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Agricultural input subsidy and outcomes for farmers in Tanzania

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Abstract: This paper examines the impact of the government input subsidy—the National Agriculture Input Voucher—on farmers' production and welfare in Tanzania as well as the factors that influence agricultural production in the country. The analysis is based on the Living Standards Measurement Study-Integrated Surveys on Agriculture for 2008–13. The study uses panel fixed effects and difference-in-difference and propensity score matching methods to examine the two objectives. The results show that the input subsidy programme resulted in an initial increase in maize and rice production but not in the long run and only in a few regions. In addition, there was a decrease in total production in the southern region and the programme had little effect on farmers' welfare. The results show that this programme only partly met the expected outcomes in Tanzania due to mistargeting, inaccurate identification of households, and poor implementation.

Key words: difference-in-difference, input subsidy, production, panel, propensity score matching, welfare, Tanzania

JEL classification: D04, D13, Q18, R28

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1 Introduction

As is the case for most developing economies, Tanzania's agricultural sector is the mainstay of its economy, accounting for approximately 30 per cent of its gross domestic product and 75 per cent of employment (Shee et al. 2020; World Bank 2019). The sector also contributes to the economy indirectly, contributing 65 per cent of raw materials to the manufacturing sector (World Bank 2019). Between 2002 and 2003, the country faced a severe drought followed by a food crisis in 2007 and 2008 brought about by food prices rising globally, which prompted the Tanzanian government to introduce agricultural support measures to remedy the situation. This gave rise to the National Agricultural Input Voucher Scheme (NAIVS) for the period 2009 to 2012.

The NAIVS programme focused on the provision of fertilizer and seed subsidies to poor farmers cultivating a maximum of one hectare of maize or rice (URT 2014). The focus on fertilizers and seeds was attributed to the need to rapidly boost production in the sector, given the political, economic, and social climate at the time. The NAIVS programme drew on the experience of Malawi's input voucher programmes of 2005 and 2008. Both programmes thrived on political goodwill and benefited from a lack of a strong opposition from parties with considerable veto power. Tanzania's national strategy for economic development was, and is, market driven, paving the way for programmes that are largely private-sector friendly (Mather and Ndyetabula 2016). This was apparent under NAIVS, which leveraged the private sector's participation to import and sell seed and fertilizer to farmers (Mather et al. 2016). The programme was discontinued in 2016 after eight years of operation due to a lack of funding (Gine et al. 2019).[1]

The body of literature on the impact of input subsidy schemes is inconclusive. Some studies argue that input subsidy schemes like NAIVS create a competitive platform through which government and private sector engagement is improved, allowing for efficiency in the allocation of resources to the poor (Basurto et al. 2020; Kelly et al. 2010). Input subsidy schemes have also been lauded for being channels for boosting food production (Lunduka et al. 2013), improving crop diversification (Holden and Lunduka 2012), and reducing the gender gap (Fisher and Kandiwa 2014). In this regard, the introduction of input subsidies is a step towards achieving developmental goals such as food security, trade promotion, and poverty reduction (Jayne et al. 2018; Jayne and Rashid 2013). Other studies, in contrast, have documented the tumultuous nature of the engagement between the private sector and governments in input subsidy schemes (Kelly et al. 2010), leading to raised input prices. Collusive pricing can result in the weakness of programmes that purport to offer support to farmers (Dorward et al. 2008). Also, subsidies can have little economic value compared to other uses of public funds. In addition, the political nature of input subsidies makes it difficult to remove them once implemented, thereby stunting progress in the agricultural sector (Jayne et al. 2018; Jayne and Rashid 2013). Looking at different input subsidy programmes in sub-Saharan Africa, Jayne et al. (2018) showed that there was an increase in production in the short run but production and welfare effects were quite low in the long run.

[1] In recent years, this is the longest that a programme has been in effect in Tanzania. Other policies that have followed NAIVS have focused on subsidies in agriculture inputs, mainly seeds and fertilizer, trying different experiments with credit systems through group and co-operative companies, voucher systems, and contracts with dealers, among others, but these programmes have not resulted in an increase in uptake of agriculture inputs by farmers (Masinjila and Lewis 2018).

Further, there is limited evidence that these programmes achieved their goals (Mason, Wineman et al. 2020).

So far, a few studies have focused on the NAIVS programme. Aloyce et al. (2014) examined the operational aspects of the programme in some regions[2] and found that there were delays in subsidized inputs and a lack of regard to the implementation guidelines. Hepelwa et al. (2013) conducted a study on the effectiveness of the fertilizer voucher system using a panel dataset for 2007 and 2012 and found that there was a double increase in yields. Other studies such as those by Kato (2016) and Gine et al. (2019) did not show any effect on agricultural productivity and welfare in different regions, while Ray (2019) found that the programme increased yields and net revenue. Thus, consensus on the effectiveness of input subsidy programmes has been elusive. This study therefore focuses on the question: what are the factors that influence agriculture production in Tanzania, and what was the effect of NAIVS subsidies on farmer production and welfare in Tanzania?

The study contributes to this literature as follows. Most studies of Tanzania use cross-sectional analysis, which makes it difficult to establish causality and some focus only on a few regions, which makes it difficult to infer for the entire population of farmers involved in the programme (Kato 2016; Ray 2019). Moreover, some authors such as Hepelwa et al. (2013) use panel data, which does not account for self-selection and endogeneity issues and therefore results in biased estimations. Our study estimates the factors that influence agriculture production using panel fixed effects, and the impact of the NAIVS programme on agriculture production is estimated using difference-in-difference and propensity score matching methods to overcome the above challenges. Unlike other studies, we use a non-separable agricultural household model using market imperfections where the NAIVS programme affects both agricultural production and consumption, which is prevalent in developing countries (Dillion and Barrett 2017; LeFave and Thomas 2016). The study uses the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) (World Bank 2020) for the period from 2005 to 2014. The surveys are representative at the national and regional levels and therefore possible to infer for the farmers involved in the NAIVS programme.

When designing programmes such as NAIVS, policy makers assume that subsidies (for example for improved seeds and inorganic fertilizers) will make these inputs available to poor farmers below market price, resulting in their adoption. Consequently, agricultural productivity and profitability will increase, resulting in greater food availability and reduced poverty, especially in rural areas. However, there is a lot of debate about the effectiveness and efficiency of subsidy programmes. As shown in previous research (see Houssou et al. 2017; Shee, et al. 2020), their success depends on the design and implementation, mechanisms for selecting target farmers, political interference, and the role of the private sector, among other factors. This study will shed light on these dynamics in the case of NAIVS in Tanzania. The findings will help policy makers and development partners to understand the dynamics behind the outcome of this programme. Furthermore, the findings will inform any future efforts to implement agricultural subsidy programmes in Tanzania and similar contexts in sub-Saharan Africa (see Gilbert 2020; Mdee et al. 2020).

The next section gives an overview of the agricultural sector and the NAIVS programme in Tanzania. This is followed by the literature review in Section 3. The theoretical framework used and the pathways through which NAIVS affects agriculture production and welfare are described in Section 4. The empirical strategy used in the estimations and the variables used are presented in

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[2] Rukwa, Mbeya, Morogoro, and Shinyanga.

Section 5, while the description of the datasets used, and the summary statistics are given in Section 6. The results and discussions are in Section 7, and the paper concludes in Section 8.

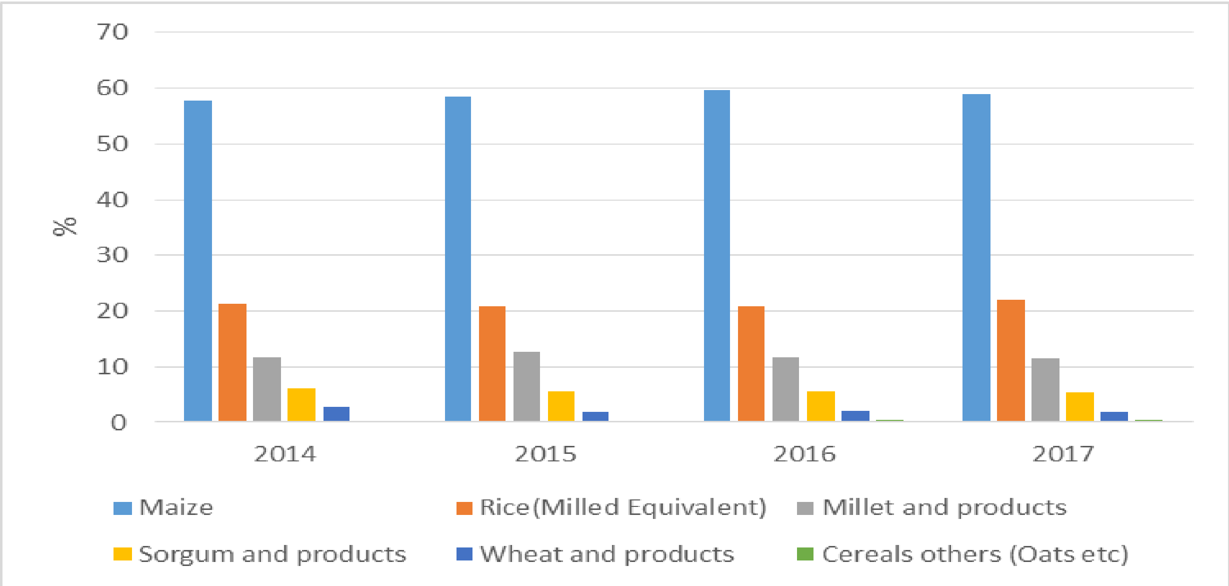
2 Overview of the agriculture sector and the NAIVS programme in Tanzania

2.1 The agricultural sector in Tanzania

The study focuses on Tanzania, which has a population of about 56 million, most of whom live in rural areas and depend on rain-fed agriculture. Most of the households rely on small-scale farming with a farm size of about 0.2–2.0 hectares (Masinjila and Lewis 2018). The productivity in these farms and farm inputs are extremely low, and the crops yield about 20–30 per cent less than their potential (Gine et al. 2019). The United Republic of Tanzania (URT) through different policies, programmes, and initiatives, such as National Agriculture Policy (URT 2013), Agriculture Sector Development Programme in 2013, Tanzania Agriculture and Food Investment Plan (2011–21), hopes to transform the agricultural sector by modernizing it through the adoption of improved seeds and inorganic fertilizers. However, little has as yet been achieved (Mkonda and He 2018). These inputs have high costs for small farmers, and government subsidies for such inputs are expected to increase agricultural production.

Maize, followed by rice, is the most-farmed crop in Tanzania. According to the government, maize occupies about 70.2 per cent of the area planted with crops, and rice occupies about 16.8 per cent (NBS 2019). Other crops include sorghum, millet, wheat, and oats. Maize accounts for about 59 per cent of the caloric supply of cereals, followed by rice (21 per cent) and millet (12 per cent), as shown in Figure 1.

Figure 1: Contribution of cereal products to daily per capita energy (kilocalories) by vegetal food group, 2014–17 (%)



Source: adapted from the Tanzania National Food Balances Sheet report (NBS 2019).

Since the 1960s, the URT has used input subsidies at different periods. Examples include the universal subsidy programme in the period from 1960 to the 1980s, maize fertilizer subsidies from the 1970s until it was phased out in 1994, the transport subsidy for fertilizers in 2003/04, and the introduction of the NAIVS voucher-based subsidy in 2008 (see Masinjila and Lewis 2018; World Bank 2014). Before NAIVS was introduced in 2008, few farmers used improved seeds (8 per cent) and inorganic fertilizer (3 per cent) (World Bank 2014). Since NAIVS, there have been other policy initiatives aimed at increasing agriculture production in Tanzania. In 2014/15, the URT adopted a credit system to distribute agriculture inputs through farmers groups and cooperatives before returning to a voucher system in 2015/16. The government decided to enter a contract with companies to sell seeds and fertilizer at subsidized cost in the period from 2016 to 2018, and then from 2018 onwards it focused on a universal fertilizer programme for basal fertilizer (DAP) and urea (Masinjila and Lewis 2018).

2.2 NAIVS programme

The NAIVS programme was developed with the help of the World Bank after the 2007/08 food crisis, with the aim of increasing the production of maize and rice in Tanzania. It was a market-smart input subsidy whose short-term goal was to increase production and introduce farmers to improved seeds and chemical fertilizer. The long-term goal was to establish local dealers to supply inputs to villages once the programme was phased out. Over the period from 2008 to 2013, US$300 million was invested in this programme. It focused on about 2.5 million small farmers who were expected to get three vouchers for three years for a 50kg bag of urea, 50kg bag of basal fertilizer (DAP), or a 50kg bag of Minjingu Rock Phosphate with N supplement, and 10kg of hybrid or OPV maize or 16kg of rice seed (Kim et al. 2019). The vouchers were redeemable with a 50 per cent subsidy by paying the difference between the market price of inputs and the face value of the voucher (Gine et al. 2019). It was expected that after three years a farmer would have learned enough from the programme to make it possible to continue without the subsidy, although this graduation process was not enforced. Using local retailers was expected to help the sustainability of the supply channels (World Bank 2014). There was a pilot phase in 2007/08 in the Mbeya and Rukwa regions, which then expanded to 58 districts in 11 regions before it became a nationwide programme (Masinjila and Lewis 2018).

Table 1 shows the number of households that benefited from the programme. In most cases, there was a small variance between the number of planned and actual households that benefited, although in 2013/14 the actual number of households that benefited was almost double the planned number of households.

Table 1: Number of households that benefited from the NAIVS programme, 2008–14

Year	Planned	Actual
2008/09	740,000	730,667
2009/10	1,500,000	1,511,900
2010/11	2,040,000	2,011,000
2011/12	1,800,000	1,779,867
2012/13	1,000,000	940,783
2013/14	500,000	932,100

Source: adapted from World Bank (2014).

2.3 NAIVS programme beneficiary selection process and implementation

The programme focused on farmers who had little or no experience of using improved seeds and inorganic fertilizers over the previous five years. Farmers had to be working full time on their farm with less than one hectare of land and be of good repute.[3] They had to be willing to pay the difference for the inputs, work with extension workers, confirm their use of the inputs, and be in mainly female-headed households (Masinjila and Lewis 2018; World Bank 2014). According to Gine et al. (2019), the selection was to be made by village voucher committees (VVC), elected through the Village Assembly. The committees were required to follow guidelines, such as being composed of three men and three women who were married and cultivated less than one hectare, etc. The committees were disbanded once they had selected the farmers.

In practice, however, the VVCs looked for farmers who were able to buy the subsidized inputs and used their own perception to determine who were the poor, needy, and deserving farmers. In some cases, the selection was made through voluntary registration and by local leaders in the village (Malhotra 2013). Once selected, these farmers would be given the three vouchers that were allocated per village. The allocation went from the national level down to the region, district and village levels, using voucher committees at each level. The VVCs were involved in distributing the vouchers equitably, which was not possible in some cases, although most of the farmers were happy with the distribution process (World Bank 2014). At the same time, there was training for the agro-input dealers at the local level, who then applied for tenders which were selected and assigned by the district council. However, sometimes the implementation was not effected well because of poor supervision of the vouchers, the involvement of unqualified input dealers, the farmers having limited information about the inputs, a lot of cheating and fraud, etc. (see Malhotra 2013; Masinjila and Lewis 2018; Pan and Christiaensen 2011). According to Shee et al. (2020), only about a one-third of the beneficiaries continued to buy seeds and fertilizers from the local input dealers because of the cost.

3 Literature review

The case for government intervention, and therefore input subsidy schemes, is based on their role in overcoming failures in markets for inputs and financing of agriculture (Gautam 2015; Jayne et al. 2018; Jayne and Rashid 2013). Subsidy programmes are designed to target poor farmers who are unable to access inputs but stand to benefit from their use. They are also intended to help develop the private sector, reduce barriers to entry, and lower costs, thereby promoting competition and developing the missing market as part of a wider strategy to develop the agricultural sector (Gautam 2015; Jayne et al. 2018; Lunduka et al. 2013; Morris et al. 2007). Subsidy programmes have been criticized for being a conduit for policy uncertainty in the African region (Jayne 2012). This is because of their tendency to augment food production, leaving them susceptible to undue political influence, bribery, and profit-maximizing behaviour by private sector actors (Chinsinga 2011; Kelly et al. 2010). Apart from this, questions have been raised about the efficacy of allocating public funds to these programmes when the returns may be lower than the public investment (Jayne and Rashid 2013).

Holden (2019) showed that most of the second generation of input subsidies in Africa have design and implementation limitations and most do not adhere to market-smart principles. Jayne et al.

[3] 2.47105 acres = 1 hectare

(2018) reviewed different input subsidy programmes in sub-Saharan Africa[4] in the 2000s and found that food production only increased in the short term and that there was little effect on welfare. This is mainly due to the incompatibility of inorganic fertilizer and soil quality, the gender gap in the use of inputs, and the use of credit for inputs (Burke et al. 2016; Hemming et al. 2018; Jayne et al. 2018; Sheahan and Barrett 2017).

Most studies focus on Malawi, where the first subsidy programme was initiated, and they have mixed results. Some show that the programme and extension services resulted in higher maize production and productivity, consumption, incomes, asset holding, and food security, and a reduction of the gender gap (Arndt et al. 2015; Bezu et al. 2014; Dorward and Chirwa 2011; Fisher and Kandiwa 2014; Lunduka et al. 2013; Ragasa and Mazunda 2018). The use of traditional leaders (chiefs) to target households to be involved in the programme enhanced the benefits by targeting poor households, which resulted in better returns to farm inputs and efficient productive outcomes (Basurto et al. 2020). The programme also resulted in participants increasing the land allocated to maize and tobacco and using less for other crops (Chibwana et al. 2012). In contrast, other studies on Malawi showed that the programme did not realize the expected improvements in maize yields and profits when compared to the Asian miracle. Some authors attributed this to high nitrogen response rates, use of inorganic fertilizer, soil fertility, and a high increase in fertilizer and seed prices (Dorward and Chirwa 2011; Harou et al. 2017; Kopper et al. 2020). There was also low usage of inputs by farmers and, therefore, the programme benefits were smaller than the cost (Gilbert 2020).

Similar results can be seen in other African countries. For example, in Mozambique, Zambia, and Nigeria, input subsidies have resulted in higher maize yields, and have resulted in reduced inter-cropping with other crops as well as poverty levels (Laajaj et al. 2020; Mason, Kuteva et al. 2020; Morgan et al. 2019; Wossen et al. 2017). However, there have been implementation challenges associated with a lack of political will rather than with the concept and design of the programmes, as shown by Chinsinga (2011) and Holden (2019). Some studies have shown that the targeting mechanism used to select beneficiary households can have an impact on the outcomes of the programme (Houssou et al. 2017; Kayode 2019; Mason and Ricker-Gilbert 2013; Wang et al. 2019). The results in Africa are contrary to studies in Asia, which show short- and long-run positive effects of subsidy programmes. For example, in China, India, and Malaysia, input subsidies have had more returns in poor areas, suggesting that targeting poor households with such investments can improve agricultural productivity and welfare both in the short and long run, partly leading to the green revolution in Asia (Bathla et al. 2019; Solaymani et al. 2019; Zhang et al. 2020).

Several studies on Tanzania have examined the impact of NAIVS on different outcomes. Pan and Christiaensen (2011) used panel data for the Kilimanjaro region to show that 60 per cent of the elected village officers received the vouchers rather than poor households, reducing the impact of the programme. Similarly, Hepelwa et al. (2013), using household-level panel data, found a difference between the farm yields of the households that were approved for NAIVS and those that were not. Even so, they reported that the majority of households were not selected for NAIVS as they could not afford the 50 per cent cash top-up payment. According to the World Bank (2014), NAIVS increased production by about 2.5 million tons of maize and rice and increased the number of agro-dealers trained. However, there were challenges for implementation related to the cost of inputs; delays in inputs and payments to agro-dealers; fraud, especially in redeeming vouchers; misuse of vouchers; the cost of other inputs; and farmers' graduating from the programme due to

[4] Ghana, Nigeria, Kenya, Tanzania, Malawi, Zambia, and Ethiopia

the cost of inputs. Ray (2019) also showed that farmers in Tanzania choose the combination of seeds, fertilizers, and labour inputs based on their yield expectation; that the NAIVS programme led to an increase in yields and net revenue; and that improved extension services can lead to better results.

On the other hand, Aloyce et al. (2014) reported that delays in input subsidies made the vouchers ineffectual since, by the time of receipt, households had already spent most of their earnings on food and, therefore, they could not afford the 50 per cent top-up. The authors attributed this to poor monitoring and evaluation systems. Similarly, Kato (2016) found that the NAIVS programme had no impact on maize yields, income poverty, and assets because of the design and implementation of the programme in the Ruvuma region. Gine et al. (2019) also found that input subsidy programmes did not result in higher agriculture productivity and welfare and that investments should be directed to other aspects such as soil quality and irrigation, which are complementary.

The results show that although the NAIVS programme influenced production in Tanzania, it did not lead to the expected green revolution and nothing much has changed. This is mainly due to mistargeting and implementation issues in the programme. According to Mdee et al. (2020), based on input subsidy programmes Malawi, Zambia, and Tanzania, agricultural institutions do not have the ability to sustain intensification in agriculture. Further, Gilbert (2020) showed that not all countries in sub-Saharan Africa have been able to increase uptake of improved seeds and the number of farmers using inorganic fertilizer, and that input subsidy programmes have not achieved their objectives. This is not because of the concept and design of the programme but is, instead, because of the targeting mechanism, politics around the programme, and training of the farmers and agro-dealers, etc. Therefore, it is evident that agricultural subsidy programmes have mixed results depending on the country, the political landscape, the involvement of the private sector, and the governance mechanisms.

4 Theoretical framework

In this section, we develop a framework through which government intervention can influence farmers' production and welfare in Tanzania. Using the farm household model, a farmer can get utility from income and leisure as shown in equation (1). The assumption here is that there is non-separability between consumption and production decisions and that farm inputs influence both decisions (Benjamin 1992; Dillion and Barrett 2017; LeFave and Thomas 2016). The preferences for the family are defined using income (I) and leisure (L), and their utility can be expressed as follows:

$$U = U(I, L) \tag{1}$$

The farmer's production function can be developed with inputs like on-farm family labour (F) and hired labour (H) and other inputs (FI) as shown below. F and H are assumed to be imperfect substitutes:

$$Q = f(F, H, FI; A) \tag{2}$$

where agricultural production is Q, and A is a fixed or exogenous factor such as land. If we assume that (1) and (2) above are twice continuously differentiable, it is possible to assume that each input is subject to diminishing returns based on the first difference of the production function. Assuming that the factors' market is competitive and that inputs are heterogeneous, the unit cost of each input will be w_0 for the off-farm family labour and w_H for the hired labour and the cost of other inputs C0.

If a household has a time endowment, it allocates time to on-farm work (F), off-farm work (O), leisure (L), and others factors such as migration for each period. Some of the farmers will be constrained in the labour market and, therefore, they might not be able to invest enough labour in agricultural production. This can be stated as:

$$T = F + O + L + M \tag{3}$$

Therefore, the main source of income for the household will be on-farm income (I_F), which comes from farm revenue less wage payment to hired labour and the cost of inputs because most smallholder farmers sell their crops to be able to meet family expenses. Other sources of income are off-farm income (I_O) and non-labour income such as dividends etc (Z). If p is the price of the products in the competitive market, we can express the total income for the household as follows:

$$I = \{p\underbrace{f(F, H, FI: A) - w_H H - C_0}_{I_F} FI\} + w_O \underbrace{(T - F - L - M)}_{I_O} + Z \tag{4}$$

When the government decided to give input vouchers to the households, it increased the on-farm incomes which can be used for different activities such as hiring labour, purchasing other inputs like pesticides, and consumption of other activities that affect the households. We can substitute equation (4) in equation (1) above to get the following equation:

$$U = U(\{pf(F, H, FI: A) - w_H H - C_0 FI\} + w_O(T - F - L - M) + Z), L \tag{5}$$

The household maximizes utility by using F, H, and L. Using the first-order conditions, we can show the marginal products and wages for the farmer as follows:

$$pf_F(F, H: A) - w_O = 0 \tag{6}$$

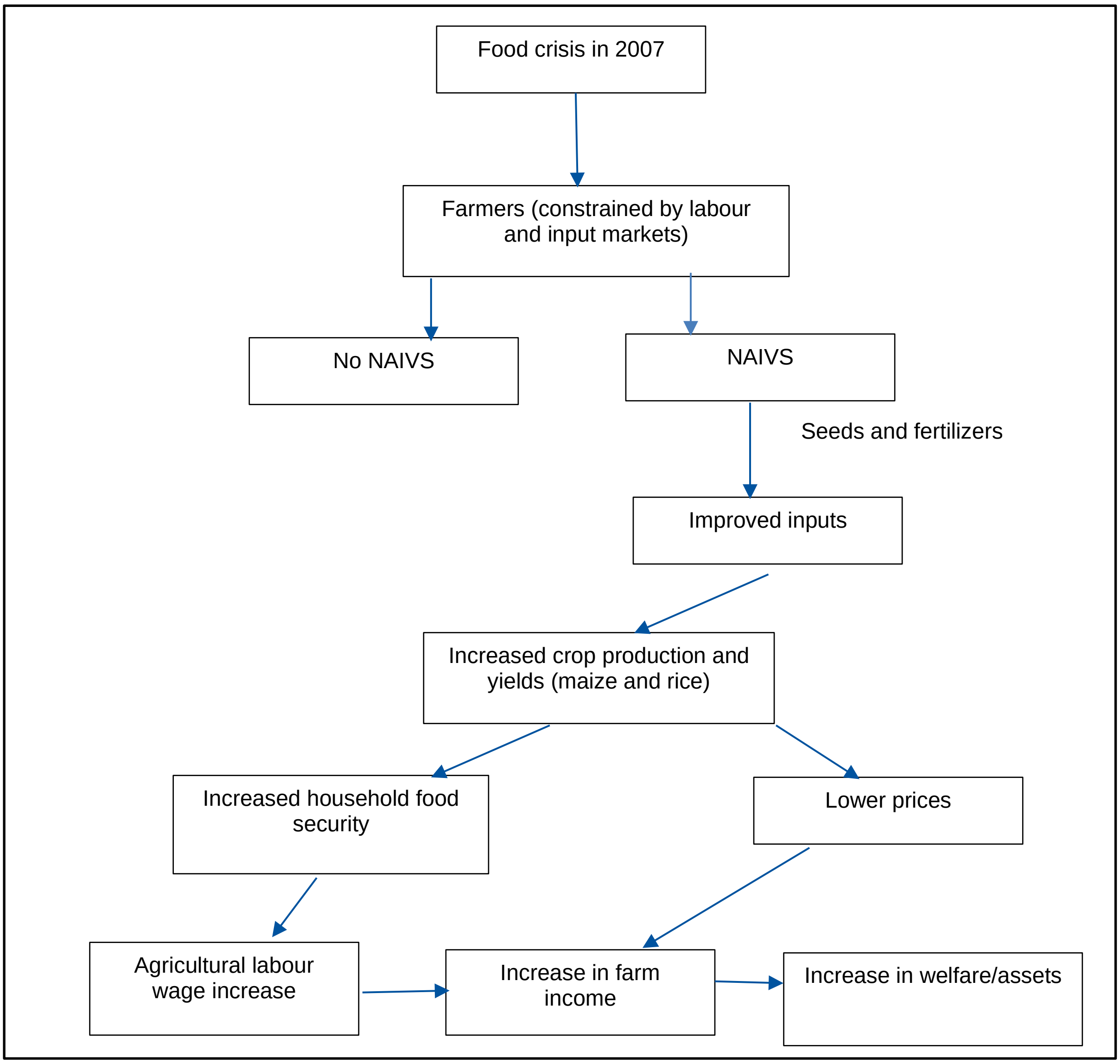
$$pf_F(F, H: A) - w_H = 0 \tag{7}$$

$$pf_{FI}(F, H, FI: A) - C_0 = 0 \tag{8}$$

$$U_I(I, L)(-w_0) + U_L(I, L) = 0 \tag{9}$$

The equations here show that the household supplies labour to the farm to the level where the value of the marginal product of on-farm labour equals the competitive off-farm wage. In addition, the hired labour is hired to the level at which the value of the marginal product of labour is equal to the hiring wage. The inputs used by the household are based on the marginal value product of input, which is equal to the cost of the inputs in the competitive market. If the farmer is constrained in the labour and input markets and the on-farm family labour (F) is scarce, then $pf_F(F, H, FI: A) > w_O$ and $pf_{FI}(F, H, FI: A) > c_0$ are labour and input shortages and therefore reduce agricultural output. However, if the farmer is not unconstrained in the labour and input markets then it does not affect the agricultural output or welfare. Similarly, if the farmer is constrained in the credit market then government intervention affects agricultural output as the farmer can hire labour or agricultural inputs such as seeds and fertilizers. Figure 2 shows the pathways through which the NAIVS programme can affect agricultural production and welfare in Tanzania.

Figure 2: Impact pathway of NAIVS, agricultural production and welfare in Tanzania



Source: author's illustration based on Kato (2016: 29).

5 Empirical strategy

We start by looking at the factors that influence maize and rice production and the impact of the NAIVS programme on total production and welfare in Tanzania. We use a panel random and fixed effects model for the first objective. This is followed by an examination of the impact of NAIVS on farmers' outcomes using both propensity score matching (PSM) and difference-in-difference methods (DiD).

In equation (10), we show the model used in the estimation of the factors that influence maize and rice production based on the production function in model (2) above:

$$Q_{ijt} = \beta_0 + \beta_1 M_{ijt} + \beta_2 R_{ijt} + \beta_1 X_{ijt} + \mu_i + \pi_t + \varepsilon_{it} \tag{10}$$

where Q is the log yields in kilogrammes per acre for household *i* and time *t* for the maize and rice cultivation by farmers. *X* is the input variables related to the household and farm, distance to the farm, and climate characteristics, as shown in Table A1 in the Appendix, μ_i is household effects, and π takes care of other fixed effects like time. ε_{it} is the error term.

Most of the studies that evaluate programmes such as the NAIVS are based on before and after treatment groups, while others use comparison of samples with and without treatments. However, because of data limitations, many studies do not focus on the net effects of treatments. We assume that most of the households are similar in terms of plot size and assets and that they live in a rural area and tend to be poor. Therefore, they are not radically different. The DiD method assumes that there is no systematic unobserved time-varying difference between the control and the treatment groups that would influence the outcomes for both groups due to trends over time (Daidone et al. 2019). Therefore, the difference between the households in 2008, 2010, and 2013 is due to variation based on the subsidy programme guidelines and they are observable demographic characteristics. The DiD method controls for time-invariant unobserved differences in the baseline when the experiment's random design, such as in the NAIVs programme, is imperfect (Boone et al. 2013). The estimation model is as follows:

$$Y_{it} = \alpha_0 + \alpha_1 V_i + \alpha_2 W_t + \alpha_3 (W_t * V_i) + \sum \alpha_i X_i + \varepsilon_{it} \tag{11}$$

where Y_{it} is the outcome of interest for household *i* in time *t*. In this paper, this is the log of total production and the log of welfare. The welfare variable is calculated as total annual consumption expenditure in real terms per adult equivalent in the household. V_i is a dummy equal to 1 if the household got a voucher (treatment group), and 0 if the household did not get a voucher (control group). The coefficient α_1 shows the unobserved time-invariant differences between the control and the treatment groups. If this coefficient is 0, it means that there is no unobserved difference between the treatment and the control groups. W_t is a time dummy which is equal to 0 in year 2007/08 (baseline) and 1 in the follow-up wave. The coefficient α_2 captures the trends over time, such as weather, that are not captured by the treatment. $W_t * V_i$ is the interaction between the voucher and the time dummies. The coefficient α_3 shows the difference between the change in the time in the treatment and control groups. This captures the effects of the vouchers on the outcomes of interest and is the difference estimator which shows the impact of the programme. The error term is ε_i. X_i is the control variables related to the household and farm characteristics. These control variables are included to increase accuracy and precision. They include eligibility criteria such as income, size of the farm, gender of the household head, and extension services. Different estimations are calculated including maize and rice estimations and regions using linear regressions, and the results are adjusted for heteroskedasticity. The variables used in the estimations are shown in Table A1 in the Appendix.

Although the DiD estimations can be enough to create reliable results in panel data (because they account for unobserved fixed effects such as household individual characteristics), matching approaches can be used given the differences in the treatment and the control groups in the baseline. In addition, when there is no counterfactual information, problems with missing data can arise, and matching approaches can overcome such challenges. Using the PSM method, the two groups are matched on the estimated probability of participation on their observed characteristics, creating a comparable counterfactual. The PSM method summarizes the baseline characteristics of each subject into one index variable, then uses the propensity score to match the subjects, in this case households. The PSM makes the following assumptions. First, there is no systematic difference between the treatment and control groups in unobserved characteristics. Further, the average treatment effects for the treatment are only defined within a region of common support (Becerril and Abdulai 2010). In addition, matching uses observed characteristics only. As a result, PSM is mainly used for cross-sectional analysis.

The study uses two matching approaches: nearest neighbour matching (NNM), which focuses on five nearest neighbours, and Kernel-based matching (KBM), which uses weights in which closer neighbours have more weight compared to distant neighbours. By combining the two approaches, it is possible to reduce observed and unobserved selection bias (see Heckman et al. 1997; Smith and Todd 2005). PSM employs a logit model to estimate the probability of the treatment group members based on observed characteristics. It then uses these estimates to get treatment group members from the counterfactual. The results of the matched groups are then compared. The criteria used determine the accuracy of the results. Therefore, we use DiD-PSM to compute the impact of the subsidy programme on farmers' outcomes in Tanzania. As a robustness test, we also use inverse probability weighted regression adjustment (IPWRA) to estimate the unbiased treatment effects due to selection bias.

6 Data and summary statistics

The study uses the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA), the Tanzanian National Panel Survey sample, conducted over three periods. The surveys cover economic and social information for households. The households were interviewed in the National Household Survey in 2007/08, prior to the introduction and implementation of the NAIVS programme, and in 2010/11, and 2011/12, following implementation. The sample is representative at the national, urban/rural, and main regional levels. The datasets are geo-referenced and contain detailed plot-level information on agriculture as well as many modules on non-agricultural facets of people's livelihoods (including employment, income, consumption, shocks, assets, and nutrition). In Tanzania, National Panel Survey datasets have fortunately maintained low attrition over the waves, thus minimizing the potential for attrition bias within the datasets. Total household attrition for the datasets from the three years is 4.84 per cent, which is low (NBS 2014).

Table 2 shows the households surveyed during this period. The sample size changed over the period, and the number of households involved in agriculture decreased from 70.3 per cent in 2007/08 to 62.5 per cent in 2013/14.

Table 2: Households surveyed, 2007–14

Year	Totals	Agriculture	%	Maize	%	Rice	%
2007/08	3,265	2,296	70.3	1,695	73.8	481	20.9
2009/10	3,924	2,768	70.5	1,940	73.6	601	22.8
2012/13	5,016	3,241	64.6	2,449	75.6	756	23.3
2013/14	3,352	2,096	62.5	1,665	79.4	441	21.0

Source: LSMS datasets (World Bank 2020).

However, the number of households involved in the cultivation of maize increased from 73.8 per cent in 2007 to 79.4 in 2014. The households involved in the cultivation of rice did not change much, remaining at around 21 per cent for the entire period.

Table 3 shows the percentage of households that received maize vouchers: less than 4 per cent for seeds and less than 10 per cent for inorganic fertilizer. In addition, the table shows that fewer farmers received vouchers after 2010. Table 4 shows a similar trend in rice cultivation, where fewer than 2 per cent of farmers received seeds and fewer than 5 per cent received inorganic fertilizer. The baseline is 2007/08 as the subsidy was initiated in 2008 with a pilot phase in 2008/09. The datasets show limited treatment samples especially for the combination of seeds and fertilizer category. Due to limited observations of vouchers in the 2013/14 datasets, the study focused on the 2008–13 period.

Table 3: Households that benefited from the vouchers in maize cultivation, 2007–14

Year	Number of HHs	HHs that received vouchers	%	HHs that received seed vouchers	%	HHs that received fertilizer vouchers	%	HHs that received seed & fertilizer vouchers	%
2007/08	1,695	-		-	-	-	-	-	
2009/10	1,940	228	11.8	83	4.3	187	9.6	42	2.2
2012/13	2,449	158	6.5	61	2.5	118	4.8	21	0.1
2013/14	1,665	54	3.4	24	1.4	38	2.3	8	0.5

Source: LSMS datasets (World Bank 2020).

Table 4: Households that benefited from the vouchers in rice cultivation, 2007–14

Year	Number of HHs	HHs that received vouchers	%	HHs that received seed vouchers	%	HHs that received fertilizer vouchers	%	HHs that received both seed & fertilizer vouchers	%
2007/08	481	-		-	-	-	-	-	-
2009/10	601	33	5.5	7	1.2	30	5	4	0.07
2012/13	756	49	6.6	19	2.5	39	5.2	9	1.2
2013/14	441	17	4	7	1.6	14	3.2	4	0.9

Source: LSMS datasets (World Bank 2020).

Table A2 in the Appendix gives the descriptive summary of the variables used in the estimations based on the 2007/08 dataset, which is the baseline. The table gives variables for the control and treatment groups and the mean differences of variables based on the eligibility criteria used to target the households, as shown in Section 2.2. There were no differences between the control and treatment groups in terms of gender, marriage, plot size, use of extension services, and off-farm activities, based on the mean difference. However, the households that received the vouchers had more access to credit compared to those that did not receive vouchers in maize cultivation. This was important because the farmers were expected to buy the subsidized inputs. In addition, most of the farmers that received vouchers were fully engaged in rice cultivation compared to those that did not receive the vouchers, who engaged more in off-farm activities. Moreover, the control group had a higher correlation welfare status compared to the treatment group, which might indicate that farmers in the control group were poorer but had access to credit to be able to purchase subsidized inputs compared to the farmers in the control group, especially in maize cultivation.

Using these baseline characteristics, the eligibility criteria were not followed strictly, which influenced farmers' outcomes (see Houssou et al. 2017; Mason and Ricker-Gilbert 2013; Wang et al. 2019). The other variables that differ in the treatment and control groups are the size of the family, the type of soil on the farm, and the location of the farmers. Most of the farmers in the treatment group were in rural areas and had larger families compared to the control group. In addition, most of the farmers in the control group had better soil compared to the farmers in the treatment group. This may have affected maize production, as shown in other African countries, due to soil quality (Harou et al. 2017; Kopper et al. 2020). The results are similar based on the NNM-PSM method using the logit model in Table A3 in the Appendix. We include these variables as controls as the study estimates the impact of NAIVS on farmers' outcomes.

7 Empirical results

In this section, using equation (10), we estimate the factors that influence maize and rice production in Tanzania. We then use equation (11) to estimate the DiD results for the entire sample and the sub-sets, i.e. maize and rice sample sizes, before focusing on estimations based on the PSM approach.

7.1 The factors that influence maize and rice production in Tanzania

In Table 5, we use pooled, random, and fixed effects models to examine the determinants of maize and rice production in Tanzania. The ordinary least squares (OLS) model is biased when there are individual-specific effects such as time and region variables. The random effects model assumes that the individual-specific effects are uncorrelated with the explanatory variables, while in the fixed effects model, the individual-specific effects are assumed to be correlated with the explanatory variables. A Hausmann test was used to determine the suitability of both random and fixed models in the study, and the test showed that the individual-specific effects are correlated with the farmers outcomes, as shown in Table 5. Therefore, the fixed effects model is suitable for determining the factors that influence maize and rice production.

The household characteristic that is correlated with total production of maize and rice is the size of the household. Households with more members have higher yields, at the 1 per cent level, compared to those with small families, mainly because they have more family labour. Many production characteristics are correlated with total production of maize and rice. These include inter-cropping, hiring of labour, sales, the quality of the soil, nutrient availability, and the cost of inputs.

Table 5: The determinants of maize and rice production in Tanzania

	OLS		Random effects model		Fixed effects model	
Total production (log)	Coef.	SE	Coef.	SE	Coef.	SE
Household characteristics						
Gender	0.01	0.07	-0.00	0.06	0.03	0.08
Size of household	0.02**	0.01	0.02***	0.01	0.03***	0.01
Location	-0.29***	0.08	-0.11*	0.07	-0.11	0.10
Productive characteristics						
Inter-cropping	0.57***	0.07	0.33***	0.06	0.26***	0.07
Hired labour	0.42***	0.09	0.22***	0.07	0.40***	0.07
Soil type	0.61***	0.07	0.28***	0.06	0.21***	0.08
Cost of inputs (log)	0.26***	0.01	0.15***	0.01	0.12***	0.01
Wages (log)	-0.01	0.01	-0.00	0.01	-0.00	0.01
Sales (log)	-0.06***	0.01	0.10***	0.01	0.10***	0.01
Credit access	0.07	0.10	-0.17**	0.08	-0.05	0.11
Off-farm	0.29***	0.08	0.30***	0.06	0.04	0.08
Extension services	-0.54***	0.09	-0.05	0.07	-0.03	0.09
Networks	-0.07***	0.02	0.01	0.01	0.03	0.02
Nutrient availability	0.04	0.03	-0.01	0.03	0.07*	0.04
Temperature	-0.00**	0.00	-0.01***	0.00	-0.01***	0.00
Distance from the farm						
Major road	0.01***	0.00	0.00***	0.00	0.00***	0.00
Headquarters	0.00***	0.00	0.00	0.00	-0.00	0.00
Crops						
Maize	1.22***	0.08	0.99***	0.07	1.14***	0.10
Rice	1.32***	0.07	1.11***	0.06	0.95***	0.09
Districts	No		Yes		Yes	
Regions	Yes		Yes		Yes	
Years	No		Yes		Yes	
Constant	1.80***	0.28	0.26	0.26	0.36	0.26
Observations	6,838		6,838		6,838	
Groups	3,199		3,199		3,199	
R2	0.40		0.61		0.68	
F (23,6814)/ F(42,3597)	195.09				186.10	
Prob >F	0.00				0.00	
Wald chi2(42)			10,988.46			
Hausmann Test (Chi2(42))					516.58	
Prob > chi2			0.00		0.00	

Note: statistical significance at 1(***), 5% (**) and 10% (*) confidence levels.

Source: author’s calculations based on LSMS data (World Bank 2020).

According to the results, having access to farm inputs increases the yields, which is also the case when the farm has good quality soil and nutrient availability. The results show that inter-cropping is positively related to total production at the 1 per cent level. Based on a meta-analysis study by Raseduzzaman and Jensen (2017), inter-cropping, especially cereal grain legume, increases total production or yields compared to sole crop production, particularly for tropical reasons. The results show that increased hired labour, expenditure on inputs, and sale of produce have a positive relationship with total production at the 1 per cent level. This is similar to other studies that show the importance of sales for purchasing farm inputs such as hired labour, seeds, and fertilizers, resulting in higher total production (Adjognon et al. 2017; Dedehouanou et al. 2018; Maligalig et al. 2019). High temperatures affect total production negatively and are significant at the 1 per cent level. The results show that climate conditions affect crop yields, as demonstrated by Epule et al. (2018) in Uganda. The results show that the distance from farm to road is positively correlated with yields at the 1 per cent level, which might imply better market access for agricultural products.

7.2 DiD estimations for the period from 2008 to 2013

Table 6 shows the DiD estimation for the periods from 2008 to 2010 and 2008 to 2013. The 2008–10 period is considered as the short run, while 2008–14 is considered the long run in the estimations. The results show that there was an increase in total production for the 2008–10 period but not a significant one. Similarly, for the 2008–13 period, there was no increase in total production. The results also show that there was no increase in welfare to the households during this period although the impact is positive.

Table 6: DiD estimations, 2008–13 in Tanzania

	Total production				Welfare			
	2008–10		2008–13		2008–10		2008–13	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Before								
Diff (Treatment-Control) (1)	-0.25	0.15	-0.34**	0.14	-0.09	0.10	-0.08	0.11
Control observations	1,552		1,552		1,552		1,552	
Treatment observations	201		201		201		201	
After								
Diff (Treatment-Control) (2)	0.05	0.15	-0.39**	0.17	-0.02	0.09	0.11	0.13
Control observations	2,381		1,814		2,381		2,381	
Treatment observations	238		127		238		238	
DiD (2-1)	0.30	0.21	-0.05	0.22	0.11	0.14	0.19	0.17
R2	0.54		0.65		0.06		0.05	

Note: means and standard errors are estimated by linear regression. Inference: *** p<0.01; ** p<0.05; * p<0.1. With controls.

Source: author's calculations based on LSMS data (World Bank 2020).

Tables 7 and 8 show the DiD estimations for maize and rice cultivation in Tanzania. The results are surprising in that there was no increase in maize and rice production and welfare over the 2008–10 period. However, there was a reduction in maize production and not much change in welfare over the 2008–13 period. The results also show that there was no increase in rice production and welfare over the entire 2008–13 period. The results from the control variables show that extension services, although used, did lead to an increase in total production or even welfare for the two crops.

Table 7: DiD estimations for maize cultivation, 2008–13

	Total production maize				Welfare			
	2008–10		2008–13		2008–10		2008–13	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Before								
Diff (Treatment-Control) (1)	-0.03	0.14	-0.06	0.14	-0.10	0.11	-0.12	0.12
Control observations	1,139		1,139		1,139		1,139	
Treatment observations	178		178		178		178	
After								
Control observations	1,701		1,324		1,701		1,324	
Treatment observations	228		107		228		107	
Diff (Treatment-Control) (2)	-0.20	0.13	-0.67	0.18	0.12	0.10	0.14	0.15
DiD (2-1)	-0.17	0.19	-0.61***	0.23	0.22	0.15	0.27	0.19
R2	0.64		0.67		0.05		0.04	

Note: means and standard errors are estimated by linear regression. Inference: *** p<0.01; ** p<0.05; * p<0.1. With controls.

Source: author's calculations based on LSMS data (World Bank 2020).

Table 8: DiD estimations for rice cultivation, 2008–13

	Total production rice				Welfare			
	2008–10		2008–13		2008–10		2008–13	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Before								
Diff (Treatment-Control) (1)	-0.72*	0.42	-1.08***	0.48	-0.16	0.25	0.01	0.25
Control observations	337		337		337		337	
Treatment observations	25		25		25		25	
After								
Diff (Treatment-Control) (2)	0.11	0.36	-1.02***	0.41	-0.31	0.21	-0.10	0.20
Control observations	565		393		565		393	
Treatment observations	33		38		33		38	
DiD (2-1)	0.83	0.55	0.06	0.52	-0.15	0.33	-0.10	0.33
R2	0.55		0.67		0.06		0.07	

Note: means and standard errors are estimated by linear regression. Inference: *** p<0.01; ** p<0.05; * p<0.1. With controls.

Source: author's calculations based on LSMS data (World Bank 2020).

7.3 PSM estimations for the 2008–13 period

Using the PSM method, the households are matched based on control and treatment groups with the same observed characteristics. PSM is inferior to DiD in cases where there is panel data because it does not consider unobserved fixed effects. The PSM methods used in the estimation of total production and welfare in Tanzania are nearest neighbour matching (NNM), which focuses on five nearest neighbours, and Kernel-based matching (KBM). Full details of the sample size are given in Appendix Tables A4 and A5. The NNM matched all observations, but the KBM did not. We also use inverse probability weighted regression adjustment (IPWRA) to estimate the unbiased treatment effects due to selection bias. This method ensures that individuals in the treatment group who might not have been selected are included, while controlling for observation in the control group that could easily be included in the treatment group. This method gives consistency even in cases where the treatment group or the outcome models could be mis-specified.

Table 9 shows the impact of subsidy inputs on total production for the different years. The paper presents the average treatment on the treated (ATT), which is the most important parameter here because it is estimated by averaging within-match differences in the yields and welfare, between the treatment and the control group. The results show a positive effect on total production for the 2010 period. Initially, there was a sharp increase in total production in 2010 but there was no increase in 2012. An additional increase in vouchers given to a household results in an almost double increase in total production of both maize and rice. Similar results are obtained using the IPWRA method in Table A12 in the Appendix.

Table 9: Estimation of the treatment effect (ATT) of voucher input on total production in Tanzania using PSM

	2008		2008		2010		2010		2012		2012	
	PSM 5NN		PSM Kernel		PSM 5NN		PSM Kernel		PSM 5NN		PSM Kernel	
Overall	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE
ATT	-0.47	0.22**	-0.36	0.26	1.14***	0.11	1.16***	0.15	0.13	0.17	0.09	0.14
Total		1,753		1,670		2,619		2,499		1,941		1,803
Maize												
ATT	-0.46	0.24*	-0.16	0.25	0.73***	0.09	0.71***	0.12	0.14	0.17	0.13	0.14
Total		1,317		1,233		1,929		1,833		1,431		1,325
Rice												
ATT	-1.24**	0.60	-1.38	1.00	0.88***	0.22	0.74***	0.29	-0.01	0.34	0.15	0.32
Total		362		285		598		559		431		417

Note: *** p<0.01; ** p<0.05; * p<0.1. ATT is the average treatment on the treated.

Source: author's calculations based on LSMS data (World Bank 2020).

Table 10 shows the effects of the voucher input on welfare. The results show that there was no increase in 2010 and 2012 in the welfare of farmers who cultivated maize and rice. However, the results obtained using the IPWRA method show that in 2012 there was an increase, at the 5 per cent level, in the welfare of farmers who cultivated maize. However, there was a reduction in the welfare of rice farmers in 2010, as shown in Table A12 in the Appendix.

Table 10: Estimation of the treatment effect (ATT) of voucher input on the welfare in Tanzania using PSM

	2008		2008		2010		2010		2012		2012	
	PSM 5NN		PSM Kernel		PSM 5NN		PSM Kernel		PSM 5NN		PSM Kernel	
Overall	Diff	SE	Diff	SE	Diff	SE	Diff	SE	Diff	SE	Diff	SE
ATT	-0.15**	0.05	-0.12**	0.06	0.05	0.10	0.06	0.10	0.14	0.17	0.07	0.15
Total		1,752		1,670		2,619		2,499		1,941		1,803
Maize												
ATT	-0.10	0.05	-0.14***	0.05	0.10	0.10	0.12	0.10	0.02	0.18	0.12	0.20
Total		1,317		1,233		1,929		1,833		1,431		1,325
Rice												
ATT	-0.13	0.11	0.01	0.17	-0.35	0.36	-0.44	0.60	-0.10	0.33	-0.1	0.38
Total		362		285		598		559		431		417

Note: *** p<0.01; ** p<0.05; * p<0.1. ATT is the average treatment on the treated.

Source: author's calculations based on LSMS data (World Bank 2020).

The results show that there was an increase in both maize and rice production in 2010 based on the PSM estimations across all different samples, i.e. total production, maize, and rice samples. Moreover, there was an increase in the welfare of farmers that cultivated maize in 2012, based on the IPWRA method. However, after considering unobserved heterogeneity using the DiD method, there was no increase in total production, maize, or rice production or in the welfare levels of farmers. In addition, there was a reduction of maize production in 2010 compared to 2008. Other studies on sub-Saharan Africa such as by Jayne et al. (2018) found a similar effect, unlike Asia where there was an increase in production and welfare in both the short and long run in rural areas (Bathla et al. 2019; Solaymani et al. 2019; Zhang et al. 2020). However, this is contrary to the findings of some studies of Tanzania, such as those by Aloyce et al. (2014), Gine et al. (2019), and Kato (2016), which found that NAIVS had no impact on agriculture production.

7.4 The impact of NAIVS on farmers' production and welfare in different regions

It is possible that NAIVS may have had different effects on farmers' production and welfare in different regions for the period from 2008 to 2013. We used both DiD and PSM methods to estimate the impact in five regions, namely the central, northern, coastal, southern, and other regions. The results, which are provided in the Appendix, show a lot of heterogeneity based on the regions. As shown in Tables A6, A7, and A8 and Tables A11 and A13 respectively in the Appendix, and based on the DiD and the matching methods in Table 11, the NAIVS programme did not have a significant effect on farmers' total production and welfare in the central and coastal regions over the entire period.

Table 11: Estimation of the treatment effect (ATT) of voucher input on the total production in Tanzania using PSM, based on regions

	2008		2008		2010		2010		2012		2012	
	PSM 5NN		PSM Kernel		PSM 5NN		PSM Kernel		PSM 5NN		PSM Kernel	
Overall	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE
Other regions												
ATT	-0.67	0.58	-0.32	0.66	0.80	0.67	1.77**	0.88	0.22	0.45	0.13	0.24
Total		293		275		414		392		322		315
Central region												
ATT	-0.50	0.36	-0.76	0.47	0.06	0.26	0.16	0.28	0.10	0.71	-0.59	0.72
Total		372		359		487		459		354		350
Northern region												
ATT	0.09	0.69	-0.48	0.83	0.57	0.33	0.63	0.58	0.86	0.85	0.52	1.15
Total		316		310		526		514		337		324
Coastal region												
ATT	0.16	1.24	0.55	0.94	0.69	0.62	0.69	0.52	-0.39	0.43	0.02	0.53
Total		234		208		688		668		395		375
Southern region												
ATT	0.30	0.38	0.21	0.37	1.04***	0.17	1.00***	0.20	0.10	0.16	0.11	0.14
Total		410		406		504		478		410		375

Note: *** p<0.01; ** p<0.05; * p<0.1. ATT is the average treatment on the treated.

Source: author's calculations based on LSMS data (World Bank 2020).

The results from the PSM and IPWRA methods show that the southern, northern, and other regions had a positive and significant effect on total production in 2010. However, from the DiD estimations, the southern region, in areas such as Ruvuma, Iringa, Mbeya, and Rukwa, had a reduction in maize and rice production in 2010 and 2012 compared to 2008. as shown in the Table A9 in the appendix. In addition, the rice farmers had an increase in welfare in the entire period. The results also show that there was a reduction of welfare in the other regions, especially in rice production, in the period 2008 to 2010, as shown in Table A10 in the Appendix. According to Kato (2016), who focused on Ruvuma in the southern region, the input subsidy did not have an impact due to poor implementation of the programme, particularly at the local level. In most cases, vouchers were missing and there were delays in delivery of inputs and vouchers to the farmers and an increase in the prices of inputs. In addition, most of the vouchers were given to the elites and this resulted in a reduction of maize and rice production in the region.

8 Conclusion

This paper examined the impact of an input subsidy programme in Tanzania—the National Agricultural Input Voucher Scheme (NAIVS 2008–13)—on agricultural production and welfare. The programme focused on maize and rice cultivation, some of the most important cereals in Tanzania grown mainly by small-scale farmers. The study used both DiD and PSM estimators. In addition, the paper examined the factors that influence farm production in Tanzania using panel random and fixed methods. The results show that the input subsidy programme had a positive effect on maize and rice production only in 2010. Although there was a sharp increase in maize and rice production initially, there was not much of an increase in maize and rice production after 2010. While most regions had no increase in total production over the entire period, the southern region had a decrease in maize and rice production during this period. The use of extension services also had little effect on the farmers who received the input vouchers. However, because of the sample size and the number of households that received vouchers, it is important to interpret the results with caution. The factors that influence farm production in Tanzania are the size of the household, level of inter-cropping, cost of inputs including hired labour, soil quality, sales of output, distance from the farm to the road, and climate considerations.

Although governments in most sub-Saharan Africa countries have endorsed input subsidy programmes in their countries because of the need to increase food security, food production, and productivity and to reduce poverty, especially in rural areas, Tanzania was only partly successful in this because of mistargeting and poor implementation of the NAIVS programme. The results show that input subsidies may have had a positive impact initially but not in the long run. Therefore, policy makers may wish to pursue other strategies to increase production and the welfare of poor farmers in rural areas as input subsidy programmes may not lead to a green revolution because of inefficiency in their design and implementation. However, such programmes can create new markets for farm inputs in rural areas. Given the cost of such programmes, priority should be given to poor farmers in a few regions and the programmes should be monitored to ensure that the expected outcomes are achieved.

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Appendix

Table A1: Variable definitions

Variable	Variable definition
Outcome variable	
Total production	Yields per acre in kgs
Welfare	Adult equivalent consumption expenditure in Tshs per annum
Household characteristics	
Gender	Dummy: 1 if household head is male; 0 if female
Age	Age of household head in years
Education	Dummy 1: if household head has formal education, 0 if otherwise
Household size	Number of household members
Location	Dummy: 1 if households live in the urban centres, 0 if otherwise
Productive characteristics	
Title	Dummy: 1 if the plot owner has a title; 0 if otherwise
Good soil	Dummy: 1 if the soil is classified as good
Firm size (acres)	Landholding in acres
Farm productive assets	Number of farm productive agricultural assets
Inter-cropping	Dummy: 1 if household inter-crops, 0 if otherwise
Access to credit	Dummy: 1 if the household has a credit facility; 0 if otherwise
Extension services	Dummy: 1 if the household received extension advice; 0 if otherwise
Hired labour	Dummy: 1 if the household hired farm labour; 0 if otherwise
Wages	Total wage paid related to farm activities such as weeding, harvesting in Tshs.
Cost of inputs	Cost of inputs such as fertilizers, seeds pesticides, etc. in Tshs.
Networks	Number of network relationships with households e.g., relatives, neighbours etc.
Shocks	Dummy: 1 if agricultural or household shocks e.g., death or a fire occurred in 5 yrs.
Distance from the farm	
Distance to the road	HH distance in (kms) to nearest road
Distance to the market	HH distance in (kms) to nearest market
Distance to the house	HH distance in (kms) to nearest house
Distance to population	HH distance in (kms) to nearest population centre with +20,000
Climate	
Temperature	Average annual temperature (°C)
Annual precipitation	Average annual rainfall (mm)
Nutrient availability	Dummy 1: constrained, 0 if otherwise

Source: author’s calculations based on LSMS data (World Bank 2020).

Table A2: Baseline selected characteristics in Tanzania based on the 2007/08 dataset

Explanatory variables	Full sample Control group N=1,552	Full sample Treatment group N=201	Full sample Mean comparison test	Maize sample Control group N=1,137	Maize sample Treatment group N=178	Maize sample Mean comparison test	Rice sample Control group N=337	Rice sample Treatment group N=25	Rice sample Mean comparison test
Eligibility criteria									
Gender of household head (Male=1)	0.76	0.75	0.54	0.76	0.74	0.55	0.79	0.72	0.77
Married	0.73	0.75	-0.41	0.73	0.73	-0.07	0.79	0.68	1.24
Firm size (acre)	2.31	2.32	-0.06	2.64	2.40	0.85	2.16	1.62	0.87
Credit access (Yes=1, No=0)	0.05	0.09	-2.29***	0.06	0.11	-2.35***	0.04	0.04	-0.04
Extension services	0.19	0.18	0.25	0.20	0.18	0.53	0.15	0.24	-1.17
Off-farm (Yes=0, No=1)	0.8	0.86	-2.03**	0.84	0.87	-1.10	0.82	1	-2.30***
Outcome									
Yields per acre(kgs)	252.5	207.54	0.18	207.78	234.36	-0.27	397.97	328.83	0.20
Welfare (total consumption/adult equivalent)	908,033.5	767,426.7	2.67***	882,128.7	740,917.2	2.82***	70,281.71	54,428.5	1.82**
Household & productive characteristics									
Formal education of household head	0.74	0.70	1.18	0.75	0.67	2.17**	0.74	0.76	-0.23
Household size	5.29	5.93	-2.88***	5.42	6.03	-2.54***	5.74	6.2	-0.72
Location (Urban=1, Rural=0)	0.16	0.09	2.68***	0.14	0.08	2.14**	0.13	0.4	1.35*
Hired Labour (Yes=1, No=0)	0.86	0.89	-1.09	0.86	0.90	-1.66**	0.85	0.80	0.69
Inter-cropping (Yes=1, No=0)	0.63	0.65	-0.39	0.76	0.70	1.64**	0.55	0.48	0.70
Soil type (good=0, poor=1)	0.11	0.15	-2.00**	0.12	0.16	-1.35*	0.17	0.08	1.25
Wages (Tshs)	48,926	37,546.32	1.10	51,866.62	31,614.28	1.75**	72,816.77	99,821.58	-0.72

Note: statistical significance at 1(***), 5% (**) and 10% (*) confidence levels.

Source: author's calculations based on LSMS data (World Bank 2020).

Table A3: Logit model for the results using the propensity score estimation to determine the factors used to get vouchers in the NAIVS programme in Tanzania

Variable	Coef.	SE
Gender	-0.11	0.18
Size of household	0.07***	0.02
Rural	-0.55**	0.27
Inter-cropping	-0.12	0.17
Hired labour	-0.13	0.26
Soil type	0.34	0.22
Wages (log)	-0.02	0.02
Sales (log)	0.03	0.02
Credit access	0.67**	0.28
Off arm	0.30	0.23
Constant	-2.56	0.34
Number of observations	1,753	
Pseudo R2	0.003	

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

Source: author's calculations based on LSMS data (World Bank 2020).

Table A4: Propensity score five nearest neighbour matching (psmatch2)

	2007/08			2009/10			2012/13	
		Total			Total			Total
Untreated	1,552	1,552	Untreated	2,381	2,381	Untreated	1,814	1,814
Treated	201	201	Treated	238	238	Treated	127	127
Total	1,753	1,753	Total	2,619	2,619	Total	1,941	1,941

Source: author's calculations based on LSMS data (World Bank 2020).

Table A5: Propensity score kernel matching

		Matched			Controls		Bandwidth
2007/08	Yes	No	Total	Used	Unused	Total	
Treated	189	12	201	1,146	406	1,552	0.000615
Untreated	1,481	71	1,552	195	6	201	0.00165
Combined	1,670	83	1,753	1,341	412	1,753	
2009/10							
Treated	225	13	238	1,701	680	2,381	0.000588
Untreated	2,274	107	2,381	234	4	238	0.001944
Combined	2,499	120	2,619	1935	684	2,619	
2012/13							
Treated	117	10	127	1134	680	1,814	0.000708
Untreated	1,686	128	1,814	125	2	127	0.004241
Combined	1,803	138	1,941	1,259	682	1,941	

Source: author's calculations based on LSMS data (World Bank 2020).

Table A6: DiD estimations of total production and welfare of farmers in Central region

	Total production				Welfare			
	2008-2010		2008-2013		2008-2010		2008-2013	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Combined								
Before								
Diff (Treatment-Control) (1)	-0.68***	0.25	-0.77***	0.23	0.02	0.07	0.07	0.07
After								
Diff (Treatment-Control) (2)	-0.64	0.32	-0.96**	0.48	0.06	0.09	0.09	0.15
DiD (2-1)	0.03	0.41	-0.19	0.54	0.05	0.11	0.01	0.17
R2	0.61		0.67		0.27		0.25	
Maize								
Before								
Diff (Treatment-Control) (1)	-0.71***	0.25	-0.95***	0.24	0.01	0.07	0.07	0.08
After								
Diff (Treatment-Control) (2)	-0.75**	0.31	-1.18**	0.49	0.07	0.08	0.16	0.15
DiD (2-1)	-0.04	0.40	-0.23	0.55	0.06	0.11	0.08	0.17
R2	0.63		0.67		0.26		0.27	
Rice								
Before								
Diff (Treatment-Control) (1)	-0.22	0.58	-0.36	0.68	-0.11	0.22	-0.03	0.23
After								
Diff (Treatment-Control) (2)	-0.05	0.95	0.02	1.15	-0.61*	0.32	-0.23	0.41
DiD (2-1)	0.17	1.17	0.38	1.32	-0.50	0.40	-0.20	0.46
R2	0.80		0.82		0.28		0.17	

Note: inference: *** p<0.01; ** p<0.05; * p<0.1. With controls.

Source: author’s calculations based on LSMS data (World Bank 2020).

Table A7: DiD estimations of total production and welfare of farmers in Northern region

	Total production				Welfare			
	2008–10		2008–13		2008–10		2008–13.	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Combined								
Before								
Diff (Treatment-Control) (1)	-0.32	0.39	-0.40	0.36	0.01	0.10	0.02	0.11
After								
Diff (Treatment-Control) (2)	-0.17	0.48	0.07	0.55	-0.02	0.12	0.22	0.16
DiD (2-1)	0.15	0.61	0.46	0.66	0.01	0.16	0.19	0.19
R2	0.50		0.60		0.25		0.22	
Maize								
Before								
Diff (Treatment-Control) (1)	-0.23	0.38	-0.17	0.38	0.04	0.10	0.06	0.11
After								
Diff (Treatment-Control) (2)	-0.23	0.45	-0.11	0.60	-0.04	0.12	0.22	0.17
DiD (2-1)	0.00	0.59	-0.06	0.71	-0.00	0.16	0.16	0.21
R2	0.55		0.57		0.25		0.22	
Rice								
Before								
Diff (Treatment-Control) (1)	-2.23	1.48	-2.03	1.42	0.13	0.35	0.08	0.33
After								
Diff (Treatment-Control) (2)	-0.80	1.09	-0.32	0.94	0.16	0.28	-0.12	0.25
DiD (2-1)	1.43	1.82	1.70	1.69	0.03	0.44	-0.20	0.41
R2	0.50		0.60		0.28		0.34	

Note: inference: *** p<0.01; ** p<0.05; * p<0.1. With controls.

Source: author's calculations based on LSMS data (World Bank 2020).

Table A8: DiD estimations of total production and welfare of farmers in Coastal region

	Total production				Welfare			
	2008–10		2008–13		2008–10		2008–13	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Combined								
Before								
Diff (Treatment-Control) (1)	-0.19	0.98	-0.29	0.78	0.14	0.26	0.14	0.27
After								
Diff (Treatment-Control) (2)	-0.26	0.50	0.24	0.56	-0.05	0.13	0.07	0.19
DiD (2-1)	-0.07	1.09	0.54	0.95	-0.18	0.29	-0.07	0.33
R2	0.55		0.72		0.37		0.35	
Maize								
Before								
Diff (Treatment-Control) (1)	-0.21	0.94	-0.21	0.84	0.16	0.29	0.21	0.30
After								
Diff (Treatment-Control) (2)	0.03	0.50	-0.09	0.56	-0.10	0.15	0.05	0.20
DiD (2-1)	-0.18	1.06	-0.30	1.00	-0.27	0.33	-0.16	0.36
R2	0.67		0.76		0.31		0.29	

Note: inference: *** p<0.01; ** p<0.05; * p<0.1. With controls

Source: author's calculations based on LSMS data (World Bank 2020).

Table A9: DiD estimations of total production and welfare of farmers in Southern region

	Total production				Welfare			
	2008–10		2008–13		2008–10		2008–13	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Combined								
Before								
Diff (Treatment-Control) (1)	0.77**	0.23	0.90***	0.20	-0.04	0.07	-0.04	0.07
After								
Diff (Treatment-Control) (2)	-0.20	0.18	-0.58***	0.20	-0.01	0.05	0.08	0.07
DiD (2-1)	-0.98***	0.28	-1.48***	0.29	0.05	0.09	0.12	0.10
R2	0.76		0.81		0.27		0.25	
Maize								
Before								
Diff (Treatment-Control) (1)	0.99***	0.22	1.06***	0.21	-0.03	0.07	-0.04	0.08
After								
Diff (Treatment-Control) (2)	-0.33*	0.16	-0.64***	0.20	0.03	0.05	0.10	0.07
DiD (2-1)	-1.32***	0.26	-1.70***	0.29	0.06	0.09	0.13	0.10
R2	0.82		0.83		0.27		0.24	
Rice								
Before								
Diff (Treatment-Control) (1)	1.29***	0.48	1.28**	0.51	-0.41**	0.17	-0.30	0.20
After								
Diff (Treatment-Control) (2)	-0.09	0.43	-0.51	0.57	0.02	0.13	0.32*	0.18
DiD (2-1)	-1.48**	0.64	-1.7**	0.756	0.43*	0.22	0.62**	0.27
R2	0.82		0.87		0.36		0.29	

Note: inference: *** p<0.01; ** p<0.05; * p<0.1. With controls.

Source: author’s calculations based on LSMS data (World Bank 2020).

Table A10: DiD estimations of total production and welfare of farmers in other regions

	Total production				Welfare			
	2008–10		2008–13		2008–10		2008–13	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Combined								
Before								
Diff (Treatment-Control) (1)	-0.88**	0.43	-0.82**	0.35	0.55	0.44	0.69	0.53
After								
Diff (Treatment-Control) (2)	0.44	0.73	-0.38	0.45	-2.44***	0.72	0.17	0.62
DiD (2-1)	1.32	0.826	0.44	0.57	-2.99***	0.84	-0.51	0.82
R2	0.37		0.59		0.27		0.23	
Maize								
Before								
Diff (Treatment-Control) (1)	-0.32	0.38	-0.62	0.38	-0.10	0.84	-0.73	0.96
After								
Diff (Treatment-Control) (2)	0.27	0.70	-0.51	0.67	-1.21	1.51	-0.93	1.67
DiD (2-1)	0.58	0.80	0.11	0.77	-1.11	1.70	-0.20	1.94
R2	0.63		0.66		0.44		0.33	
Rice								
Before								
Diff (Treatment-Control) (1)	-1.00	1.61	-0.77*	0.42	-0.98	1.39	0.01	0.25
After								
Diff (Treatment-Control) (2)	0.95	1.60	-0.65*	0.35	-5.31***	1.37	-0.10	0.20
DiD (2-1)	1.95	2.27	-0.13	1.55	-6.29***	1.91	-0.10	0.33
R2	0.36		0.58		0.25		0.07	

Note: inference: *** p<0.01; ** p<0.05; * p<0.1. With controls.

Source: author's calculations based on LSMS data (World Bank 2020).

Table A11: Estimation of the treatment effect (ATT) of voucher input on welfare in Tanzania using PSM based on the regions

	2008		2008		2010		2010		2012		2012	
	PSM 5NN		PSM Kernel		PSM 5NN		PSM Kernel		PSM 5NN		PSM Kernel	
Overall	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE
Other regions												
ATT	-0.41***	0.11	-0.37**	0.17	-0.28	1.87	-1.86	1.93	1.07	0.84	1.59	0.92*
Total		293		275		414		392		322		315
Central region												
ATT	0.03	0.08	-0.05	0.09	0.02	0.11	0.06	0.12	0.17	0.20	0.17	0.29
Total		372		359		487		459		354		350
Northern region												
ATT	0.10	0.12	0.04	0.15	0.12	0.15	0.12	0.15	0.25	0.19	0.32	0.21
Total		316		310		526		514		337		324
Coastal region												
ATT	-0.02	0.28	0.02	0.18	-0.05	0.20	0.04	0.18	0.19	0.32	0.16	0.48
Total		234		208		688		668		395		375
Southern region												
ATT	-0.06	0.10	-0.06	0.10	0.03	0.06	0.03	0.08	0.08	0.10	0.09	0.08
Total		410		406		504		478		410		375

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

Source: author's calculations based on LSMS data (World Bank 2020).

Table A12: Estimation of the treatment effect (ATT) of voucher input on total production and welfare in Tanzania using inverse probability weighting

	Total production						Welfare					
	2008		2010		2012		2008		2010		2012	
Overall	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE
ATT	-0.25	0.17	1.32***	1.00	-0.99	0.88	-0.07	0.05	-0.08	0.21	0.21**	0.10
Total		1,753		2,619		1,941		1,753		2,619		1,941
Maize												
ATT	-0.02	0.20	0.78***	0.09	-1.28	1.93	-0.09**	0.05	0.20	0.09	0.29**	0.14
Total		1,317		1,929		1,431				1,929		1,431
Rice												
ATT	-1.02***	0.39	0.94***	0.13	-0.02	0.33	-0.23***	0.08	-3.38*	2.00	-0.15	0.31
Total		362		598		431		362		598		431

Note: *** p<0.01; ** p<0.05; * p<0.1. ATT is the average treatment on the treated.

Source: author's calculations based on LSMS data (World Bank 2020).

Table A13: Estimation of the treatment effect (ATT) of voucher input on total production and welfare in Tanzania using inverse probability weighting based on regions

	Total production				Welfare			
	2010		2012		2010		2012	
Overall	Diff.	SE	Diff.	SE	Diff.	SE	Diff.	SE
Other regions								
ATT	2.60***	0.43	0.17	0.63	-9.97	6.30	0.90*	0.50
Total		414		322		414		322
Southern region								
ATT	1.09***	0.13	0.62***	0.14	0.03	0.05	0.05	0.08
Total		504		410		504		410
Northern region								
ATT	0.53**	0.24	-3.50	5.60	-0.03	0.08	-0.18	0.59
Total		526		337		526		337

Note: *** p<0.01; ** p<0.05; * p<0.1. ATT is the average treatment on the treated.

Source: author’s calculations based on LSMS data (World Bank 2020).