds[3]. Harou (2018) used similar instruments to examine the effects of the FISP on child nutrition[4].

Assume that district IV is Z_d, and $FISP_{dc}$ is the proportion of FISP vouchers in some cluster c found in district d. The IV must fulfill two conditions; it must be relevant, formally $cov(Z_d, FISP_{dc}) \neq 0$, and must meet the exclusion restriction requirement, formally $cov(Z_d, \mu_{dc}) = 0$. Thus, the instrument must significantly increase the probability of benefiting from FISP in a cluster, but increase maize yields only through the FISP coefficient. Mason & Ricker-Gilbert (2013) conducted their study using data from earlier years of FISP implementation and found the ruling party's IV stronger determinant id FISP than the district level coverage of FISP IV. Harou (2018) used relatively recent data (2013) and found that it was the opposite: the ruling party's IV became a weak determinant while the district coupon coverage gain traction.

In this data, which is more recent (2016), the study found that the ruling party's IV was no longer significant determinant of FISP, while the district FISP coverge was a stronger determinant (87.3 percent at $p<0.001$) (Table B.3 of Appendix B) which therefore limited its identification to use only the second IV: district FISP coverage. The rationale is that an increased concentration of FISP vouchers in a district, whether caused by political or non-political reasons, increases the proportion of voucher for clusters within the district. Moreover, the study controlled for agro ecological zones and rainfall patterns in both the first and the second stages to account for other unobserved socioeconomic patterns across clusters. Furthermore, regional dummies were included to capture generic spatial patterns. Harou (2018) used the same approach to her study.

The relevance of the instrument is formally tested in the results section that follows. For the exclusion restriction, the study argues that the district FISP

[3] They specifically examined this using data from 2007, where the 2004 general elections results were the closest.

[4] She used 2013 data, where the 2009 general elections were the closest.

coverage increases the probability of obtaining a voucher in a cluster but not the reverse. However, one might argue that the opposite for other reasons. For instance, they may say that districts that received more vouchers did so because their clusters had more area under cultivation and were highly productive. Nevertheless, the FISP implementation during the period in which our 2016 data is located does not support this premise. Specifically, the FISP distribute most vouchers in areas that had more land under maize cultivation only from 2005 to 2008 (Dorward & Chirwa, 2013). From 2009 onwards, the FISP targeted areas with large number of farm households. Most maize land is in the central region of Malawi, while most farm households are in the densely-populated southern region(Dorward & Chirwa, 2013). Therefore, there is no reason to believe that the IV is endogenous, at least no through this channel.

Furthermore, the study formally tested the validity of the IV. It specifically estimates the direct relationship between maize yields and the district proportion of FISP vouchers, while direct relationship between maize yields and district proportion of FISP vouchers, while controlling for the main treatment, cluster FISP. If there was a significant relationship between the IV and maize yields, then the IV would be invalid. The study conducted this test for both yields reported by farmers and satellite-generated yields. Results, represented in Table B.7, of Appendix B, reveal that there is no direct relationship between the yields and the IV. Therefore, the study proceeds to use the IV in estimating the effects of FISP as done by Mason & Ricker-Gilbert (2013) and (Harou, 2018).

Another potential limitation to the identification of the effects of interest, besides reverse causality, would be if beneficiary farmers sold their inputs instead of using them on their farms. If selling is a serious case, then the results estimated here could be underestimated. However, in this sample, only 0.8 percent of farmers reported having sold their FISP inputs and controlling them or dropping them did not change the findings of the study.

Study Limitations

While this study makes efforts to eliminate selectivity bias through the use of the instrumental variables, the results obtained should still be treated with caution. This is particularly because it used cross-sectional data that may not control time-invariant unobserved bias. Therefore, estimates obtained here should be interpreted as associations but not implying causations. This also has a bearing on the conclusions drawn. Thus, the findings should be regarded as only an important exploratory basis for the topic at hand. The study also wishes to highlight that it was not possible to isolate inter-cropped fields.

However, there is no reason to believe that inter-cropping could happen systematically due to the misreporting bias measured here.

5. Results

Descriptive Statistics

Table 1 shows cluster averages used in the paper. The table presents their definitions, means standard deviations, and minimum and maximum values. Maize yields reported by farmers are lower than those depicted by satellite data. Malawi experienced a severe drought in 2016, notably erratic rains that negatively affected the maize productivity(McCarthy et al., 2021).

Table 1: Summary of Variables used in the paper

Number: 694	Definition	Mean	Std Dev.	Min	Max
Farmers yields	Kilograms per hectare	1132.32	974.36	10.59	10455.51
Satellite yields	Kilograms per hectare	1934.26	404.09	1107.25	5571.06
Farmer land area	Hectares	0.45	0.17	0.01	1.80
GPS land area	Hectares	0.45	0.21	0.04	1.41
Farmer production	Kilograms	490.37	425.22	3	3573.867
Satellite production	Kilograms	853.71	435.43	58.55	4023.93
FISP	Proportion	0.23	0.20	0	1
Distance from household to farm	Kilometers	1.30	2.31	0	27.50
Slope	Percentage	5.28	4.71	0	38
Elevation	Meters	833.15	333.31	42.5	1711.00
Rainfall	Milimeters	839.65	92.73	686.00	1228.33
Tropical warm semiarid	Proportion	0.45	0.50	0	1
Tropical warm subhumid	Proportion	0.00	0.04	0	1
Tropical cool semiarid	Proportion	0.00	0.04	0	1

Tropical cool subhumid	Proportion	0.00	0.04	0	1
Northern region	Proportion	0.15	0.36	0	1
Central region	Proportion	0.35	0.48	0	1
Southern region	Proportion	0.49	0.50	0	1

Because satellite data predicts yield using pre-harvest crop cover, the discrepancy suggests that the actual harvested crop yield was less than that predicted by satellite using on-field crop cover. The clusters show similar average areas under maize cultivation when either farmers' reports or GPS technology is used. However, the total maize production reported by farmers is less than that predicted by satellite data. Therefore, the similarity of land areas measurements combined with the mismatch in maize production reports suggests that production drove yield differences between farmers' and satellites' data.

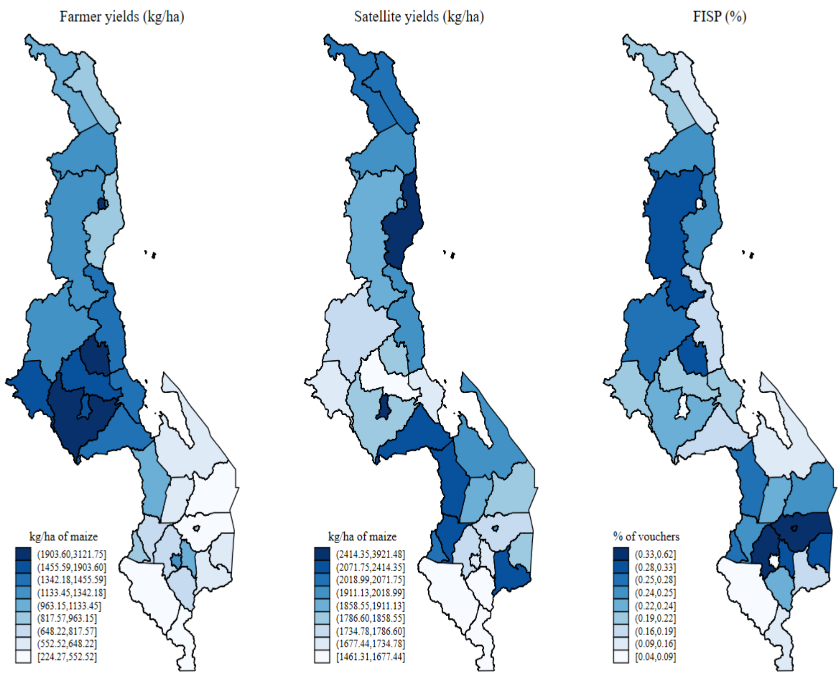
Within the clusters, 23 percent of farmers obtained FISP, and the average distance from a household to a farm was 1.3 kilometers. The average slope was 5.2 percent, elevation was 833.2 meters, and rainfall was 839.7 millimeters. Most of the clusters were samples in tropical warm semiarid agriecological zones, and most of them were from the southern region, followed by the central region, and the rest were from the northern region.

Figure 1 represents a geographical distribution of the main variables of interest across the districts[5], within three regions of Malawi: northern, central and southern. Panels 1 shows maize yields reported by farmers, while Panel 2 shows maize yields as calculated by satellite data. Yields reported by farmers and those projected by satellite data are more closely correlated in the northern region: they are both high. Differences between these two types of yields exist in the central and southern regions. Particularly in the central region, farmer-reported yields are higher than satellite-calculated yields, while in the southern region, farmer-reported yields are higher than satellite-calculated yields. Were the satellite-calculated yields over-predicted, taking into account low harvest due to the 2016 drought, these geographical patterns suggest that the southern region reported yields more accurately, while the central and northern regions over-reported yields.

[5] The HIS survey was stratified at district level, hence this geographical distribution is a good representation of the data patterns in 2016.

These spatial variations in the distribution of FISP beneficiaries could also offer differing incentives for misreporting yields. Particularly where FISP beneficiaries are few, and thus easier to lose than to obtain FISP vouchers, FISP farmers would likely over-report yields. This would allow the farmers to signal productivity (Basurto et al., 2020), and thus retain their beneficiary status. Figure 1 supports this hypothesis by showing that yields were more over-reported in the central region, where FISP vouchers were in low concentration, relative to the northern and southern regions.

Figure 1: Yields and FISP



Source: Author’s own calculations from HIS-4

In what follows, the study tested the relationship between FISP and misreporting. Because yields can be erroneous due to misreported land or production, it analyzed the relationship between FISP and land measurement errors, and that FISP and production measurement errors, separately. If measurement error in either land or production relate significantly to FISP, then yields are reported with strategic bias. Furthermore, if the relationship between FISP and production errors is positive and larger than that between

FISP and land errors, then FISP farmers strategically over-reported yields. This would support the spatial evidence observed in Figure 1.

Evidence for strategic misreporting of yields

Table 2 shows the correlation between measurement errors and FISP. All control variables described in Equation 2 are included in the model. However, for parsimony, the table does not display them: for full results that display coefficients of control variables, see Table A.1 of Appendix B. Column 1 reveals that increasing FISP coverage from zero to 100 percent is associated with a 16 percent rise in over-reporting land area. Column 2 shows that a similar increase in FISP coverage is associated with a 39.2 percent increase in maize production over-reporting. These results confirm the presence of strategic bias that is systematic among recipients, suggesting unique incentives for misreporting, implying an erroneous increase in production per hectare, also referred to as yields or productivity.

The study also tested the correlation between land area, and both land and production misreporting in Column 1 and 2. Clusters with more land under maize cultivation over-report land and production the most. In Malawi, the central region has more land under maize cultivation, and the central region farmers hold larger pieces of land, while the northern

Table 2: The relationship between FISP and measurement errors of land and production

	(1) Land Error	(2) Production Error	(3) Production Error	(4) Production Error
FISP	0.160**	0.392***	0.422***	0.327***
	(0.066)	(0.144)	(0.140)	-0.133
GPS area (log)	-0.456***	-0.444***		-0.259***
	(0.024)	(0.062)		-0.076
Satellite Output (log)			-0.488***	
			(0.062)	
Land error (log)				0.406***
				(0.126)
Constant	-0.107	-7.601*	-6.497*	-7.558*
	(1.185)	(3.914)	(3.853)	(3.924)

Geographical controls	Yes	Yes	Yes	Yes
Agro-ecological zone controls	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes
Observations	694	694	694	694
R^2	0.632	0.539	0.562	0.55

Notes: * p <0.1 ** p<0.05 *** p<0.01

All variables are averages at cluster level. *Land error* and *Production error* are logical continuous variables, generated by dividing farmer reported quantities by satellite generated quantities. *FISP* is a continuous variable, capturing the proportion of the households in cluster who benefited from the program.

Standard errors are displayed in parentheses. The sample is limited to cluster where there was at least a household which cultivated their land in the 2016 growing season. Control variables include *Average distance from a household to its farm; Slope of the cluster; Elevation of the cluster; Rainfall; Tropical warm subhumid dummy; Tropical cool semiarid dummy; Tropical cool subhumid dummy; Central region dummy; and Southern region dummy.*

Source: Own calculations using 2016 IHS data

Southern regions have relatively less land under maize cultivation and have small land holdings (G. Li et al., 2017). Referring back to Figure 1, which shows that the central region over-reported yields more than the other two regions, the results in Table 2, Columns 1 and 2, suggest that large-scale farmers over-reported yields, more than small-scale farmers did.

In columns 3 of Table 2, the study tested whether the scale of production correlates with production misreporting. The results reveal that clusters that have large-scale maize producers over-reported the maize production more than those that produce less maize. Because Malawi's central region produces more maize than the northern and southern regions, this results also supports the geographical evidence in Figure 1. Thus, the central region over-reports yield with the highest magnitude than the other two regions.

Column 4 of Table 2 reveals results from testing the correlation between land and production misreporting and finds that these two errors are positively correlated. This correlation is robust to the inclusion of land area as part of the controls. In addition, just as it is the case in all production specifications of Table 2, FISP remain positively correlated with production misreporting, confirming evidence of strategic bias in yield reporting (Non-Classical Measurement Error), which could distort the reported impacts of FISP on maize yields.

In the following subsection, the study presents from estimating the relationship between maize yields and FISP. OLS results are presented first as a benchmark, followed by instrumental variables results, which account for potential bias in the FISP framework treatment. Thereafter, it shows results from a sensitivity analysis that adjusts the fertilizer-yield conversion factors for the satellite data. The study used the sensitivity analysis as a robustness check for its main results.

Maize yields and FISP: Ordinary Least Squares

Table 3 present results from estimating the relationship between maize yields and FISP, using the OLS technique. For full results that include control variables see Table B.2 of Appendix B. Column 1 shows that, when generating yields using farmer-reported production and farmer-reported land area, increasing the coverage of FISP in a cluster from zero to 100 percent associate with a 34 percent increase in maize yields. Column 2 use GPS technology to measure farmers' production and land area. FISP is associated with a 40 percent increase in maize yields. Column 3 display results when yields are generated using satellite production and the farmers' land area. FISP does not relate maize yields. Finally, Column 4 presents results from yields that are generated by satellite production and satellite area. Results remain insignificant.

Table 3: The association between maize yields and FISP

	(1) Output 1	(2) Output 2	(3) Output 3	(4) Output 4
FISP	0.341***	0.395***	0.044	0.003
	(0.124)	(0.138)	(0.103)	(0.031)
Farmer area (log)	-0.190**		0.213***	
	(0.087)		(0.075)	
GPS area (log)		-0.453***		-0.009
		(0.059)		(0.012)
Constant	-4.951	-6.363*	5.487***	1.238
	(3.791)	(3.753)	(2.093)	(0.918)
Geographical controls	Yes	Yes	Yes	Yes

Agro-ecological zone controls	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes
Obs.	694	694	694	694
R^2	0.555	0.575	0.177	0.184

Note: * p < 0.1 ** p < 0.05 *** p < 0.01
Output 1, 2, 3 and 4 are
$\log\left(\frac{Farmer\ output}{Farmer\ area}\right)$,
$\log\left(\frac{Farmer\ output}{GPS\ area}\right), \log\left(\frac{Satellite\ output}{Farmer\ area}\right)\ and\ \log\left(\frac{Satellite\ output}{Satellite\ area}\right)$ respectively.
Production and *Land area* are logged continuous variables. *FISP* is a continuous variable, capturing the proportion of households in a cluster who benefited from the program.
Standard errors are displayed in parentheses. The sample is limited to clusters where there was at least a household which cultivated their land in 2016 growing season. Control variables include *Average distance from a household to its farm; Slope of the cluster; Elevation of the cluster; Rainfall; Tropical warm subhumid dummy; Tropical cool semiarid dummy; Tropical cool subhumid dummy; Central region dummy; and Southern region dummy.*
Source: Own calculations using HIS 2016 data

Table 4: Instrumental variable estimates: the effects of FISP and maize yields

	(1) Output 1	(2) Output 2	(3) Output 3	(4) Output 4
FISP	0.757***	0.622**	0.635**	0.031
	-0.324	-0.315	-0.282	-0.08
Farmer area (log)	-0.243***		0.138*	
	-0.088		-0.08	
GPS area (log)		-0.470***		-0.011
		-0.062		-0.013
Constant	-5.051	-6.402*	5.436**	1.233
	-3.726	-3.708	-2.116	-0.912
Geographical controls	Yes	Yes	Yes	Yes
Agro-ecological zone controls	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes
Obs.	694	694	694	694
First-stage statistic	58.992	70.975	58.992	70.975
R^2	0.547	0.572	0.01	0.183

Note: * p < 0.1 ** p < 0.05 *** p < 0.01

Output 1, 2, 3 and 4 are
$\log\left(\frac{Farmer\ output}{Farmer\ area}\right)$,
$\log\left(\frac{Farmer\ output}{GPS\ area}\right), \log\left(\frac{Satellite\ output}{Farmer\ area}\right)\ and\ \log\left(\frac{Satellite\ output}{Satellite\ area}\right)$ respectively.
Production and *Land area* are logged continuous variables. *FISP* is a continuous variable, capturing the proportion of households in a cluster who benefited from the program.

Standard errors are displayed in parentheses. The sample is limited to clusters where there was at least a household which cultivated their land in 2016 growing season. Control variables include *Average distance from a household to its farm; Slope of the cluster; Elevation of the cluster; Rainfall; Tropical warm subhumid dummy; Tropical cool semiarid dummy; Tropical cool subhumid dummy; Central region dummy; and Southern region dummy.*

Source: Own calculations using HIS 2016 data

Maize yields and FISP: Instrumental Variables

Table 4 presents results from estimating the effects of FISP on maize yields using IV technique. For full results that include control variables see Table B.4 of Appendix B. The results reveal that the instrument, the proportion of FISP vouchers in the district, is relevant, with first-stage statistics that are above the rule of thumb (10) across all specifications. Table B.3 of Appendix B confirms the instrument relevance, by showing first-stage relationship between the IV and FISP, that is positive and significant.

Column 1 of Table 4 reveals that using both production and land area that is reported by farmers, FISP increase maize yields by 76 percent. Column 2 uses production that is reported by farmers but the land area that is recorded by GPS technology, and FISP increases maize yields by 62 percent. Column 3 shows results when using satellite-generated production but land area reported by farmers, and FISP increases maize yields by 64 percent. Column 5 reveal that when using both satellite-generated production and land area, FISP does not affect maize yields.

Comparing the IV results in Table 4 with the OLS results in Table 3, one can observe that OLS underestimated the biased relationship between FISP and maize yields, as all FISP coefficients in Table 4 are larger than those in Table 3 across all specifications. Moreover, the relationship between FISP and maize yields that are generated by satellite output and farmers' production is significant only in Table 4. These outcomes highlight the presence of estimation bias in the OLS coefficients of FISP and thus support the use of the IV.

The results in Table 4 also reveal that using both production and land area that are reported by farmers are thus prone to strategic bias, leads to coefficient with the largest reported effects. Using only production or land areas that are reported by farmers, but not both, reduces the size of the coefficient of FISP. However, significant effects of FISP remain with this [atrial cleaning of strategic bias. The effects of FISP on maize yields disappear only when production and land area are generated using satellite data.

Because satellite products calculate maize yields by combining data collection and calibration, this study follows Messina et al. (2017) to change the value of the Harvest Index (HI) used in generating satellite yields. The HI is the ratio of harvested production to total shoot dry matter (Fan et al., 2017). The HI signals that nutrition available for a crop to grow, as it is a function of environmental suitability for the cultivated crop (Li et al., 2022). Conditional on the environmental suitability, the same quantity of applied fertilizer has different returns on plots with different HI. In the case of maize, a high HI translates into more kilograms of corn per kilogram of applied fertilizer (Hütsch & Schubert, 2017). The HI, therefore, allows one to understand if the effects of FISP on maize yields. This study also uses instrumental variables in the tests. The results for this sensitivity analysis are presented in the subsection that follows.

Maize yields and FISP: sensitivity analysis

Table 5: Satellite yields and harvest indices

Harvest Index	Satellite yields (kg/ha)
0.2	967.13
0.3	1450.7
0.4	1934.26
0.5	2417.83
0.6	2901.39

Source: Own calculations using HIS 2016 data

Table 5 presents different levels of satellite yields achieved when adjusting the HI between 0.2 and 0.6. Those ranges of HI are chosen following Hay & Gilbert (2001) who show that Malawian Harvest indices range from 0.2 at the lowest harvest to 0.6 at the highest harvest. As the HI increases, maize yields increase. The increase in HI would, however, only affect the effects of FISP on maize yields if it is related to the distribution of FISP. In the results that follow, the study presents the effects of FISP on maize yields when yields are generated by the minimum HI of 0.2, then the maximum HI of 0.6. Recall that the main results, already presented in Table 4, use the intermediate HI of 0.4. Hence, the sensitivity results are discussed in relation to the results in Table 4.

Table 6 presents results when using an HI of 0.2. For full results that include control variables, see Table B.5 of Appendix B. Because satellite products are only used when yields are generated using either satellite production or land area, the study does not anticipate the change in the effects of FISP on maize yields when both production and land area are reported by farmers. And indeed, Column 1 of Table 6 confirms this showing that results are the same as those presented in Column 1 of Table 4. If levels of HI matter, then using an HI of 0.2 should affect the coefficients of FISP in columns 2, 3, and 4, where satellite products are used. This is not the case because the coefficients remain the same as those presented in Table 4, where an HI of 0.4 is used. However, the constants for the models in the two tables, Columns 2, 3 and 4, differ. Particularly, constants that use the HI of 0.2 are lower than those using HI of 0.4.

Table 6: Sensitivity analysis: using a Harvest Index of 0.2

	(1) Output 1	(2) Output 2	(3) Output 3	(4) Output 4
FISP	0.757***	0.622**	0.635**	0.031
	(0.324)	(0.315)	(0.282)	(0.080)
Farmer area (log)	-0.243***		0.138*	
	(0.088)		(0.080)	
GPS area (log)		-0.470***		-0.011
		(0.062)		(0.013)
Constant	-5.051	-6.402*	5.436**	1.233
	(3.726)	(3.708)	(2.116)	(0.912)
Geographical controls	Yes	Yes	Yes	Yes
Agro-ecological zone controls	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes
Obs.	694	694	694	694
First-stage statistic	58.992	70.975	58.992	70.975
R^2	0.547	0.572	0.01	0.183

Note: * p < 0.1 ** p < 0.05 *** p < 0.01

Output 1, 2, 3 and 4 are $\log\left(\frac{Farmer\ output}{Farmer\ area}\right)$, $\log\left(\frac{Farmer\ output}{GPS\ area}\right)$, $\log\left(\frac{Satellite\ output}{Farmer\ area}\right)$ and $\log\left(\frac{Satellite\ output}{Satellite\ area}\right)$ respectively. *Production* and *Land area* are logged continuous variables. *FISP* is a continuous variable, capturing the proportion of households in a cluster who benefited from the program.

Standard errors are displayed in parentheses. The sample is limited to clusters where there was at least a household which cultivated their land in 2016 growing season. Control variables include *Average distance from a household to its farm; Slope of the cluster; Elevation of the cluster; Rainfall; Tropical warm subhumid dummy; Tropical cool semiarid dummy; Tropical cool subhumid dummy; Central region dummy; and Southern region dummy.*
Source: Own calculations using HIS 2016 data

Table 7 repeats the estimation, but now uses an HI of 0.6. For full results that include control variables see Table B.6 of Appendix B. The coefficients pf FISP remain the same as those observed in Table 4 and 6. However, the constants of estimations differ. Particularly, Table 7 displays larger constants than those that are shown in Table 4 and 6.

Results for the sensitivity analysis therefore reveal that the effects of FISP on maize yields are robust to changes in the level of yields, as the study adjusts the size of calibration parameters. Thus, different parameters adopted by the satellite prediction do not alter the impacts of FISP. These results suggest that the strategic bias in reporting yields by FISP beneficiaries remains stable at different levels of fertilizer to yields conversion ratios. Besides following Messina et al. (2017) in adjusting HI, the study also tried the rest of the parameters indicated in Equation 1. Just as is the case with HI, changes in the other parameters only modified constants for models that use satellite products, but not the effects of FISP on maize yields.

The results in Table 4, 6 and 7 confirm what was found in Table 2, that FISP farmers strategically over-report yields, introducing NCME, and their reports bias the relationship between FISP and maize yields. Table B.3 in Appendix B. adds that these FISP farmers reside in clusters that have large areas under maize cultivation.

Table 7: Sensitivity analysis: using a Harvest Index of 0.6

	(1) Output 1	(2) Output 2	(3) Output 3	(4) Output 4
FISP	0.757***	0.622**	0.635**	0.031
	(0.324)	(0.315)	(0.282)	(0.080)
Farmer area (log)	-0.243***		0.138*	
	(0.088)		(0.080)	
GPS area (log)		-0.470***		-0.011
		(0.062)		(0.013)
Constant	-5.051	-6.402*	5.436**	1.233
	(3.726)	(3.708)	(2.116)	(0.912)
Geographical controls	Yes	Yes	Yes	Yes
Agro-ecological zone controls	Yes	Yes	Yes	Yes
Regional controls	Yes	Yes	Yes	Yes
Obs.	694	694	694	694
First-stage statistic	58.992	70.975	58.992	70.975
R^2	0.547	0.572	0.01	0.183

Note: * p < 0.1 ** p < 0.05 *** p < 0.01
Output 1, 2, 3 and 4 are
$\log\left(\frac{Farmer\ output}{Farmer\ area}\right)$,
$\log\left(\frac{Farmer\ output}{GPS\ area}\right)$, $\log\left(\frac{Satellite\ output}{Farmer\ area}\right)$ and $\log\left(\frac{Satellite\ output}{Satellite\ area}\right)$ respectively.
Production and *Land area* are logged continuous variables. *FISP* is a continuous variable, capturing the proportion of households in a cluster who benefited from the program.
Standard errors are displayed in parentheses. The sample is limited to clusters where there was at least a household which cultivated their land in 2016 growing season. Control variables include *Average distance from a household to its farm; Slope of the cluster; Elevation of the cluster; Rainfall; Tropical warm subhumid dummy; Tropical cool semiarid dummy; Tropical cool subhumid dummy; Central region dummy; and Southern region dummy.*
Source: Own calculations using HIS 2016 data

6. Discussion

Because evaluations (for instance, see Jayne et al. (2018) and Messina et al. (2017)) disagree on whether or not farm input subsidies increase crop productivity, the impacts of farm input subsidy programs remain widely contested. They are contested despite evidence that the subsidies bolster food security through self-sufficiency (Sibande et al., 2017). The past evaluations however examined the impacts of subsidies on crop productivity using yields that were prone to strategic bias (Jerven, 2014). Strategic bias is hypothesized to exist especially where targeting of subsidy beneficiaries is loose to allow inclusion errors(Chinsinga & Poulton, 2014), and where misreporting yields is politically attractive (Jerven, 2014).

This study used Malawi as a case study and found evidence that the country's subsidy program, popularly known as FISP, does not associate with increased maize productivity once strategic bias in reporting production and area under maize cultivation (inputs in maize yields generation), is eliminated. It specifically shows that FISP beneficiaries over-report harvest. Furthermore, those beneficiaries are *de facto* large-scale farmers, residing in areas with more land under maize cultivation, who were supposed to be excluded from the FISP, in favour of the *de jure* small-scale farmers. The results reveal that allowing for over-reporting of yields among beneficiaries leads to positive and significant impacts of FISP on maize productivity. These positive impacts are however all absent once the over-reporting bias is eliminated using maize yields that are generated by satellite products.

Over-reporting of yields to justify positive impacts of subsidy programs is not unique to Malawi agricultural subsidy. In India, political pressure was applied to ensure that a green belt initiative, that aimed to boost food production, reflected unambiguous success in national statistics, even in times when the achievements of the program were minimal (Jerven, 2014). Similarly, in the 1990s, Chinese' Collectivization programs and the Green Leap Forward involved gross over-reporting of harvests, which masked a severe famine (Li & Yang, 2005). In both Indian and Chinese experiences, over-reporting was politically attractive.

In the case of the Malawi FISP, over-reporting maize yields to signal program success was one way to justify the continued implementation of FISP (Nkhoma et al., 2019). Particularly at the macro-level, FISP lacked an exit strategy because its associated increase in maize production portrayed goods governance for the ruling party(Banik & Chasukwa, 2019). At the micro-level, reporting bumper yields assisted agriculture extension workers and smallholder farmers in maintaining high subsidy voucher concentration in their areas (Chinsinga & Poulton, 2014; Jerven, 2014). Because of this political *clientelism*, FISP concentrated in some areas that are politically strategic to voting patterns (Harou, 2018) , but where the subsidy was not always necessarily needed the most.

When the distribution of vouchers violates the aims of extending input access to the most vulnerable and credit-constrained farmers, the impacts of subsidies on productivity are minimal (Ricker-Gilbert & Jayne, 2017). This is because the wealthier farmers who obtain the FISP do not need a subsidy to improve their productivity. They rather use the subsidy as a substitute for commercial inputs. This is informed by Mason et al. (2013) in Zambia and Malawi, that subsidized fertilizer crowded out market-accessed fertilizer when targeted at wealthier farmers. And indeed Ricker-Gilbert & Jayne (2017) provide support by finding that the FISP crowded in the market-accessed fertilizer only when targeted at poor farmers. It is therefore not surprising that I found not relationship between FISP and maize yields in the period when the program grossly mistargeted the poor(Kilic et al., 2015).

The challenges of failing to accurately target the poor due to loosely defined beneficiary selection criteria is that evaluations of FISP become potentially biased. Wealthier farmers, who now have more FISP access (Kilic et al., 2015), but obtain relatively less marginal gains in maize productivity from the FISP (Ricker-Gilbert & Jayne, 2017) needs to over-report their yields to signal that FISP increase their productivity.

While satellite data evades such strategic bias it also has its own challenges such as misclassification of marginal maize yields (Lobell et al., 2020). However, because satellite errors are unrelated to farmer's reports, they do not lead to strategic bias. Therefore, if targeting was improved by using objective measures such as income means tests, the FISP's representation of the poor, who might experience objective increases in maize production, would grow. Improved targeting would also reduce incentive for misreporting since unintended beneficiaries who must maintain the beneficiary status by misreporting would be eliminated. Ultimately, the strategically unbiased effects of FISP on Maize productivity would be possible to establish even with farmer-reported yields that are provided through surveys.

While the scope of this paper did not include establishing the strategically unbiased effects of FISP on the amount of land dedicated to maize cultivation, the results found here confirm that the increase in maize production observed under the implementation of FISP did not result from increased productivity, at least in 2016. This paper's results. Therefore, support studies (Chibwana et al., 2012) that suggest that FISP increased maize production in the extensive margin, through an increase in area under maize cultivation but not maize productivity. To take advantage of available cheap maize inputs, farmers dedicated more land to maize even when this led to reduced productivity(Chibwana et al., 2012). Because land is limited in Malawi's southern region (Li et al., 2017), it is likely that these expansions occurred in the northern and central regions, where there is more arable land, and wealthier farmers with large land holdings (National Statistics Office, 2005).

7. Conclusions and Recommendations

This study has shown that FISP does not associate with an increase in maize productivity once strategic misreporting errors are eliminated using satellite data. Furthermore, it found support for previous literature (Kilic et al., 2015) that FISP targets the wealthy, instead of the intended poor farmers. Moreover, the past literature (Mason et al., 2013) revealed that FISP's targeting of wealthy farmers led to crowding out of commercial fertilizer. Because the wealthy could even afford market-priced inputs and maintain high maize productivity without FISP, the program induced little or no marginal increases in maize productivity (Ricker-Gilbert et al., 2011; Ricker-Gilbert & Jayne, 2017). This paper's findings therefore provide support to the argument that FISP only increased maize production in the extensive margin: more land under maize cultivation. Nonetheless, if the aim of policy makers is to increase maize production in the intensive margin: high productivity, more harvests per same piece of land, then FISP may not be the most cost-effective program to achieve this. Rather the program's targeting guidelines should be strengthened in defining the poor and enforced when selecting them, if productivity has to increase in response. One way to achieve this would be through the use of income means testing when selecting vulnerable beneficiaries (Nichols & Zeckhauser, 1982). The results from this paper also suggest that universal subsidies may not be effective at improving productivity, because they would increase the number of wealthier beneficiaries who dampen the impacts of FISP on maize productivity. Therefore, if farm input subsidies are a policy to go by, they better still focus on the targeted version.

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Appendices

A measurement erros and farm input subsidies

Table A.1: The relationship between FISP and measurement errors of land and production

	(1) Land error	(2) Production error	(3) Production error	(4) Production error
FISP	0.160**	0.392***	0.422***	0.327**
	(0.066)	(0.144)	(0.140)	(0.133)
GPS area (log)	-0.456***	0.444***		-0.259***
	(0.024)	(0.062)		(0.076)
Satellite output (log)			-0.488***	
			(0.061)	
Land area errors (log)				0.406***
				(0.126)
Distance from household to farm	0.000	0.026***	0.032***	0.026***
	(0.004)	(0.007)	(0.007)	(0.007)
Slope	0.006*	-0.01	-0.01	-0.012*
	(0.003)	(0.007)	(0.007)	(0.007)
Elevation	0.000	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall (log)	-0.054	0.739	1.113**	0.761
	(0.172)	(0.562)	(0.533)	(0.565)
Tropical warm subhumid	0.215***	0.066	0.012	-0.021
	(0.029)	(0.062)	(0.061)	(0.064)
Tropical cool semiarid	0.327***	-0.363***	-0.330***	-0.496***
	(0.028)	(0.077)	(0.073)	(0.078)
Tropical cool subhumid	0.463***	0.258***	0.286***	0.07
	(0.034)	(0.076)	(0.070)	(0.099)
Central region	0.001	0.485***	0.546***	0.484***

	(0.050)	(0.142)	(0.136)	(0.141)
Southern region	0.026	0.111	0.137	0.101
	(0.056)	(0.159)	(0.153)	(0.159)
Constant	-0.107	-7.601*	-6.497*	-7.558*
	(1.185)	(3.941)	(3.853)	(3.924)
Obs	694	694	694	694
R^2	0.632	0.539	0.562	0.55

Standard errors in parentheses

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

Table B.2: The association between FISP and maize yields

	(1) Output 1	(2) Output 2	(3) Output 3	(4) Output 4
FISP	0.341***	0.395***	0.044	0.003
	(0.124)	(0.138)	(0.103)	(0.031)
Farmer area (log)	-0.19		0.213***	
	(0.087)		(0.075)	
GPS area (log)		-0.453***		-0.009
		(0.059)		(0.012)
Distance from household to farm	0.039***	0.038**	0.016***	0.012
	(0.007)	(0.007)	(0.004)	(0.002)
Slope	-0.016***	-0.009	-0.014***	0.001
	(0.006)	(0.006)	(0.005)	(0.002)
Elevation	0.001***	0.001***	0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall(log)	1.502***	1.667***	0.343	0.928***
	(0.547)	(0.538)	(0.309)	(0.312)
Tropical Warm Subhumid	-0.219***	-0.044	-0.375***	-0.110***
	(0.058)	(0.060)	(0.050)	(0.013)
Tropical Cool Semiarid	-0.539***	-0.365***	-0.118**	-0.002
	(0.076)	(0.072)	(0.058)	(0.019)
Tropical Cool Subhumid	-0.068	-0.346***	-0.596***	0.088***
	(0.062)	(0.070)	(0.054)	(0.015)
Central region	0.608***	0.609***	0.124	0.125***
	(0.135)	(0.136)	(0.078)	(0.038)
Southern region	0.135	0.195	-0.069	0.083*
	(0.151)	(0.152)	(0.088)	(0.044)
Constant	-4.951	-6.363*	5.487***	1.238
	(3.791)	(3.753)	(2.093)	(0.918)
Obs.	694	694	694	694
R^2	0.555	0.575	0.177	0.184

Standard errors are displayed in parentheses.

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

Output 1, 2, 3 and 4 are $\log\left(\frac{Farmer\ output}{Farmer\ area}\right)$, $\log\left(\frac{Farmer\ output}{GPS\ area}\right)$, $\log\left(\frac{Satellite\ output}{Farmer\ area}\right)$ and $\log\left(\frac{Satellite\ output}{Satellite\ area}\right)$ respectively.

Table B.3: First-stage estimates: FISP participation

	(1) FISP	(2) FISP
The ruling party won in the district	0.003	0.015
	(0.026)	(0.028)
Proportion of recipients in the district	0.873***	0.848***
	(0.120)	(0.123)
Farmer area (log)	0.164**	
	(0.068)	
GPS area (log)		0.037***
		(0.012)
Distance from household to farm	-0.006**	-0.006**
	(0.002)	(0.002)
Slope	0.001	0.001
	(0.002)	(0.002)
Elevation	0.000	0.000
	(0.000)	(0.000)
Rainfall (log)	-0.005	-0.012
	(0.132)	(0.128)
Tropical warm subhumid	0.083***	0.106***
	(0.026)	(0.029)
Tropical cool semiarid	-0.294***	-0.243***
	(0.029)	(0.018)
Tropical cool subhumid	0.128***	0.165***
	(0.022)	(0.022)
Central region	-0.006	-0.011
	(0.033)	(0.033)

Southern region	-0.003	-0.012
	(0.039)	(0.038)
Constant	-0.02	0.13
	(0.918)	(0.879)
Obs	694	694
R^2	0.26	0.252

Standard errors are displayed in parentheses.

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

Table B.4: Instrumental variable effects: the effects of FISP on maize yields

	(1) Output 1	(2) Output 2	(3) Output 3	(4) Output 4
FISP	0.757**	0.622**	0.635**	0.031
	(0.324)	(0.315)	(0.282)	(0.080)
Farmer area (log)	-0.243***		0.138*	
	(0.088)		(0.080)	
GPS area (log)		-0.470***		-0.011
		(0.062)		(0.013)
Distance from household to farm	0.044***	0.040***	0.023***	0.012***
	(0.007)	(0.062)	(0.005)	(0.002)
Slope	-0.017***	-0.01	-0.015***	0.001
	(0.006)	(0.006)	(0.005)	(0.002)
Elevation	0.001***	0.001***	-0.000**	-0.000***
	(0	0	0	0
Rainfall(log)	1.500***	1.666***	0.341	0.928***
	(0.534)	(0.529)	(0.311)	(0.131)
Tropical Warm Subhumid	-0.346***	-0.12	-0.555***	-0.120***
	(0.102)	(0.099)	(0.083)	(0.027)
Tropical Cool Semiarid	-0.432***	-0.314***	0.035	0.004
	(0.109)	(0.102)	(0.087)	(0.025)
Tropical Cool Subhumid	-0.175*	0.273**	-0.748***	0.078***
	(0.100)	(0.107)	(0.067)	(0.026)
Central region	0.612***	0.611***	0.129	0.125***

	(0.135)	(0.135)	(0.079)	(0.038)
Southern region	0.123	0.187	-0.086	0.083*
	(0.147)	(0.140)	(0.092)	(0.044)
Constant	-5.051	-6.402*	5.346**	1.233
	(3.726)	(3.708)	(2.116)	(0.912)
Obs.	694	694	694	694
First-stage statistic	58.992	70.975	58.992	70.975
R^2	0.547	0.572	0.101	0.183

Standard errors are displayed in parentheses.
* p < 0.1 ** p < 0.05 *** p < 0.01
Output 1, 2, 3 and 4 are $\log\left(\frac{Farmer\ output}{Farmer\ area}\right)$, $\log\left(\frac{Farmer\ output}{GPS\ area}\right)$, $\log\left(\frac{Satellite\ output}{Farmer\ area}\right)$ *and* $\log\left(\frac{Satellite\ output}{Satellite\ area}\right)$ respectively.

Table B.5: Sensitivity analysis: using a Harvest Index of 0.2

	(1) Output 1	(2) Output 2	(3) Output 3	(4) Output 4
FISP	0.757**	0.622**	0.635**	0.031
	(0.324)	(0.315)	(0.282)	(0.080)
Farmer area (log)	-0.243***		0.138*	
	(0.088)		(0.080)	
GPS area (log)		-0.470***		-0.011
		(0.062)		(0.013)
Distance from household to farm	0.044***	0.040***	0.023***	0.012***
	(0.007)	(0.062)	(0.005)	(0.002)
Slope	-0.017***	-0.01	-0.015***	0.001
	(0.006)	(0.006)	(0.005)	(0.002)
Elevation	0.001***	0.001***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall(log)	1.500***	1.666***	0.341	0.928***
	(0.534)	(0.529)	(0.311)	(0.131)
Tropical Warm Subhumid	-0.346***	-0.12	-0.555***	-0.120***

	(0.102)	(0.099)	(0.083)	(0.027)
Tropical Cool Semiarid	-0.432***	-0.314***	0.035	0.004
	(0.109)	(0.102)	(0.087)	(0.025)
Tropical Cool Subhumid	-0.175*	0.273**	-0.748***	0.078***
	(0.100)	(0.107)	(0.067)	(0.026)
Central region	0.612***	0.611***	0.129	0.125***
	(0.135)	(0.135)	(0.079)	(0.038)
Southern region	0.123	0.187	-0.086	0.083*
	(0.147)	(0.148)	(0.092)	(0.044)
Constant	-5.051	-6.402*	5.346**	1.233
	(3.726)	(3.708)	(2.116)	(0.912)
Obs.	694	694	694	694
First-stage statistic	58.992	70.975	58.992	70.975
R^2	0.547	0.572	0.101	0.183

Standard errors are displayed in parentheses.

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

Output 1, 2, 3 and 4 are $\log\left(\frac{Farmer\ output}{Farmer\ area}\right)$, $\log\left(\frac{Farmer\ output}{GPS\ area}\right)$, $\log\left(\frac{Satellite\ output}{Farmer\ area}\right)$ and $\log\left(\frac{Satellite\ output}{Satellite\ area}\right)$ respectively.

Table B.6: Sensitivity analysis: using a Harvest Index of 0.6

	(1)	(2)	(3)	(4)
FISP	0.757**	0.622**	0.635**	0.031
	(0.324)	(0.315)	(0.282)	(0.080)
Farmer area (log)	-0.243***		0.138*	
	(0.088)		(0.080)	
GPS area (log)		-0.470***		-0.011
		(0.062)		(0.013)
Distance from household to farm	0.044***	0.040***	0.023***	0.012***
	(0.007)	(0.062)	(0.005)	(0.002)
Slope	-0.017***	-0.01	-0.015***	0.001
	(0.006)	(0.006)	(0.005)	(0.002)
Elevation	0.001***	0.001***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall(log)	1.500***	1.666***	0.341	0.928***
	(0.534)	(0.529)	(0.311)	(0.131)
Tropical Warm Subhumid	-0.346***	-0.12	-0.555***	-0.120***
	(0.102)	(0.099)	(0.083)	(0.027)
Tropical Cool Semiarid	-0.432***	-0.314***	0.035	0.004
	(0.109)	(0.102)	(0.087)	(0.025)
Tropical Cool Subhumid	-0.175*	0.273**	-0.748***	0.078***
	(0.100)	(0.107)	(0.067)	(0.026)
Central region	0.612***	0.611***	0.129	0.125***
	(0.135)	(0.135)	(0.079)	(0.038)
Southern region	0.123	0.187	-0.086	0.083*
	(0.147)	(0.148)	(0.092)	(0.044)
Constant	-5.051	-6.402*	5.346**	1.233
	(3.726)	(3.708)	(2.116)	(0.912)
Obs.	694	694	694	694

First-stage statistic	58.992	70.975	58.992	70.975
R^2	0.547	0.572	0.101	0.183

Standard errors are displayed in parentheses.
* p < 0.1 ** p < 0.05 *** p < 0.01
Output 1, 2, 3 and 4 are
$\log\left(\frac{Farmer\ output}{Farmer\ area}\right)$,
$\log\left(\frac{Farmer\ output}{GPS\ area}\right)$, $\log\left(\frac{Satellite\ output}{Farmer\ area}\right)$ and $\log\left(\frac{Satellite\ output}{Satellite\ area}\right)$ respectively.

Table B.7: Validity test for the IV

	(1) Farmer-yields	(2) Satellite-yields
FISP	0.260*	-0.003
	(0.138)	(0.034)
District FISP (IV)	0.423	0.03
	(0.309)	(0.077)
Farmers' land area (log)	-0.207**	
	(0.085)	
GPS area (log)		-0.01
		(0.012)
Average distance from farm to household	0.041***	0.012***
	(0.007)	(0.002)
Slope	-0.016***	0.001
	(0.006)	(0.002)
Elevation	0.001***	-0.000**
	(0.000)	(0.000
Rainfall(log)	1.493***	0.927***
	(0.546)	(0.132)
Tropical Warm Subhumid	-0.301***	-0.116
	(0.079)	(0.019)
Tropical Cool Semiarid	-0.566***	-0.004
	(0.078)	(0.019)
Tropical Cool Subhumid	-0.11	0.084***
	(0.070)	(0.017)

Central region	0.606***	0.125***
	(0.135)	(0.038)
Southern region	0.12	0.082*
	(0.150)	(0.045)
Constant	-4.958	1.242
	(3.801)	(0.917)
Obs.	694	694
R^2	0.557	0.184

Standard errors are displayed in parentheses.

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

Mission

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Middle East Bank Towers,
3rd Floor, Jakaya Kikwete Road
Nairobi 00200, Kenya
Tel: +254 (0) 20 273 4150
communications@aercafrica.org