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IMPACT OF INTEGRATED PEST MANAGEMENT TECHNIQUES' ADOPTION ON MAIZE PRODUCTIVITY IN SOUTHWEST, NIGERIA

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ABSTRACT

The study specifically determined the factors influencing farmers' adoption of the integrated pest management (IPM) and the impact of IPM adoption on farmers' productivity in the study area. These were done with a view to investigating how adoption of IPM affects farmers' productivity and efficiency in Southwestern Nigeria. A multi-stage sampling procedure was employed to select respondents. In the first stage, purposive sampling technique was used to select three States (Ekiti, Ogun and Osun) based on their prominence in maize production in Southwestern Nigeria. In the second stage, four Local Government Areas (LGAs) per State and three villages per LGA were purposively selected. In the third stage, stratified sampling was used to categorize maize farmers into adopters and non-adopters of integrated pest management techniques (IPM) and ten maize farmers were randomly selected in each stratum to give a total of seven hundred and twenty maize farmers for the study. Data were collected with the use of a pre-tested structured questionnaire on farmers' socioeconomic characteristics, farm characteristics, adoption status, integrated pest management techniques (IPM), quantities and maize of inputs and output. Data were analysed using inferential statistics. Tobit regression estimates showed that farmer's age, net farm income, farm size and availability of integrated pest management (IPM) techniques significantly influenced adoption behaviour of integrated pest management techniques (IPM). Results of the Propensity Score Matching showed a significant positive impact of (267.34 kg/ha) on maize productivity while instrumental variable regression showed an impact of 338.29 kg/ha. It was concluded that adoption of integrated pest management techniques (IPM) significantly improved maize productivity in the study area.

Keywords: Adoption, Integrated Pest Management Techniques (IPM), Instrumental Variable Regression Productivity Impact, Propensity Score Matching, Maize farmers, Southwest, Nigeria

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INTRODUCTION

Maize (*Zea mays*) is an important food crop widely grown in the tropics. The crop forms the staple foods for most of the population especially in areas adaptable for its production (Ofor *etal*., 2019). Most rural farmer grow the crop either for food, cash or both (Ofor *et al*, 2019). However, profitability and productivity of the crop is low in developing countries which have been blamed for poverty among rural farmers as well as the world food problems (CIMMYT, 2021). The low profitability and productivity of the crop in those countries, Nigeria inclusive have been found to be less than those from developed countries owing to a number of factor suchas pests and diseases (Alimi, 2022), poor soil fertility and lack of inputs (Iken and Amusa, 2004) and poor resource use (Adeyemo and Akinola, 2020; Idumah and Okunmadewa, 2017; Tijani and Osotimehin, 2017).

There is much great concern in Nigeria for the damages caused by pests and diseases on maize crop which have resulted in poor yield, poor returns, poverty and food insecurity among rural farmers. In addressing the problems of maize damage caused by insect pests, farmers have adopted conventional methods of control (Tijani and Sofoluwe, 2022; Tijani and Osotimehin, 2017). The conventional methods involves the application of chemicals which has increased cost of production, contaminate produce, threaten the ecosystem, impair human health and hence reduced farmers‘ net returns with attendant poverty (Ofuoku *et al*., 2018; Tijani *et al*., 2018). To alleviate the problems of high cost of production caused by high cost of pesticides, several IPM technologies were developed and introduced to the farmers. IPM is a pest management technology that emphasised the reduced or total non-use of synthetic chemicals in the control of pests and diseases for the purposes of enhancing farms‘ yield and profit while aspiring a healthy environmental (Samiee *et al*., 2009; Rahman and Hamid, 2012; IITA, 2010). Despite the established potential positive benefits of the technology on both the yield, farm profit and hence poverty and food security, the adoption rate in Nigeria is still very low (Ofuoku *et al*., 2018; Uwagboe *et al*., 2022). The low rate of adoption of IPM has been traced to several factors such as socio-economic, farm and institutional. Also, farmers’ risks attitude plays prominent roles in technology choice. Farmers are however known to be risk averse and hence analysis of technology adoption must take into account the risk attitudes or perception of the farmers (Adesiyan, 2021; Juma *et al*., 2019). Aside from market constraints, socio-economic and institutional constraints, risk-aversion dominates the discussion on the behavioural determinants of technology adoption (Juma *et al*., 2019). These may contribute to farmers’ unwillingness to use a new technology or abandon the conventional method. Since maize is a major arable crop grown in the study area, any beneficial technology will definitely improve returns and productivity with attendant effects on poverty and food security among the responding households. Since the adoption of the technology will definitely improve farmers’ net returns, productivity, food security and reduce poverty.

Objectives of the Study

The main objective of the study is to empirically evaluate the effects of integrated pest management techniques’ adoption on farmers’ productivity in Southwestern Nigeria.

The specific objectives are to:

(i) determine the factors influencing farmers adoption of integrated pest management techniques;

(ii) analyse the impact of integrated pest management techniques’ adoption on farmers’ productivity in the study area.

Research Hypotheses

The hypotheses tested are stated in the null form as:

(i) $H_{01:}$ Farmers adoption decisions on integrated pest management techniques are not influenced by farmer-, resource-, and institutional- specific characteristics;

(ii) $H_{02:}$ Adoption of integrated pest management techniques does not impact on maize productivity

RESEARCH METHODOLOGY

Area of Study

The study was carried out in the Southwestern geo-political zone of Nigeria. Southwestern Nigeria lies between longitude 2^0 42' and 6^0 03'East of Greenwich and latitude 5^0 49' and 9^0 17' North of the equator (Balogun, 2013). The Southwest comprises Osun, Ogun, Ondo, Ekiti, Oyo, and Lagos States. Three states were selected (Ekiti, Ogun and Osun) based on their prominence in maize production.

The study area enjoys a bi-modal rainy season which lasts from April to October and a dry season from December to March (mean annual rainfall of 135mm and mean daily temperature of 35^0C (BBC Weather Centre, 2008). The total population of the six states according to the 2006 National Census is 27,722,427 (NPC, 2007), while the total land mass of the study is 67,174.6 km^2. Majority of the inhabitants are predominantly small holder farmers who depend on agriculture for their livelihood. The prevailing vegetation, soil, and weather conditions determine the type of crops grown in different areas of southwest Nigeria.

and plantain. Maize is however becoming an important food crop in the area. There are maize processing industries in the study area. The people live mostly in organized settlements, towns and cities.

A multi-stage sampling procedure was employed for the selection of respondents for the study. In the first stage, purposive sampling technique was used to select three states Ekiti, Ogun and Osun states based on their predominance in maize production in Southwestern, Nigeria. In the second stage, four LGAs per state and three villages per LGA were purposively selected. In the third stage, a list of adopting farmers was obtained from the Agricultural Development Programme Office (ADPO) in each village. Ten adopters and ten non-adopters of integrated pest management techniques were randomly selected in each village to give a total of seven hundred and twenty maize farmers for the study.

Sources of Data and Data Collection Methods

Primary data were collected from the maize farmers in 2023 with the assistance of extension agents who are familiar with the farmers using a pre-tested questionnaire. The information collected include farmers' characteristics such as age, gender, educational level, marital status, household size, membership of cooperative society, extension contact, years of farming experience and fallow. Information on adoption status and use of integrated pest management techniques, their availability and sources as well as size of farmers' maize plots, farm labour force, cropping practice and tenure arrangements were also obtained.

Impact Assessment Techniques: The following techniques were used to analyse the impact of integrated pest management techniques on productivity of maize farm. These are the Tobit, Propensity Score Matching and Instrumental variable regression.

Tobit Regression Model

Tobit model was employed to determine the factors influencing integrated pest management techniques' adoption.

$Y^* = \beta X_i + \mu_i$

This can be represented algebraically for the ith farmer as:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_N X_N \ldots ; \quad i = 1,2, \ldots . N$$

Such that

$$Y_i = \begin{cases} 0 \text{ if } Y_i^* \leq T \\ Y_i \text{ if } 0 < 1; \quad (i = 1,2, . . . , n) \\ 1 \text{ if } Y_i > T \end{cases}$$

Where,

Y_i = observed dependent variable: the share of total maize area of ith farmer under integrated pest management techniques.

Y_i^* = non-observable latent variable representing the continuous dependent variable When positive decision occurs for the use of the technology (e.g. integrated pest management techniques).

T = non-observable threshold (cut-off) point.

N = number of observations.

Description and Measurement of Variables

Tobit regression analysis was performed on primary data in the study area to determine the type of relationship existing between specific explanatory variables and farmer's adoption behaviour of integrated pest management techniques using STATA 10.0 software package. In the Tobit model, data on the dependent variable can be classified into two groups. One portion of the data, the non-adopters equal to limit usually zero and the other portion, the adopters, is above the limit to be estimated.

The dependent variable (Y_i): This is a continuous and discrete variable for the ith farmer. The continuous part was measured by the share of total maize area of a farmer under integrated pest management in hectare; while the discrete part takes on a value of either zero

or one. A farmer is scored one if he adopts the technology, and zero if otherwise. It is hypothesized that this decision is influenced by the independent variables.

The independent variables: These include all those variables that are associated with the adoption of integrated pest management techniques along with those whose evidences from previous studies have been inconsistent. They include farmers' characteristics, resource/technology characteristics and institutional characteristics.

Farmers' Characteristics

Farmers' Age (X_1):- This is the age of the ith farmer measured in years. Age has been included in the model as evidence from previous studies shows that the age of an individual affects his mental attitude to new ideas and may influence adoption in one of several ways. For instance, as the farmer ages, it is expected that his willingness to embrace new ideas would diminish. Younger farmers have been found to be more knowledgeable to new practices (Ogundari and Ojo, 2017; Ayanwale and Amusan, 2022); more receptive and adaptable to new technological innovations and may be more willing to bear risk and adopt a technology (Gould *et al*., 1989; Spencer, 2014). The older the farmer, the less likely he adopts new ideas as he tends to be more conservative by gaining more confidence in his old ways/methods as newly introduced technology usually comes with additional cost (Ajibefun *et al.*, 2020; Hossain, 2014)

Gender of Farmer (X_2): - Women farmers are generally perceived to face more constraints on their farms and this will negatively affect their adoption of new ideas. This variable is expected to have a negative sign on the dependent variable. Male farmers are scored 1, while female farmers score zero (Ajibefun *et al.*, 2020).

The adoption of improved technology is a managerial concern that requires some managerial skills. Such skills are often gained through education (Manyong *et al.*, 2014; Ayanwale and Amusan, 2022). Also, education reduces the level of ignorance of an individual by improving his ability to decode, understand and process information and therefore is a measure of the ability to assess new technology (World Bank, 2019). Adesina *et al.* (1998), posited that education and experience are two common measures of human capital (the ability to acquire and process information about a new technology) which may be used as proxies for risk. It is therefore expected to have a positive impact on the decision to use integrated pest management techniques. Uncertainty and risk aversion have been shown to decrease the propensity for individual to adopt technologies (Feder *et al.*, 1985;). However, while measuring an individual's risk perceptions and risk aversion is difficult, economic theory posits that their perceptions are influenced by information and human capital. Thus, following earlier empirical findings, the maintained *a priori* expectation is that level of literacy is positively related to adoption behaviour. It is measured as number of years of schooling.

Household Size (X_4): This is defined as the total number of people living with the farmer family unit. That is, it comprises all the people living under the same roof and who eat from the same pot with the ith farmer. This variable is brought into the model because it plays an important role in determining what occurs on the farm. Some previous studies show this variable is positively related to adoption behaviour as it provides a larger supply of family labour while other studies viewed that this variable has a negative relationship with adoption since increased household size increases consumption pressure. Thus, it is difficult to predict this variable 'a priori'. Hence, household size and adoption will depend on the balance of the opposing forces of family demand (Nsoanya *et al*., 2021; Matsumoto *et al*., 2013). The variable was measured by the number of persons in the household.

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Net Farm Income (X_5): This is the net farm income per hectare of the farm. Since this variable can be viewed as a proxy for wealth, the options to acquire and use technologies may be expanded by it (Kinkingninhoun, 2020). It is included to determine whether the potential adopters' social status and purchasing power have an effect on technology use. This is because wealthy farmers have sufficient resources to absorb the cost and risk of failure of the innovation. The variable is expected to have a positive relationship with adoption as the farmer tends to experiment with new ideas that tend to increase net farm income. This variable was measured in naira.

Off-Farm Income (X_6): Off-farm income is measured as the total amount of income earned from external off-farm sources during the season. Income from these sources is relevant since they enable the farmer to undertake new agricultural practices. Off-farm-income can also help to overcome a working capital constraint or may actually support the purchase of some fixed-investment type of innovation (Okoruwa, 2014). It is therefore postulated that the coefficient of this variable will be positively correlated with the farmer's adoption behaviour.

Cropping Practice (X_7): This variable is expected to have a positive relationship with adoption behaviour. This is because the cropping system employed by a farmer many suggest the need for use of some technologies (Diewart and Nakamura, 2015; Ogada, 2014). For example, sole cropping is considered suitable for easy use of machinery (e.g. tractors) than mixed cropping. This variable was measured as dichotomous variable with sole cropping scored 1 and mixed cropping, 0.

Labour Force (X_8): This is defined as the number of 'man-equivalents' of people working on the farm. New technologies may increase the seasonal demand for labour, in which case adoption may be less attractive for those operating in areas with less access to labour markets (Nsoanya *et al*., 2017). This variable is therefore expected to have a positive influence on adoption behaviour.

Technology Characteristics;
Total Maize Farm Size (X_9) - This is the hectarage of the farm planted and managed under IPM techniques. This variable is expected to have a positive relationship with IPM technology adoption decision as shown by various studies (Nelson and Batie, 1987; Akinola, 1987; Polson and Spencer, 1991; Okoruwa, 2014). This is because, the larger the maize farm size cultivated, the higher the tendency to adopt new technological innovations such as IPM

techniques. The variable was measured in hectares.

Availability of IPM techniques (X_{10}): The adoption of a technology is promoted by its availability since it is obvious that the technology will not be used unless made available in the right quantity, form and time (Adekoya and Babaleye, 2017; Okoruwa, 2014). This variable will determine whether adoption behaviour of the potential adopter is supply-constrained. It was measured as a dichotomous variable with adequate technology supply attracting one and inadequate supply, zero. The variable is hypothesized to have a positive sign.

Institutional Access:

Membership in Association/Cooperative Society (X_{11}): Cooperatives enhance the interaction and cross-fertilization of ideas among farmers. The influence of credit for instance, on IPM techniques' use is measured in terms of membership in cooperatives as its use is promoted by cooperatives. If a farmer is a member of a cooperative, credit and new technological innovations such as IPM techniques are provided to him as a package. Thus, membership in a cooperative is very important in the adoption of a technology since it indicates higher socio-economic status (Dawe *et al*., 2020). Having access to other sources of credit may not have much effect on the purchase of IPM because a farmer may not know where to buy them. A positive sign is hypothesized for this variable. It was measured as a dichotomous variable with respondents' membership attracting one and non-membership, zero.

Extension Contact (X_{14}):- This variable incorporates the information which farmers obtain during the year on the importance and application of new technological innovations through counseling and demonstrations by extension agents on a regular basis. The impact of this information on adoption decisions vary, however according to its channel, sources, content, motivation and frequency (Lee, 2018; Rajan, 2022). Thus, based on the innovation-diffusion literature, the expected sign for the coefficient of this variable is positive. It is measured as a dichotomous variable with respondents contact during the period recorded as one, and zero otherwise.

Propensity Score Matching Method (PSM): The propensity score matching method was used to analyse the impact of IPM techniques' adoption on maize productivity and efficiency of production by the farming households. Similar studies such as Awotide (2012) have used propensity score matching to evaluate productivity impact of technology adoption. Propensity score matching (PSM) method is a quasi-experimental approach that controls for the self-selection that normally arises when technology adoption is not randomly assigned and self-selection into adoption occurs.

However, in quasi-experimental approaches, adoption is not randomly distributed to the two groups of the households, but rather the household itself deciding to adopt given the information it has. The main parameter of interest in a non-experimental framework is the average treatment effect for the treated population (ATT), expressed as:

$$\tau ATT = E\,(Y_i - Y_0 \mid D = 1) = E\,(Y_i \mid D = 1) - E\,(Y_0 \mid D = 1)$$

Where Y_1 denotes the value of the outcome of adopters of IPM techniques (1), and Y_0 is the value of the same variable for the non-adopters (0). The problem that arises with unobservability is by virtue of the fact that $E\,(Y_i \mid D = 1)$ can be estimated but not $E\,(Y_0 \mid D$

= 1). Although Ʈ = E (Y_i │ D = 1) - E (Y_0 │ D = 0) can normally be estimated, it is potentially a biased estimator of ƮATT**.** This kind of bias is a central concern in non-experimental studies (Smith and Todd, 2005). D = {0, 1} is the indicator of exposure to treatment.

Rosenbaum and Rubin (2105) suggest using the propensity score matching (PSM) model to account for sample selection bias that results due to observable differences between treatment and comparison groups. PSM controls for self-selection by creating the counterfactual for the group of adopters.

PSM estimates will be reliable, provided participants and controls have the same distribution of unobserved characteristics. The failure of this condition to hold is often referred to as a problem of "selection bias" in econometric, or "selection on unobservables" (Heckman and Robb, 2005). Secondly, the support for the comparison and the program participants should be the same. Finally, it is desirable that the same questionnaire is administered to both groups and that participants and controls be derived from the same economic environment.

Instrumental Variable (IV) Regression Method

Instrumental variable is an important quasi-experimental technique with numerous applications in agriculture. IV allows us to get unbiased estimate of causal effect even when there is selection bias, unobserved confounding or imperfect compliance. Although PSM technique controls for biases due to observed characteristics, it still cannot correct biases due to unobserved characteristics or endogeneity. The idea of IV is to first identify suitable instruments that are correlated with maize variety adoption by farmers but are uncorrelated with the unobserved factors that affect the outcome. For this study, these instruments were however subjected to over-identification tests to check their validity. The IV estimation to achieve the objective is specified below as:

$Y_i = \alpha X_i + \beta T_i + \varepsilon_i$Where Y_i is an effect outcome variable for maize farmer i and X_i is a vector of observable control covariates. β_i is a binary variable representing whether farmer i adopted IPMtechique (=1 for adopter, 0 otherwise), X is a vector of parameters to be estimated, T is the adoption effect parameter to be estimated, and ε_i is the unobserved error term. To isolate the part of the treatment variable that is independent of other unobserved characteristics affecting the outcome, Two-Stage Least Squares (2SLS) approach to IVs was used. The first stage was to regress the treatment on the instrument Z, the other covariates in equation 41, and a disturbance, ε_i. This process is known as the first-stage regression:

$T_i = \gamma Z_i + \varphi X_i + u_i$ The predicted treatment from this regression, $^{\wedge}T$, therefore reflects the part of the treatment affected only by Z and thus embodies only exogenous variation in the treatment. $^{\wedge}T$ is then substitute for treatment in equation 41 to create the following reduced-form outcome regression:

$Y_i = \alpha X_i + \beta(\gamma Z_i + \varphi X_i + u_i) + \varepsilon_i$The IV (also known as two-stage least squares, or 2SLS) estimate of the program impact is then $^{\wedge}\beta_{IV.}$

RESULTS AND DISCUSSION

TABLE 1

Tobit parameter estimates of the factors affecting adoption of improved maize varieties

Variable	Adopters (n=360)	
	Normalized Coefficient	Asympotic t-ratio
Farmers Age (X_1)	-0.3263	- 4.3936*
Gender (X_2)	-0.4540	- 1.8665
Years of Education (X_3)	0.1157	3.3695*
Household size (X_4)	-0.3223	- 2.8416*
Net Farm Income (X_5)	0.0406	2.4759*
Off-Farm Income (X_6)	-0.3457	-1.8421
Cropping Practice (X_7)	0.2405	1.0315
Labour Force (X_8)	0.2141	1.9891*
Total maize farm size (X_9)	1.5416	5.1417*
Availability of IRV (X_{10})	0.0376	3.0883*
Membership of Ass. (X_{11})	0.3214	2.7105*
Extension Contract (X_{12})	0.5758	4.1782*
Constant	2.7911	0.6155

Source: Data analysis, 2023

*Significant at 5% level

The predicted prob. of Y > Liimit given average X(1)	0.7892
The observed frequency of Y > Limit	0.7350
At mean values of all X(1), E(Y)	7.5238
Log likelihood function	-847.54559
Mean square error	46.042150
Mean absolute error	0.39795132
Squared correlation between observed and expected values	0.87033
Limit observations	360
Non-limit observations	

Household size (X_4) bears negative and significant ($p<0.05$) relationship to adoption decision of IPM techniques. This is also similar to the results of some studies that increased household size increases consumption pressure. This may also be attributed to little farm assistance rendered farmers' wives and children who might engage themselves in other non-farm activities such as trading and attending schools.

Net farm income (X_5) was positively signed and statistically significant at 5% in explaining IPM adoption. This means that one unit increase in adopting farmers' net farm income increases the probability of adoption of IPM techniques by 0.04 units. Off farm income (X_6) had negative and non-statistical significance on adoption behaviour. It is therefore not a major determinant of adoption decision.

The positive coefficient of cropping practice (X_7) may be due to the predominantly mixed cropping practice for maize. However, sole cropping according does not enhance technology adoption and its practice by farmers is mainly to reduce the risk of production loss from a single crop enterprise. Access to labour (X_8) had positive and significant effect on IPM adoption behaviour. A unit change in access to labour increases the probability of IPM adoption by 0.214.

Total maize farm size (X_9) was significant (positive) in explaining IPM adoption decisions. This is similar to the results of some studies. A unit change in total maize farm size increases the probability of adoption of IPM by 1.542. Availability of improved maize varieties (X_{10}) was positively and significantly related to adoption of IPM. It is therefore an essential component of the adoption process. A unit change in availability of IPM increases the probability of adoption by about 0.034. This is consistent with results obtained by some studies (Lee, *et al.*, 2012). Membership in association/cooperative society (X_{13}) and Access to extension contact (X_{14}) positively and significantly influenced adoption of IPM techniques.

Effect of Adoption of Integrated Pest Management Techniques on Maize farmer's Productivity

Due to the problem of selection bias and particularly non-compliance or problem of endogenity, this study uses a combination of methods to access the impact. The impact of IPM techniques on maize productivity was estimated by the use of Average Treatment Effect using propensity score matching techniques and Local Average Treatment Effect (LATE) model using instrumental variable regression for the purpose of comparism. The LATE estimate was carried out for the outcome (maize productivity). The result of the impact of IPM techniques adoption on farmer's productivity is presented in Table 2. The Average Treatment Effect (ATE) in the entire population was 239.54 kg/ha, the ATEI on the sub-population of adopters was 267.34. This implies that the adopters had an increase of 267.34 kg/ha in maize productivity. Also, the instrumental variable regression estimates suggest that the adoption of IPM techniques significantly increases maize productivity by 318.29 kg/ha. This could be interpreted as the change in maize productivity that is attributed to a change in IPM techniques.

TABLE 2

Estimation of effects of Integrated Pest Management Techniques'adoption on output/hectare of adopting farming household

Estimation methods	Parameters	Std. Error
Propensity score matching	-	-
Average Treatment Effect (ATE)	239.54*	123.00
Average Treatment Effect (Adopters) (ATE1)	267.34*	107.16
Average Treatment Effect (Non-adopters) (ATE0)	210.93*	136.29
Instrumental variable regression	318.29*	117.22

Source: Data analysis, 2023
*Significant at 5 percent level of probability

CONCLUSION AND RECOMMENDATIONS

Adoption of IPM techniques significantly improved maize productivity in the study area. Based on the conclusion of this study, the following recommendations are made in order to improve maize production in the study area.

(i) The federal government and developmental agencies/private organisation should make IPM technologies available and accessible to farmers, particularly the non-adopters in the study area. Access to IPM technologies is a necessary condition for enhanced maize production, therefore efforts should be geared toward making adequate IPM technologies available to the rural farmers in order to encourage its adoption.

Since the adoption of IPM technologies led to increase in maize productivity, then it means that one of the ways to achieve Nigeria's goal of self-sufficiency in maize production is through IPM technology adoption, hence all necessary efforts such as creation of awareness about the potential benefits inherent in the adoption of IPM technologies such as increase in farmers education, more publicity about the IPM technologies released through the media should be intensified. Credit facilities as well as extension service should also be adequately provided.

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