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FACULTY OF AGRONOMY AND FORESTRY ENGINEERING

Drivers of irrigation technology adoption and impact on maize productivity among smallholder farmers in Mozambique

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In

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DECLARATION

I, Adongo Immaculate declare that to the best of my knowledge, this dissertation titled "Drivers of Irrigation Technology adoption and Impact on maize productivity among smallholder farmers in Mozambique" represents my own authentic work and it has never been presented for consideration of any certification at this or any other University or institution of higher learning. This thesis has been complemented by references duly acknowledged. This dissertation is presented in partial fulfillment of the requirements for obtaining the degree of masters of science in Agricultural Economics, from Eduardo Mondlane University.

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LIST OF ACRONYMS

ATET	Average Treatment Effect on the Treated
CYMMIT	International Maize and Wheat Improvement Center
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
MADER	Ministry of Agriculture and Rural Development
NGOs	Non-Governmental Organizations
OLS	Ordinary Least Squares
PSM	Propensity Score Matching
SDGs	Sustainable Development Goals
IAI	Integrated Agricultural Survey
USD	United States Dollar
WFP	World Food Programme
VIF	Variance Inflation Factor
RUT	Random Utility Theory
IWMT	Implementation of integrated water Management Technology
ANOVA	Analysis of Variance
NNM	Nearest Neighbor Matching

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ABSTRACT.

Irrigation stands as a cornerstone of agriculture that can improve crop productivity supporting food security, and poverty alleviation, especially against surging populations and shifting climates. However, the diffusion of irrigation technologies among small-scale cultivators in Mozambique is very low, swayed by factors that affect the farmers' capacity to implement them. This research analyzed the on-farm, socio-economic and institutional drivers of irrigation technology uptake and impact on maize productivity among smallholder farmers in Mozambique. Using secondary data from the 2023 Agricultural and Livestock Survey (IAI 2023), the study used Logit regression model to establish the key drivers of irrigation uptake, while propensity score matching (PSM) via nearest-neighbor estimation quantified the causal effect of adoption on productivity. Results revealed 20% maize farmers in Mozambique adopted irrigation technology, where majority 25.1% of these adopters were located in Maputo province, 6% in Gaza and 8% in Inhambane province. Household size, education, extension access, size of the farm, credit access and location positively influence the probability of irrigation technology adoption. On the other hand, off -farm income negatively influenced the decision to take up irrigation. The average treatment effect estimated on the treated (ATE) demonstrated that irrigation adoption increased maize productivity for the adopters of irrigation technology by 590.41kg/ha. The findings reaffirm irrigation's contribution to food security and improving household income, and offers insights for policy formulation. Further, there is need to improve credit access by the government and redesign credit schemes that tailor agricultural credit products.

Keywords: Smallholder farmers, Irrigation, Mozambique, Maize productivity, Agriculture.

CHAPTER ONE

1. INTRODUCTION

1.1 Background

Globally, the effects arising from changing weather patterns are already being felt especially in the agricultural sector, now facing devastating challenges in production, causing decreased crop output (Iqbal & Ghauri, 2011). The problems associated with the changes in weather are expected to intensify heightening the risk of food insecurity, poverty and hunger, more so in Africa, which is one of the continents in the World highly affected by climate change (Field, 2014). According to the new World Bank flagship report "Rising to the Challenge", Keeping global temperature increase within 2^0C is becoming increasingly impossible, making it essential for farmers to change their ways of farming and embrace adaptive strategies (World Bank, 2024). Rising temperatures, shifting rain patterns are already causing severe impacts to agriculture causing low yields. And in spite of these difficulties, agriculture is still tasked with feeding the rapidly growing world population, anticipated to reach 8.6 billion by 2030 (Kucuk & Cobanoglu, 2024).

Mozambique is one of the 10 African countries highly affected by changes in weather patterns (Mavume et al., 2021). It has a warm, humid climate characterized of two main seasons. November to April, is the first season and it rains a lot during these months, then between May to October is the second season with little or no rainfall. Rainfall is generally higher along the coast (800-1200mm annually) and lower in southern inland areas (as low as 300mm). The central plateau and northern regions receive moderate rainfall (600 -1000mm annually)(World Bank., 2020). In certain instances, rain-fed agriculture faces challenges of this uneven distribution of rainfall resulting in water deficits, crop losses, and diminished yields. Additionally majority of subsistence smallholders who practice their farming under rain-fed conditions experience modest household income (Benfica et al., 2023; Jorge, 2024; Manuel et al., 2021a; Nobre et al., 2023). Noteworthy, the smallholder farmers produce nearly 95% of the agricultural output in Mozambique (Abbas et al., 2024).

Most small-scale cultivators in Mozambique rely upon maize farming for food, income and it is dominantly grown on 82.8% across the cultivated lands (African Development Bank, 2024; World Bank. 2017.; MADER, 2023). Based on reports from agriculture survey 2023 (IAI), the land area dedicated to maize cultivation in Mozambique in 2023 was approximately 2,688,164 hectares, representing 39% of the country's total cultivated land. Recently, there has been an increased demand for maize because of expanding breweries, millers, and feed millers. However, its production has not significantly increased to meet this demand (Mole & Popat, 2024).The Ministry of rural development and agriculture reported in 2023 that, maize yields remained relatively low at 0.79 tons per hectare (MADER, 2023). In some regions like Maputo Province, yields dropped to as low as 0.419 tons per hectare compared to 2022 agricultural season. This is significantly lower compared to neighboring countries in the same year. For example, maize yields ranged from about 1.96T/ha in Malawi, 2.3T/ha in Zambia and 2.85 tons in Angola to as high as 6.35 tons per hectare in South Africa according to FAOSTAT (2023).

Low adoption of modern agricultural technologies is regarded as a major contributing factor associated with Mozambique's agricultural sector sub-optimal performance, particularly on maize production (Chandio & Yuansheng, 2018; Jack, 2013a; Khainga et al., 2021; Woodhouse, 2012). This limited technological uptake, especially the inability to obtain better seeds, fertilizers, animal traction and irrigation has led to stagnating maize yields. Furthermore, several studies have noted that changes in maize yields is largely due to changes in rainfall patterns rather than the uptake of better cropping practices (Cavane et al., 2013; Come et al., 2021). The findings above illustrate the vulnerability of rain-fed agricultural systems, where maize production can be very erratic due to weather variability.

Irrigation technologies are highlighted in research as an important approach to address the problem of low agricultural productivity in Sub-Saharan Africa (SSA), including Mozambique (Bjornlund et al., 2020). Research has shown various benefits of irrigation, which include increased crop output, non-seasonal production, and higher incomes (Omondi & Shikuku, 2013; Yılmaz & Yurdusev, 2011). According to Makone et al. (2021), irrigation is valuable in nutrient circulation, soil fertility enhancement and boosting crop productivity. Additionally, regions with frequent irrigation practices tend to experience lower poverty rates due to improved food security and increased income levels (Adeoti, 2008a). Therefore, expanding the use of technologies has become a crucial tactic for raising crop productivity particularly in Mozambique's dry and semi-arid regions.

Irrigation development in Mozambique has been given attention and priority in the National Development Plan where the government of Mozambique, through the Ministry of Agriculture and Rural Development (MADER) have been promoting climate smart agricultural practices, including the adoption of water conservation and storage to boost the productivity of crops (World Bank, 2017). The government of Mozambique also partnered with World Bank in 2017 to invest over 70 million USD to develop irrigation (Editorial, 2017). In Mozambique, just half of the 6% land quipped with irrigation infrastructure is currently completely functional, based on World Bank, (2018) research. This implies that increasing the amount of irrigated land still has a lot of potential and capacity to boost agricultural productivity.

1.2 Statement of the Problem

Due to its geographic location, Mozambique has historically been vulnerable to natural catastrophes; nevertheless, within the last 20 years, the frequency and severity of droughts, floods, and cyclones have grown, adversely affecting the country's whole economy especially agriculture (Manuel et al., 2021b). Droughts in Mozambique affect 46% of the population every year (Lombe et al., 2024). These effects go beyond diminishing crop yields or degrading pastures and woodlands, as it also lowers earning for smallholder farmers, soaring food costs and hunger. Maize which is a very important food security crop in Mozambique is severely impacted by droughts and due to water stress, maize yield losses can go as high as 25%, 50% and 21% during vegetative, flowering and grain filling stages respectively (Sah et al., 2020).

Irrigation helps to supply water for agriculture during the entire year and has the possibility to mitigate climate change impacts and enhance agricultural productivity (Bagos et al., 2010). It has been globally promoted as a measure to the water stress, however, the extent of its adoption among small-scale farmers in Mozambique is very low. As stated by the ministry of Agriculture and Rural Development (2023), currently, only 7.7% of the small and medium-sized farms use irrigation (MADER., 2023). Several factors have influenced the adoption or not of a given agricultural technology. In the case of irrigation technology, Mwangi & Kariuki, (2015), demonstrate that farmers' decisions about adoption are influenced by the dynamic interplay between the features, the configuration of the farm's environment, and the institutional elements.

Numerous studies on the uptake of agricultural technology in Mozambique have explored irrigation in combination with other agricultural technologies like fertilizers, improved seeds and animal traction (Come, 2021; Guanziroli & Guanziroli, 2015; Uaiene, 2011 Cunguara & Darnhofer, 2011). While existing literature on irrigation specific research has focused on system governance, water rights, crop diversification, and policy frameworks (Chaúque et al., 2024; Hoogesteger et al., 2023; De Sousa et al., 2017; Beekman et al., 2014; Veldwisch et al., 2013a). These studies which demonstrate irrigation's potential to enhance productivity and climate resilience are largely descriptive and institutionally oriented, with mixed findings on the factors that influence the adoption of irrigation technologies. The benefits associated with irrigation technology uptake are often mentioned but not empirically measured or estimated which affects decision making and policy formulation by farmers and the government. Moreover, there are limited studies in Mozambique on drivers of irrigation uptake particularly at household level.

Understanding the drivers of irrigation innovation uptake and its effect on maize productivity is essential in order to create effective adoption boosting tactics that improve yields. Therefore, this thesis provides a thorough comprehension of the elements contributing to the uptake of irrigation innovation in order to improve maize yields through effective and efficient targeting initiatives. This research also offers actionable findings for policy formulation by the government to plan programs that promote irrigation adoption among smallholder farmers. This study will also be an effective instrument for agriculture extension in order to strategically transmit irrigation practices in Mozambique.

1.3 Research objectives

1.3.1 General objective

To establish a thorough relationship that demonstrates the effect of irrigation technology adoption among maize smallholder farmers in Mozambique.

1.3.2 Specific objectives

i. To examine the key factors influencing the adoption of irrigation technologies by smallholder farmers in Mozambique.
ii. To estimate the effect of irrigation technology adoption on maize productivity for smallholder farmers in Mozambique.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 The present condition of irrigation in Mozambique

Mozambique possesses around 3 million hectares of potential for irrigation yet, about 118,000ha of it has been developed with irrigation systems (World Bank., 2022). The vast majority of this irrigated land, (approximately 99%) relies on surface water, mainly from rivers, while ground water supports just 2% (Aquastat., 2022). In Mozambique, irrigation systems are divided into extensive or multi-user public projects covering 30,000ha and small -scale, privately managed plots as small as 1ha (Beekman et al., 2014a). In this context, small-scale irrigation refers to systems owned or privately operated by individual farmers or farmer groups. A cross Africa, small-scale irrigation is more prevalent than other methods due to its affordable infrastructure and simpler management requirements (McCarthy et al., 2023). Conversely, government agencies and development groups, finance and oversee extensive public projects.

In Mozambique, smallholder farmers employ diverse array of irrigation techniques, such as drip systems, gravity-fed methods, furrow irrigation along mountainous slopes, sprinkler systems powered by portable diesel pumps in valley regions, watering cans, and floodplain irrigation along coastal areas (Beekman et al., 2014b). To enhance accessibility and affordability of irrigation equipment, initiatives like the Gorongosa and the World Bank programs are actively supplying solar-powered irrigation systems and compact irrigation kits, particularly in drought-stricken regions of the country (Gorongosa, 2020; World Bank, 2021). According to the Integrated Agriculture survey report 2023 (IAI), The vast majority of farmers who have implemented irrigation technologies are situated in the southern, majorly Gaza and Maputo province (MADER, 2023). This is because the region is vulnerable to drought and it is also semi-arid. With 27,000 hectares, the Chokwe Irrigation Scheme (CIS) is Mozambique's largest irrigated region. It is a home to a thieving agricultural community (including sheep farming, rice farmers, maize cultivation and horticulture) (Ismael et al., 2021).

Across Mozambique, irrigation supports the farming of horticultural crops, fruits, Sugarcane and staples like cassava, rice and maize. Rice occupies the largest irrigated land area spanning 18,000 hectares, followed by sugarcane(13,000ha) and tomatoes(10,000ha) (MADER, 2023). Rice farming is particularly prominent in Gaza and relies on controlled flooding during its early growth stages, making flood plain and gravity-fed irrigation systems the common systems used by rice farmers (Ponguane et al., 2023). Sugarcane cultivation, largely commercial, is concentrated in large estates such as Maragra, Mafambisse and Xinavane. As a water-intensive perennial crop, sugarcane demands consistent and substantial irrigation for optimal development (Aiuba & Nova, 2022). Majority of the smallholder farmers that are currently using irrigation for farming are located near the Zambezi River, Zambezi Lake and near the coast and own plots ranging from 0.5-2 hectares.

2.2 Factors influencing the adoption of irrigation technologies

Improving agricultural output relies on integration of agricultural innovations and effective practices (Rehman et al., 2016). The subjects of technology adoption and diffusion are connected, including the choice to accept or reject a specific technology and its spread across economic entities. The timeline for the uptake of a technology fluctuates based on economic units, ecological regions, and traits of the technology (Chen., 2020). However, this study focuses on the factors driving farmer's decisions to take up an irrigation technology. The factors are grouped into three including, farm characteristics, institutional factors, and traits of the farmer. Below is the discussion of these factors;

Farm size has been highlighted in numerous studies as an important factor determining the uptake of irrigation technologies. Research has noted a positive connection between farm size and the likelihood of taking up irrigation technology. Particularly, Chuchird et al., (2017) in their study to explore factors determining the uptake of irrigation technologies in Thailand, discovered that bigger farms had a higher likelihood of implementing these innovations compared to smaller ones, because of economies of scale and also due to resource availability. Similarly, in their study to examine groundwater irrigation uptake in Ghana, Owusu et al., (2013) identified a positive connection between size of the farm and technology uptake, implying that larger farms have easy accessibility to financial resources and technical services. This was also corroborated by Belaidi et al., (2022), who argued the capacity of large farm owners to use their farms as collateral for obtaining loans for acquisition of irrigation equipment, strengthening the positive connection between adoption and farm size. Yuan et al., (2021); Wang et al., (2023) also reinforced this relationship, where Yuan et al., (2021) noted that farmers with bigger farms were more inclined to take up irrigation technologies as a result of their ability to manage risks and absorb initial investment costs. Wang et al., (2023) who studied wheat and maize in Northern China, observed that larger farms were able to use portions of their farm land for testing new irrigation innovations, an alternative unavailable to smaller farm owners.

In resource constrained rural settings, off-farm income is a very important factor for the uptake of irrigation technology, as noted by Mwangi & Crewett., (2019) in Kenya in their analysis of small-scale indigenous vegetable growers, off-farm income serves as a critical financial resource, substituting for credit in areas where credit is un-accessible. Off-farm income facilitates farmers investment in irrigation technologies reducing dependance on loans, accelerating adoption rates and reducing risk. This was also noted by Diiro, (2012); Ellis & Freeman, (2004), who demonstrated that off-farm income enables farmers to take up costly innovations for instance irrigation systems. In South Africa, Mango et al., 2018, also found off-farm income to positively enhance the uptake of technologies. Their findings noted that farmers that had higher off-farm earnings were more inclined to adopt time-efficient irrigation systems, as it enabled them balance off-farm work and agricultural responsibilities.

In countries where agriculture is the main economic activity, the use of extension services is crucial for facilitating the uptake of technologies. These services are used as means for spreading knowledge and information about agriculture to farmers and stakeholders. Koundouri et al., (2006), in their research indicated that frequent engagement of farmers with extension services encourages them to take up technologies as compared to those that have limited engagements. These findings were also supported by Yuan et al., (2021), in China, using Tobit who established the fact that access to extension, positively enhanced the uptake of surface and drip irrigation innovations. Their research validates the value of extension services as a key element of technological integration in the agricultural sector of developing nations. Using logit model, Mohammadzadeh et al., (2014), also found a positive interaction between uptake of irrigation and extension access. Using ordinary least squares (OLS), Adeoti, (2008) revealed that number of extension visits enhanced farmers' perceptions about agricultural technologies. Same trend was noticed in Kenya by Madukwe, (2012) stressing regional reliability of this phenomenon.

As affirmed by Akudugu et al., (2012), social capital is a vital institutional element shaping the uptake of particular farming technologies. Studies including Gautam et al., (2024), Mabohlo et al., (2021), Mulenga, (2011), Quintana-Ashwell et al., (2020), and Serote et al., (2021) have established three various ways through which social networks enhance the uptake of irrigation technology: (1) People learn practical applications of techniques by observing from their counterparts; (2) individuals benefit from their roles as friends or neighbors in a community; (3) people gain comprehension of the benefits of the technology through interactions with their peers. Additionally, participation in in farmers' entities, such as unions, associations, and cooperatives, has been acknowledged as a supportive instrument in the uptake of irrigation technology. For instance (Nejadrezaei et al., 2018), in Northern Ireland employing a logit model, established that membership to a farmer group positively enhanced the uptake of pressurized irrigation technologies. Nevertheless, some studies found a contradictory perspective about social networks, where they found them to have a negative effect on uptake. For instance Foster & Rosenzweig, (1995), noted that the presence of free riders in community groups hinders technology adoption by creating negative side effects.

Credit access has been demonstrated as an significant element in enhancing uptake of farming technologies by numerous authors (M. Mwangi & Kariuki, 2015b). Credit acts as a core stream for financial resources, especially for small and mid-sized farmers. Numerous studies including Adeoti, (2008), Awotide et al., (2015), and Shiferaw et al., (2015), confirm that farmers that have access to credit facilities have a positive and strong ability to embrace irrigation technologies. These financial resources which may come from either formal or informal sources, are shown to positively association between credit and the uptake of irrigation technologies. As further revealed by Awotide et al., (2015), credit reduces liquidity challenges and enhances households' capacity to bear risks, hence encouraging the adoption of risk-intensive technologies. On the other hand, Mohan et al., (2024) in India, examined factors influencing and the obstacles to water conservation innovations, which included drip and sprinkler irrigation systems. The results illustrated that availability of financing fosters the uptake of drip hydro technologies. Additionally, Namara et al., (2007) in India, analyzed the determinants and impacts of micro-irrigation in India. Their findings illustrated that the uptake of micro-irrigation was positively influenced by the availability of finances.

Acquiring knowledge about a technology significantly enhances its uptake and implementation in agriculture. Theis et al. (2018) emphasized that information acquired either through radio, television, newspapers, equips farmers with awareness about the existence of a technology and ways of applying it. Using probit model, Zhang et al., (2019) noted that farmers only take up innovations they are well versed with or have heard about. Wang et al., (2023), utilizing Heckman model, found a positive connection between information access and the uptake of irrigation technology, confirming that acquisition of information decreases uncertainties involving the performance of a technology, hence changing farmers' assessments from subjective to more objective. The above positive interaction was further confirmed by Mabohlo et al., (2021). On the other hand, Shiferaw et al. (2015) noted that information acquisition does not confirm adoption, as farmers may assess technologies differently from scientific point of view leading to diverse adoption outcomes.

Mwangi & Kariuki, (2015); Nejadrezaei et al., (2018); Teha & Jianjun, (2021), have all identified education as a very important determinant of technology uptake. The acquisition of education by the head of the house always noted to be a primary driver influencing the uptake of such innovations. Numerous researchers have established a positive connection between the uptake of irrigation systems and education attainment. For instance, Ngango & Hong, (2021), in their study involving irrigation uptake by smallholder farmers in Rwanda, discovered that higher levels of education positively enhanced the uptake of small-holder irrigation technologies. This was also discovered by other studies including Darko et al., (2020), Pokhrel et al., (2018) and Serote et al., (2021). Similarly, in their analysis pertaining micro-irrigation technology uptake in India Namara et al. (2011), found that education positively and significantly influenced adoption rates, linking this to the role of education in enhancing critical thinking and effective utilization of information. Conversely, some studies reported a contradictory association between education and technology uptake. For instance in Tunisia Foltz, (2003), discovered that higher education levels reduced uptake of drip irrigation systems illustrating that highly educated individuals tend to pursue careers outside agriculture.

Gender of the house hold head has also been frequently explored by several researchers as a crucial determinant in the uptake of agricultural technologies. In Ethiopia, Marie et al. (2020) explored the socio-economic aspects influencing irrigation among smallholder farmers, using a cross-sectional survey with a multinomial logistic model. Findings from their study showed that irrigation adoption was positively influenced by male headed household heads as compared to female headed households. This is attributed to social dynamics that gives more resource access and decision-making authority to males. These findings were also corroborated by Kamwamba-Mtethiwa, (2016), in Malawi who examined the uptake of small-scale pumps and Mulenga, (2011), in Zambia who explored factors affecting drip irrigation uptake. However, contradicting evidence exists for instance, In Zambia Pék et al. (2019), in their research assessing the livelihood effects of micro-scale irrigation projects, identified that families that were headed by women were more inclined than the male counterparts to take up micro irrigation technology.

Age of the household head is a major determinant in the adoption of irrigation technologies, but its effect remains a subject of debate and discussion in academic literature. Several studies on agricultural technologies have yielded contradictory findings on age. Some of them show a negative connection between age and the uptake of irrigation systems for instance Alcon et al., (2011), Genius et al., (2014), Koundouri et al., (2006) and

Nejadrezaei et al., (2018), illustrating that younger farmers are more likely to take up irrigation innovations due to their openness to innovation and higher level of education. While studies report a positive connection between age and adoption of irrigation technology, for instance Kariyasa & Dewi, (2013) and Mignouna et al. (2011), illustrating the older farmers are more experienced and have accumulated resources over time to enable them acquire irrigation systems. Belaidi et al., (2022) and Asante, (2013) further supported this notion, arguing that older farmers benefit from accumulated knowledge and assets that enables them make investments that require financial stability.

2.3 Effects of adoption of irrigation technologies on crop productivity

Irrigation technology has been acknowledged as one of the important inputs that enhance crop productivity in agriculture (Faures & Mukherji, 2009). Its impacts are seen through improved crop production, increased crop yields and the expansion of land under agriculture. Yields increase because of improved nutrient circulation in the soil and improvement in water absorption by the crops (M. H. Ali & Talukder, 2008). Over the last twenty years, a growing body of literature has examined the association between the uptake of irrigation technologies and crop productivity, particularly among small-scale cultivators. Employing diverse empirical methodologies, these studies consistently identified a positive interaction between the implementation of irrigation systems and enhanced crop yields.

Using Propensity Score matching (PSM), Ngango & Seungjee, (2021) examined the determinants of small-scale irrigation technology (SSIT) and its impact on land productivity among smallholder farmers in Rwanda. Their results demonstrated a statically significant and positive casual effect of SSIT uptake on land productivity. The adopters achieved markedly higher productivity than non-adopters with an average treatment effect of 193-200kg/ha of maize much higher than non-adopters.

Habineza et al., (2020) in his study to assess the effect of small-scale irrigation adoption to farmers in Nasho sector, Kirehe District in Rwanda, found a positive and significant relationship between uptake of irrigation technology and maize yields. From a cross-sectional data from 193 maize farming households and applying Propensity Score matching, they discovered that adopters of irrigation technology achieved an average yield of 12,309.73 Kg/2.62 ha or 4698.73 Kg/ha while the average treatment effect (ATT) illustrated that adopters outperformed non-adopters by between 2819.63 Kg to 4766.59 Kg per unit area of production. These yield gains increase farmer income, reinforcing the economic viability of irrigation.

A study by Nhamo et al., (2016) in Malawi, to compare maize and rice grown under irrigation and rain-fed agriculture from 2000 to 2013 showed valuable differences in productivity levels. In 2013, maize grown under rain-fed conditions occupying 1,492,930 hectares, produced about 2.08t/ha. On the other hand, maize produced under irrigation occupying only about 181,246 hectares, produced 3t/ha more compared to rain fed conditions. Nhamo et al., (2016) concluded that sustained investment in smallholder-managed irrigation infrastructure offers a viable pathway to close yield gaps, enhance food security, and build climate resilience in rain-fed-dominated systems typical of the region. These national-level findings provide important contextual support for household-level impact studies and highlight the potential returns to scaling small-scale irrigation among maize smallholders.

Another study by Chavula et al, (2019) in Malawi, using PSM to evaluate simple irrigation adoption among smallholder farmers discovered that, the adopters of irrigation produced on average 244.21kg/ha more maize than non-adopters. This led to increase in household expenditure by 6562.79 Malawian. These finding illustrate that irrigation use helps to enhance resilience improving food security among farming households.

In Ethiopia, Tesfaye Haregewoin (2021) conducted one of the most comprehensive micro-level analyses using cross-sectional data from 350 maize producing households across four major regions. using Propensity score matching approach, the study discovered that irrigation users achieved an average maize productivity of 3.86t/ha compared of 2.30t/ha for non-users. The average treatment effect estimates indicated that irrigation raised maize productivity by 45%. The author concludes that irrigation offers substantial scope for increasing maize yields in Ethiopia's smallholder systems.

In Botswana, Jagadeesh et al, (2024) focused explicitly on climate-smart irrigation technologies among 271 smallholder maize farmers across five districts. Employing PSM, the study reported statistically significant ATT on gross maize production ranging from 650kg/ha to 2,489kg/ha. This productivity gain was particularly pronounced for poorer and female-headed households, confirming CSIT's pro-poor and climate-adaptive benefits in semi-arid conditions.

CHAPTER THREE

3. METHODOLOGY

3.1 Theoretical framework.

In many developing nations, the uptake of innovations is slowed down by restricted financial capabilities, inadequate knowledge sharing and poor rural infrastructure (Ahmed & Ahmed, 2023). Despite these challenges, Kalungu & Leal Filho, (2018) argued that farmers should only take up an agricultural technology if it has the ability to benefit them. Following Kalungu & Leal Filho,(2018), this study relied on random utility theory (RUT) for the uptake of irrigation technology.

Random utility theory, provides a framework for comprehending decision-making by assuming that individuals select the option that offers the greatest benefit. This utility is comprised of an observable and unobservable element. The researcher can estimate models by using Random Utility theory to elicit preferences for complicated multidimensional goods

(Walker & Ben-Akiva, 2002). Because Random Utility theory includes a random component, it is challenging to forecast personal preferences. This random element enables researchers to model decisions of farmers in a randomized manner. In this study, there are two alternatives a farmer is faced with that is, adoption of irrigation technology and continuing with rain-fed farming. A smallholder farmer in Mozambique therefore, decides to take up irrigation innovation only if the anticipated utility from doing so exceeds the utility of continuing with rain-fed practices. And it is assumed that farmers are risk neutral that is, they base their decisions solely on expected returns such as increased yields and profitability rather than factoring in possible negative outcomes like equipment failure or financial losses (Hardaker et al., 2015).

Assuming that a farmer (Y) has two alternatives given by Y_m and Y_p where m is irrigation technology and p is rain-fed system. Their representative utilities are denoted by U^m and U^p in order to simulate a farmer's decision-making process. Although the unobserved utilities are not revealed, the observed choice between the two alternatives shows which one provides the farmer Y the most benefit. The observed utilities is equal to 1 if the utility of $U^m > U^p$ and 0 if the utility of $U^m \leq U^p$ (Walker & Ben-Akiva, 2002)

The linear utility model is:

$$U^m = X^1\alpha_m + \varepsilon_m \text{ and } U^p = X^1\alpha_p + \varepsilon_p \qquad (1)$$

If a farmer adopts an irrigation technology(Y = 1)the farmer's choice of option m, will be:

$$P[Y=1|X] = P[U^m > U^p] \qquad (2)$$

$$= P[X^1\alpha_m + \varepsilon_m - X^1\alpha_p - \varepsilon_p > 0|X] \qquad (3)$$

$$= P[X^1(\alpha_m - \alpha_p) + \varepsilon_m - \varepsilon_p > 0|X] \qquad (4)$$

$$= \int_\varepsilon \sqcup(\varepsilon_m - \varepsilon_p < 0|X)\ f(\varepsilon)\ d_\varepsilon \qquad (5)$$

Where:

α is the deterministic factor (utility) of Y_m for alternative U^m, ε represents the stochastic component that captures unobserved factors and X represents the observed characteristics (education, age, hired labor, size of the farm, household size, off-farm income, extension, credit) that affect a farmer's decision making.

In equation (5), we assumed that the stochastic component follows a standard logistic distribution making the logistic model suitable for modeling the adoption of irrigation technology. A popular binary choice paradigm for analyzing how people make decisions when presented with two possibilities. The process of implementing irrigation is complex and impacted by various of elements, including traits of the farm, institutional elements and farmer traits that affect a farmer's decision-making. In agriculture, adoption studies typically aim to identify the variables that affect a technology's uptake in a particular area (Zeweld et al., 2015). In order to analyze that uptake of irrigation innovation in this study, Logit model was chosen. A farmer's decision whether to adopt or not an irrigation innovation based on the above theoretical framework is influenced by socio-economic, institutional and farm traits (X) which determine the likelihood (P) of taking up irrigation technology.

The logit model is written as;

$$P(Y=1|X) = \frac{1}{1+e^{-x_i'}\alpha} \quad (6)$$

In which (P) represents the likelihood of taking up irrigation innovation, (X) the list of predictor variables (farmer characteristics, social-economic, and institutional factors).

3.2 Descriptive Statistics.

Using STATA 17 and Excel, data analysis was performed. Descriptive statistics was performed where frequency analysis was conducted. This involved using t-test and chi-square to determine the means, standard deviations Minimum and Maximum values were also established to identify the range in which the values in data set ranged. Furthermore, histograms were used to show how the adopters of irrigation technology were distributed across the provinces. The differences between adopters and non- adopters were established using t-test.

3.3 Empirical model for Objective 1: Factors affecting the adoption of irrigation technology

To evaluate the drivers of irrigation technology uptake, a logistic regression model was constructed to predict the likelihood of adoption. While there were alternative models that could be used to model binary outcomes (like probit regression, Linear Probability Model), the logistic regression model was highly suitable for this study since it ensured that the predicted probabilities lie between 0 and 1, addressing the issue of non-linearity that would arise if we tried to predict a probability using a linear regression model (Myeni & Moeletsi, 2020). Furthermore, the logit model unlike probit as outlined by Semykina & Wooldridge, (2010) has the ability to Handle extreme Probabilities. The logistic function has heavier tails, making logit models more suitable when extreme probabilities (close to 0 or 1) are relevant.

In this study, the uptake of irrigation technology was treated as a dummy variable, that is, it presented two possible responses: (1) uptake of irrigation technology and (0) non-adoption, and binary logistic regression fits events that are presented in a dichotomous quantitative form (Y=1) to describe the occurrence of events of interest and (Y=0) the occurrence of the non-events)

And according to Belfiore, (2015), the dependent variable Y follows a Bernoulli distribution, given that it has only two values that vary between 0 and 1. However, it is necessary to connect the explanatory variables denoted as (X) to the distribution present in the outcome variable. This connection is called logit ()

$$Y_{i=} \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \ldots + \alpha_n X_n \qquad (7)$$

One of the patterns of the Bernoulli distribution is the knowledge of the likelihood that a specific event will occur. In the logistic regression, this probability is not known. Thus, the objective of logistic regression is to approximate the probability (p) for an independent variable combination that is linear. To connect the Bernoulli distribution to a linear combination of variables, a function that joins them was needed. This function is known as the probability ratio or odds ratio, as illustrated in equation (8)

$$\text{odds}\ (Y_i = 1|x_{i)} = \left(\frac{P_i}{1-P_i}\right) \quad (8)$$

According to Favero & Belfiore, (2017) in binary regression the logit model is described as the natural log odds, represented by expression 9 and 10.

$$Y_i = \ln\left(\frac{P_i}{1-P_i}\right) \quad (9)$$

Substituting the variables and parameters of equation (9), we obtain equation (10):

$$\ln\left(\frac{P_i}{1-P_i}\right) = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 \ldots + \alpha_n X_n \quad (10)$$

As mention previously, the aim of the logistic regression model is to approximate the probability (P), therefore, it is necessary to isolate P. To do this the antilogarithm was used as showed by (equation 11)

$$\left(\frac{P_i}{1-P_i}\right) = e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\ldots+\alpha_nX_n} \quad (11)$$

Thus, the model for estimating the probability of occurrence of the uptake of irrigation technology was defined by relating equation (8) and (9), with all quantitative explanatory variables transformed to their natural logarithmic form to address potential non-linearity and facilitate the interpretation of coefficients. Which resulted in the following equation (12) (Fávero & Belfiore, 2017)

$$P_i = \frac{e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\ldots+\alpha_nX_n}}{1+e^{\alpha_0+\alpha_1X_1+\alpha_2X_2+\ldots+\alpha_nX_n}} = \frac{1}{1+e^{-(\alpha_0+\alpha_1X_1+\alpha_2X_2+\ldots+\alpha_nX_n)}} \quad (12)$$

Where;

$P_i = \alpha_0 + \alpha_1 Age + \alpha_2 Age^2 + \alpha_3 Educ + \alpha_4 Crdt + \alpha_5 Frm$
$Sz + \alpha_6 HdSz + \alpha_7 Labor + \alpha_8 Educ^2 + \alpha_9 Ext + \alpha_{10} Income + \alpha_{11} Infor + \alpha_{12} Farmer$
$gp + \alpha_{13} Gender + \alpha_{14} location$
(13)

3.3.1. Model estimation method

Parameter estimation was performed using the maximum likelihood procedure. This approach aimed to find the estimates for the logistic regression model, which are the values that maximize the logarithm of the maximum likelihood function. Maximum likelihood estimation allows observations in the sample data (Garcia et al., 2006).

The impact of the predictor variables was determined by calculating the marginal effects (ME). When the predictor variable rises by one unit, the change in probability is shown by marginal effects. In logistic regression, the method for estimating ME differs for quantitative and qualitative variables.

For quantitative variables, it represents the instantaneous change since the unit can be very small(equation14)

$$ME = \frac{\partial P_i}{\partial x} = \frac{\partial\left(\frac{1}{1+e^{-(\alpha_0+\alpha_1X_1+\alpha_2X_2+\ldots\alpha_nX_n)}}\right)}{\partial X_i} \qquad (14)$$

For binary predictors, the adjustment is from 0 to 1, so it made sense to seek to understand how the predicted probabilities changed when the independent binary predictor adjusts from 0 to 1 (equation 15).

$$ME = E(P_i|x_i = 1) - E(P_i|x_i = 0) \qquad (15)$$

3.3.2 Logistic Model Evaluation methods.

The relevance of the variables in the model had to be confirmed after the coefficients were estimated. This study employed the likelihood ratio test. This test simultaneously checks to see if all of the regression coefficients linked to β except β_0 are all zero. The following is the expression for the likelihood function comparison between the observed and expected values (Cabral et al., 2024);

$$D = -2\ln\frac{\text{Likehood of the fitted model}}{\text{Likelihhod of the saturated model}} \qquad (16)$$

$$D = -2\sum_{i=1}^{n}\left[Y_i \ln\left(\frac{\hat{Y}_i}{Y_i}\right) + (1-Y_i)\ln\left(\frac{1-\hat{\pi}_i}{1-Y_i}\right)\right] \quad (17)$$

The model is said to be saturated if it contains all the variables, while the adjusted model corresponds to the model with only the variables desired for the study. This function D, also called deviance, is always positive and the smaller it is, the better the model's fit.

Wald test.

A statistically significant linkage between the explanatory variables and outcome variable is confirmed by the Wald test. By contrasting a coefficient's maximum likelihood estimate with its standard error estimate, the test's value was determined (Batista & Costa, 2016):

$$W_j = \frac{\hat{\beta}_j}{var(\hat{\beta}_j)} \quad (18)$$

COX and Snell Pseudo R^2.

The Pseudo R^2 of Cox and Snell was also used, it shows the degree to which the predictors used in the empirical model explain the dependent predictor Y (the adoption of irrigation technology) as shown by equation (19)(Smith & McKenna, 2013).

$$R^2 = 1 - \left(\frac{L(\beta)_0}{L(\beta)_M}\right)^{\frac{2}{n}} \quad (19)$$

3.3.3 Definition of variables and expected signs of parameters

Variables in the table below were selected based on the literature previously reviewed. it is expected that the parameters affiliated with the predictors that were incorporated into the model present the following expected signs as showed by (Table 1) below.

Table 1: Variables and signs associated with parameters

Independent Variables	Measurement	Expected Sign	Source
Age	Years	(-)	(Burney et al., 2013)
Education	Years of schooling	(+)	(Adebayo et al., 2018)
Household size	Number of people	(+)	(Adebayo et al., 2018)
Off-farm Income	Metical	(+)	(Gebregziabher, 2019)
Gender	1-Male, 0-female	(+)	(Akudugu et al., 2012b)
Extension	1-Yes 0-No	(+)	(Bako & Moumouni-Moussa, 2019)
Credit	1-Yes, 0-No	(+)	(Burney et al., 2013)
Farmer group	1-Yes, 0-No	(+)	(Kambali & Panakaje, 2022)
Hired labor	1-Yes, 0-No	(+)	(Akudugu et al., 2012b)
Farm size	Hectares	(+)	(Asante, 2023)

From Table 1 above, Age was expected to be negative in the logistic regression results because, older farmers often exhibit risk aversion and lack the physical stamina and long-term planning needed to invest in and maintain irrigation systems. While farmers of younger age are typically more inclined to experimenting with new methods, and are equipped with knowledge and technical familiarity leading to an increased uptake of irrigation systems. This was noted by Alcon et al, (2011); Khonje et al, (2015) Alternatively, education was expected to be positive because higher levels of formal education equip farmers with better analytical skills, enabling them to comprehend the technical aspects of irrigation and water management as noted by Asante, (2013) in Ghana.

Household size was expected to be positive due to its role in alleviating labor constraints, spreading fixed investment costs and enhancing risk-bearing capacity. Irrigation systems require substantial labor for installation, operation, and maintenance. Larger households possess a greater endowment of working age members effectively reducing the per-capita labor burden and opportunity cost of adopting such technologies. This was noted by Gebregziabher et al, (2009) in Ethiopia who found that each additional household member increases irrigation uptake probability by approximately 8%. While Farm size was expected to provide positive results too due to the fact that farmers managing larger plots have economies of scale that make irrigation investments more viable (Owusu et al., 2013).

Off-farm revenue was anticipated to portray a positive sign because it provides supplementary earnings from non-agricultural sources diversifying household finances, allowing smallholder farmers to allocate funds towards irrigation without compromising essential needs (Fernandez-Cornejo et al., 2007). For gender, the results were expected to be positive if the household head was male because male farmers in societies like Mozambique regularly have preferential access to assets, including land ownership, making choices, authority, which facilitates easy adoption (Mishra et al., 2020).

For institutional factors like access to advisory services, credit, belonging to a farmer association and access to information were also expected to show a positive outcome. This is because, engagement with agricultural extension agents delivers tailored advice, demonstrations to farmers enabling them to embrace the technology and credit enables resource constrained farmers to purchase these technologies while membership to a farmer group promotes knowledge sharing, fosters peer to peer and also access inputs positively influencing technology uptake. This association was reflected by authors such as (Serote et al., 2021; Yuan et al., 2021; Zhang et al., 2019 ; Diiro, 2012;)

3.4 Empirical model for objective 2: Effect of irrigation technology adoption on Maize productivity

3.4.1 Propensity score matching

This research adopted the propensity score matching (PSM) model to measure the effect of irrigation technology uptake on maize productivity. PSM has been widely applied and recommended for impact studies and several researchers have used it for example, Mojo et al., (2017); Habineza et al., (2020); Adebayo et al., (2018). This model helps address potential selection bias by pairing adopters and non-adopters based on observable features. However, PSM often discards unmatched units, reducing the sample size and potentially leading to loss of statistical power. This is problematic in studies with small sample sizes (Ho et al., 2007). Prior researchers have employed various econometric techniques, such as instrumental factor approach, Heckman's two stage procedure, difference in difference

(DID) matching. However, the Heckman's two stage approach depends on the assumption that unobservable factors follow a normal distribution (Becerril & Abdulai, 2010). On the other hand, IV experiences difficulty in finding an instrumental variable for the model to accurately inform the outcome estimation (A. Ali & Abdulai, 2010). DID matching provides robust, unbiased results by correcting for selection bias, however it's use is limited to panel data studies (A. Ali & Abdulai, 2010). To address the limitations reflected by the methodologies above, thus the selection of PSM approach as proposed by Rosenbaum, (2002).

In the first phase of the analysis, we obtained the propensity scores of the users and non-users for five paired provinces to account for ecological and institutional heterogeneity while ensuring matches occurred only within comparable agro-ecological zones. The paired provinces were defined as follows: (1) Niassa and Cabo Delgado, (2) Nampula and Zambezia, (3) Tete and Manica, (4) Sofala and Inhambane, and (5) Gaza and Maputo. A logit model was fitted to determine the probability of adoption (the treatment) as a function of covariates that were significant in influencing irrigation uptake (education, credit, extension, off-farm income, farm size, Region, Household size) (Baek et al., 2015). The model output a predicted probability (propensity scores) for each unit varying from 0 to 1, which represents the likelihood of obtaining the treatment given the covariates. By estimating propensity scores separately for each ecological and institutionally aligned pairs, the procedure minimized cofounding due to regional differences and ensured that subsequent matching occurred only between comparable units within the region. The logit model is specified in (equation 12 in section 3.3).

In the second stage, those who implemented irrigation were then paired with non-adopters based on their propensity scores using a caliper of 0.01 and nearest neighbor matching. This algorithm was chosen because it had the smallest pseudo R^2 after matching as compared to kernel and Radius matching. Using t-tests and chi-square, the imbalances in the observable covariates were corrected. While nearest neighbor matching (NNM) was used to balance observed covariates, it did not deal with unmeasured confounders. To address this, the study used sensitivity analysis using gamma to estimate any impact of unobserved variables on the outcome (ATT) (Haviland et al., 2007). Rosenbaum Bounds (RB) method, which assesses the sensitivity of findings to any hidden bias or unobserved confounding was adopted in this study (Peel & Makepeace, 2012).

To measure the effect of irrigation uptake on maize productivity, Average Treatment Effect on the Treated (ATET) was estimated. This is illustrated by equation 20:

$$ATET = E\left[E\{Y_1|D=1, p(X)\} - E\{Y_0|D=0, p(X)\}|D=1\right] \qquad (20)$$

Where Y_1 represents the outcome, maize productivity (Yield) for the treatment groups (adopters of irrigation technologies), Y_0 represents maize productivity in the control group (non-adopters), $D = 1$ represents the adopters (treatment group) and $D = 0$ represents the non-adopters (control group). To reduce potential bias, control variables like, acquisition of extension services, association to a farmer group, were included in the model. And since this study was non-experimental, two key assumptions were considered to address the issue of selection bias; (1) Conditional Independence (Confoundedness), (2) Common support (Overlap).

3.5 Data sources

This research used secondary data from the 2023 Agricultural and Livestock Survey (IAI 2023), collected from September to December by the National Institute of Statistics (INE) a cross 145 predominantly rural districts in Mozambique. The target population for the IAI 2023 consisted of agricultural holdings active during the 2022/2023 agricultural season. The sampling structure for the IAI 2023 was grounded on the Master Sample Frame for Agricultural Survey (MSF), which was developed using statistics from the 2017 General Population and Housing Census (IV RGPH 2017, Section F- Agriculture and Livestock). A probabilistic two-phase sampling approach was implemented. In the first phase, primary sampling Units (PSUs) were selected within each province and district using stratified random sampling based on administrative and agroecological zones. In the second stage, eight households classified as small agricultural holdings (PE) were randomly selected from primary sampling Unit. From the total of 26,000 agricultural holdings surveyed nationwide, a subset of 19,282 households will be used for this study. This subset includes only the farms that reported cultivating maize, both with and without the use of irrigation.

CHAPTER FOUR

4. RESULTS AND DISCUSSION.

4.1 Multicollinearity diagnosis.

Multicollinearity within the various predictors employed in the logistic analysis was checked using Variance Inflation Factor (VIF), From the results in Table 2, The VIF obtained confirmed that each independent variable contributes unique explanatory power to the model, with no redundant or highly correlated predictors inflating standard errors or destabilizing coefficient estimates since their VIF was under 10. According to Gujarati, (2009), if the VIF score exceeds 10, then that variable is almost perfectly linearly predictable from a combination of the other independent variables in the model, indicating multicollinearity.

Table 2:Variance Inflation Factor for continuous explanatory Variables

Explanatory Variable	VIF	1/VIF
Gender	1.02	0.98
Age	1.16	0.86
Household Size	1.13	0.88
Education	1.10	0.91
Off-farm Income	1.41	0.70
Farm Size	1.12	0.89
Hired Labor	1.04	0.96

Credit	3.81	0.26
Extension	1.40	0.72
Location	1.45	0.69
Information	1.01	0.99
Farmer Group	3.66	0.27
Mean VIF	1.61	

4.2 Descriptive Statistics.

Results presented in Table 4 below illustrate that 20% of the maize growers in Mozambique adopted irrigation technology. Male headed households of the maize farmers constituted 47% compared to 53% female-headed households. These findings challenge convectional narratives that associate female-headed households with marginalization in agricultural production due to restricted access to land, finances and advisory services (Mpinda et al., 2025). According to Gebre et al., (2019); Nyathi, (2018), this statistic shows that there is changing labor dynamics and more females are taking lead in food production as compared to males.

The household head in the sample had a mean age of 34 years. This shows that maize farming is dominated by younger household heads. This dominance illustrates socio-economic changes in Mozambique, changing urban migration patterns, and rural labor market (Da Maia, 2012). The sampled heads of the house had an average education level of nearly 5 years of primary learning, implying that most of the farmers have attained only primary level education. These findings correspond findings from the Integrated Agricultural Survey report 2023, that indicated the mean years of education attainment of smallholder farmers to be 6.8 years. On average these households consist of about 3 household members, who cultivate maize on roughly 3 hectares of land and achieve a harvest of approximately 443.54kg/ha. 49% of these households are located in the urban centers. This enables them access resources and agricultural inputs.

Table 4: Summary statistics and description of variables

Variable	Description	Min	Max	Mean	Std. Dev.
Outcome Variable					
Yield	Maize yield(kgs/ha)	50.56	2771.2	443.54	1584.63
Treatment Variable					
Adoption of Irrigation Technology	1 if the farmer adopts, and 0 otherwise	0	1	0.2	0.4
Independent Variables					
Access to information	1 if a farmer has accessibility, and 0 if not	0	1	1.49	0.499
Gender	1 if the household head is male, 0 if female	0	1	0.47	0.49
Credit	1 for accessibility and 0 if not	0	1	0.34	0.47
Extension	1 for extension accessibility,0 if not	0	1	0.55	0.49
Hired labor	1 for used of hired labor and 0 for not	0	1	1.91	0.28
Education	Number of years of schooling	0	13	5.72	0.88
Farmer Group	1 for belonging to a farmer group and 0 for not	0	1	0.46	0.49
Age	Age of the household head(years)	22	78	34.63	10.3
Region	1 if a farmer is located in the north, 2 central, 3 southern	1	3	2.48	1.28
Farm size	Land under maize production(hectares)	1	3	3.12	1.54
Off-farm Income	Income earned from activities outside the farm(metical)	0	5000	1246.58	1505.58
Household size	Total number of people	3	13	3.67	2.31
Observations		19,282			

The descriptive statistics presented in Table 5 below, provide a comprehensive comparison of the farm-level and socioeconomic characteristics of farmers who implemented irrigation technologies and those that did not. From the results shown, adopters and non- adopters showed several differences and some similarities. Maize yield between adopters was 1,153kg/ha which was very high compared to 311.6kg/ha for non-adopters. Other differences included, larger farm size of 2.25ha for adopters compared to 1.5ha for non-adopters. This shows that adopters are better positioned to use their land as collateral for acquiring credit to purchase irrigation equipment which is not applicable to non-adopters. These findings align with economic theories of technology uptake, which states that resourceful farmers are more inclined to take up technologies due their ability to absorb financial risks (Jack, 2013b).

Adopters also had household size number of 4 members compared to 3 members for non-adopters which provides them with more labor required to manage and run the irrigation systems. In terms of education level, adopters were more educated than non-adopters providing them with the ability to comprehend technical information. Furthermore, Adopters had better access to credit facilities providing them with the financial capacity required to purchase irrigation equipment, they were also members to farmer association and enjoyed frequent extension visits which provides them with knowledge and information about irrigation technologies which supports sound decision making. 50% of the households owned by adopters were headed by male compared to 47% for non-adopters which supports easy access to resources and also quick decision making for investments. Adopters also earned more off-farm income which is important in areas where credit is un available.

Table 5:Differences in Social-economic characteristics by adoption category

Variable	Adopters(n=3644)	Non-adopters (n=15638)	Mean difference	t-value
Yield	1153.54	311.6	841.93	21.95
Age	34.73	34.61	0.13	0.7
Gender	0.5	0.47	0.04	3.95
Education	2.12	2.02	0.1	6.35
Household Size	4.11	3.56	0.56	13.5
Extension Access	0.59	0.55	0.05	5.05
Credit Access	0.49	0.3	0.19	22.95
Group Membership	0.51	0.45	0.06	6.6
Farm Size	2.25	1.5	0.75	94.1
Off-farm Income	3068.48	2703.67	364.81	6.15
Location of the farm	0.11	0.58	-0.01	-56.55

statistical significance at 1 % level

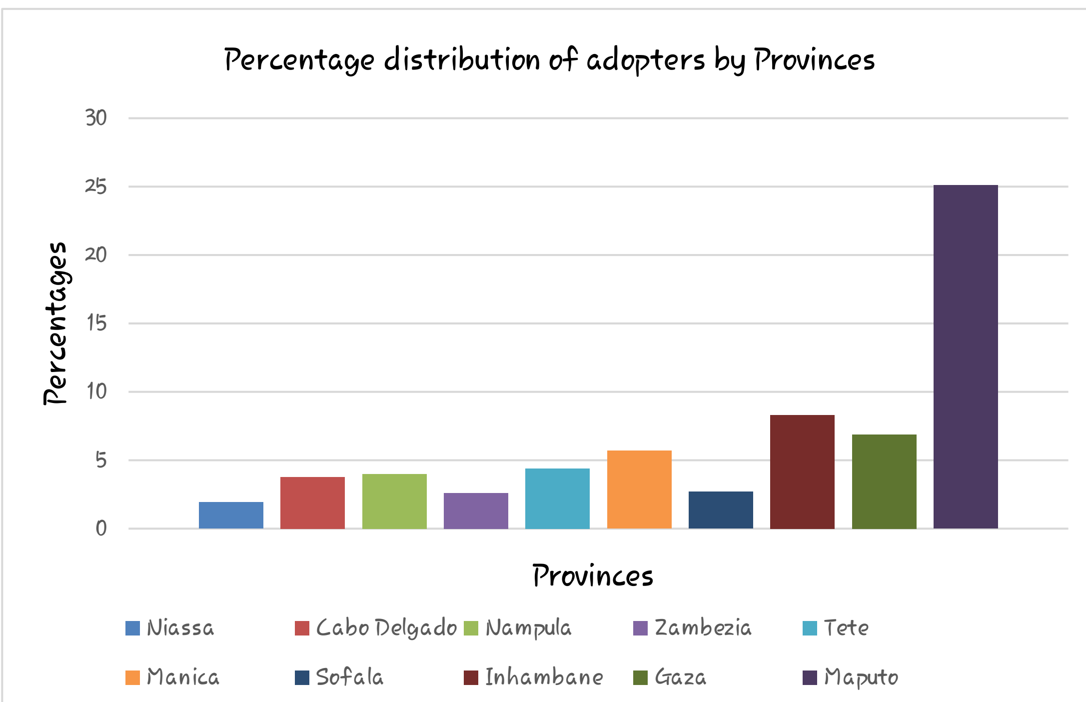

Figure 1: Distribution of Adopters by Provinces

Mozambique is made up diverse agro-ecological zones, from the figure above, majority of the adopters (25%) for Maputo, 8% for Inhambane and 6% for Gaza were found in the southern part of the country. This is because the southern part of the country is semi- arid compared to the northern part (Nhantumbo et al., 2021). The southern part also benefits from historical investments in hydraulic schemes. Whereas the northern part lags behind due to infrastructural deficits and knowledge gaps. This trend in the disparities of irrigation adopters was also reported by the Ministry of Agriculture and Rural Development (MADER, 2023)

4.3 Drivers of irrigation technology adoption in Mozambique.

The logit model in this research was estimated using the maximum likelihood method with sampling weights applied to ensure that the results correctly account for the whole population of maize cultivators in Mozambique rather than just the sampled households. By incorporating these weights, each farmer's observation contributed to the model in matching their prevalence in the actual population giving more influence to underrepresented groups, such as remote farmers, and less to those oversampled. This adjustment reduces bias in the estimated effects of the predictor variables on irrigation technology uptake. The weights were directly applied to the model inform of an explanatory variable. The findings obtained from the logistic regression analysis, for the drivers influencing the uptake of irrigation technology and their marginal effects are displayed in Table 7 below:

Table 7: Logit estimates for adoption of irrigation technology and marginal effects.

		Coefficient estimates		Marginal Effects		
Variables	Expected sign	Coefficients	Standard Error	Marginal Effects	Standard Errors	P-Value
Credit	(+)	0.27***	0.14	0.0049	0.0026	0.054
Age squared	(+)	-0.00051	0.21	-0.0013	0.0039	0.729
Age	(-)	0.055	0.75	0.0053	0.015	0.695
Education squared	(-)	-0.0090	0.07	0.00016	0.0051	0.121
Education	(+)	0.14**	0.28	0.0026	0.0051	0.038
Membership to farmer group	(+)	0.071	0.91	0.10	0.014	0.938
Use of hired labor	(+)	0.20	0.30	0.079	0.0015	0.490
Access to Extension	(+)	0.017*	0.53	0.072	0.0069	0.000
Information	(+)	1.32	0.91	0.034	0.014	0.150
Gender	(+)	0.15	0.14	0.0027	0.0026	0.309
Off-farm Income	(+)	-0.0013***	0.025	-0.000024	0.0089	0.000
Farm Size	(+)	0.50***	0.27	0.063	0.0044	0.000
Household Size	(+)	0.077***	0.03	0.0014	0.00054	0.009
Region						
Central	(+)	0.86***	0.79	0.058	0.028	0.000
Southern	(+)	0.35***	0.59	0.051	0.0088	0.000
Model diagnosis						
Number of observations		19,220				
Wald chi2(15)		551.85				
Prob>chi2		0.000				
Pseudo R2		0.8633				
Log Likelihood		-238,488				

Source: Author's Computations. *Statistical significance at 10%; ** 5% level; and *** 1% level.

From the results presented in Table 7 above, several of the independent variables presented the anticipated signs with a few exceptions. Findings indicate that the likelihood of implementing irrigation innovations aligned with the expected signs for variables such as Education, extension, Farm size, credit access, household size, association with farmer groups, access to information, gender, and region. While for variables such as Age, off-farm income did not align with the expected signs. The model accurately predicted 86.33% of the likelihood of taking up irrigation technology.

The results illustrate that seven out of twelve variables were statistically significant in contributing to the likelihood of a farmer taking up irrigation technology. Particularly, one of the important findings from this study was access to credit which demonstrated a statistically significant and positive influence on the uptake of irrigation technology at the 5% level of significance (Table 7). Farmers who accessed credit facilities enhanced the likelihood of taking up irrigation technology on average by 0.49% compared to those without. Access to credit contributes highly to the uptake of new technologies because these technologies require a lot of financial investments. Farmers who have capital either inform of accumulated savings or capital markets are better positioned to implement new technology. Many authors have found similar findings on credit for instance, Asante, (2013) in Ghana in his study on irrigation technology profitability analysis found that credit access influenced uptake of irrigation by 16.08%. Studies performed in Zambia, Ethiopia and Ghana showed that more than 80% of small-scale cultivators did not have any credit access and therefore depended on their savings to finance irrigation equipment (Giordano & de Fraiture, 2014). On the other hand (Adeoti, 2008; Chuchird et al., 2017; Ngango & Seungjee, 2021; Serote et al., 2021 and Bhandari & Pandey, (2006) all found credit to positively and significantly influence uptake of irrigation technology corroborating the findings of this study.

Empirical results in Table 7, indicate a statistically significant and positive connection between the schooling level of the head of the house with probability of irrigation uptake. Specifically, a one- year increase in formal education increases the likelihood of adoption on average by 0.26% significant at 5% level. Although this marginal effect is modest, the results align with emerging body of research that highlights the contribution of education in facilitating agricultural technology uptake by farmers. Education enhances farmers' cognitive capacity to process information, evaluate risks, and make well informed judgments on resource allocation and technology adoption (Christian et al., 2018; Feder et al., 1985). Education also improves the capacity of the farmers to comprehend technical guidelines, manage irrigation equipment, and engage effectively with extension agents and input providers. Mdemu et al., (2017) discovered that in Tanzania, farmers with higher education levels were significantly more inclined to adopt irrigation technologies, a pattern which was similarly observed in Kenya by Ogada et al., (2010), where education emerged as a key predictor of irrigation adoption among subsistence farmers. However, the findings above, were not in line with (Foltz, 2003b), in his study on the uptake of drip irrigation in Tunisia where he discovered the relation between education and adoption to be negative. In Mozambique, the majority of farmers operate at smallholder level, with limited access to information and extension often constraining technology uptake. Farmers with more time spent in of school are better positioned to interpret technical advice, access credit and understand long-term benefits of irrigation.

Access to extension services as shown by Table 7, has a positive and significant relationship at 1% level. Specifically, access to advisory services increases the likelihood of taking up irrigation innovation on average by 7.2%. This positive relationship is because extension agents serve as conduits for technical knowledge, offering farmers practical guidance on the installation, running and regular servicing of irrigation systems. Moreover, extension services contribute to building farmers' adaptive capacity by integrating irrigation knowledge with broader agronomic practices, such as soil fertility management, crop diversification, and climate-smart agriculture (Wang et al., 2020; Wheeler et al., 2017; Anderson & Feder, 2007; Genius et al., 2014). These finding were in line with those of (Mdemu et al., 2017; Ogada et al., 2010; Adeoti & Adekunle, 2007), who also reported a positive connection between irrigation technology adoption and extension services.

Another key finding from this study was off-farm income. From our findings (Table 7), Off-farm employment exhibited a negative sign. This is interesting because off-farm income contributes not only to household liquidity but also to smallholder farmer's ability to invest in capital-intensive innovations such as irrigation. However, from the results obtained, off-farm income decreases the likelihood of irrigation technology uptake on average by 0.0024% significant at 1% level. This is because the agricultural sector in Mozambique employs over 80% of the working population hence few people are involved in formal jobs especially in rural areas (World Bank, 2024). Also based on the findings from our descriptive statistics in (Table 5), the average off-farm income was 3,068 metical which illustrates that this income is insufficient to finance irrigation equipment. This is consistent with other researchers elsewhere in Africa such as Tesfaye et al., (2021) in their study on constraints to small-scale irrigation innovation uptake in Ethiopia who discovered that off-farm income negatively influenced the uptake of irrigation by 19.77%.

Furthermore, the findings obtained in Table 8 also indicate a positive interaction between farm size and irrigation uptake, at 1% level of significance. Specifically, farm size enhanced the probability of adopting irrigation technology on average by 6.3%. From these findings, it's clear that larger farms enable farmers to diversify and also serves as collateral in situations where the farmer requires extra income in terms of loans for acquiring irrigation equipment (Yuan et al., 2021). These findings were also confirmed by several authors like (Belaidi et al., (2022); Chuchird et al., (2017); Wanyama et al., (2017); Owusu et al., (2013), who found a significant and positive relationship between farm size and uptake of irrigation technology. Additionally, Asante, (2013) in his study on smallholder irrigation technology and impact on profitability discovered that farm size increased the probability of taking up manual pumps by 2.43%, surface pumps by 11.7% and ground water pumps by 6.90%. This perfectly aligns with this study's findings on farm size.

Household size is frequently considered as an alternative source of labor as it reduces labor constraints in farms. From our findings, household size positively influenced adoption of irrigation technology at 1% significance level. It enhances the probability of taking up irrigation technology on average by 0.14%. Larger households are able to handle the intensive nature of managing irrigation systems that require high labor requirement which also reduces the costs of investing in hiring additional labor on the farm. These findings have been corroborated by several studies including Adeoti, (2008), in Ghana in his study on factors influencing irrigation technology adoption and its impact on household poverty who also found a positive connection. Furthermore, Ngango & Seungjee, (2021) in Rwanda also found that household size increased the probability of taking up small-scale irrigation technology by 0.3%. This result supports the labor endowment hypothesis, implying that households with more available labor are inclined to take up technologies requiring significant manual effort (Feder et al., 1985).

Farming households situated in the central and southern parts of Mozambique had a positively significant influence on uptake of irrigation technology, precisely, farming households located in the central and southern parts of the country, were 5.85% and 5.14% respectively, on average more inclined to take up irrigation technology relative to the northern region. This pronounced difference, particularly the strong effect in the central region, suggests that in the central region particularly in Manica and Sofala provinces benefit from proximity to rivers like Buzi and Muda, facilitating irrigation infrastructure development (De Sousa et al., 2017). Similarly, the southern parts of Mozambique, particularly regions like Gaza province, have seen significant rehabilitation of irrigation schemes like Chokwe, which encourages farmers to adopt technologies that enhance water efficiency.

4.4 The effect of irrigation technology adoption on Maize Productivity

The next objective of this research was to evaluate the influence of irrigation technology uptake on maize productivity. The study examined whether the use of irrigation technology had a significant influence on maize productivity among smallholder cultivators. In the first stage of the propensity score matching, a logistic regression analysis was employed to approximate the propensity scores for both the users and non-users. Findings from (Table 8), point to the fact that the estimated model is appropriate for the matching analysis. The observed moderate pseudo-R^2 value of 0.2647, implies that farming households in the sample do not exhibit highly distinct characteristics, which align with the statement that maize farmers lack pronounced differences. This homogeneity makes it easier to find comparable matches between the users and non-users for the matching exercise, as there are fewer confounding differences to control for. The matching procedure aims to pair households with similar probabilities of adopting or not adopting the irrigation technologies. In this stage of PSM estimation, only covariates that were significant in influencing the uptake of irrigation technology were considered.

Table 8: Logit results for propensity score estimates

Variables	Coefficient	Std. Err.	P>z
Access to credit	0.59	0.055	0.000

Education	-0.018	0.077	0.018
Farm size	3.33	0.069	0.000
Household size	0.049	0.011	0.000
Extension	0.48	0.056	0.000
Off farm Income	-0.00089	0.000028	0.000
Location	1.0031	0.027	0.000
_const	-8.33	0.34	0.000
Number of Observations	17,701		
LR chi2(13)	3,641.81		
Prob > chi2	0.000		
Pseudo R2	0.2647		
Log likelihood	-5,058.092		

Source: Author's computation

4.4.1. The common support condition

Following the approximation of the propensity scores for irrigation technology users and non-users, the next phase involved establishing the common support condition. Figure 2, illustrates the spread of the propensity scores and the common support region for adopters and non-adopters. According to Caliendo & Kopeinig, (2008), the density distributions of the propensity scores estimated for irrigation technology users and non-users must meet the common support requirement. From our results, 1,708 adopters were found to be in the off-support region. Therefore, the treatment effect was not estimated for these households.

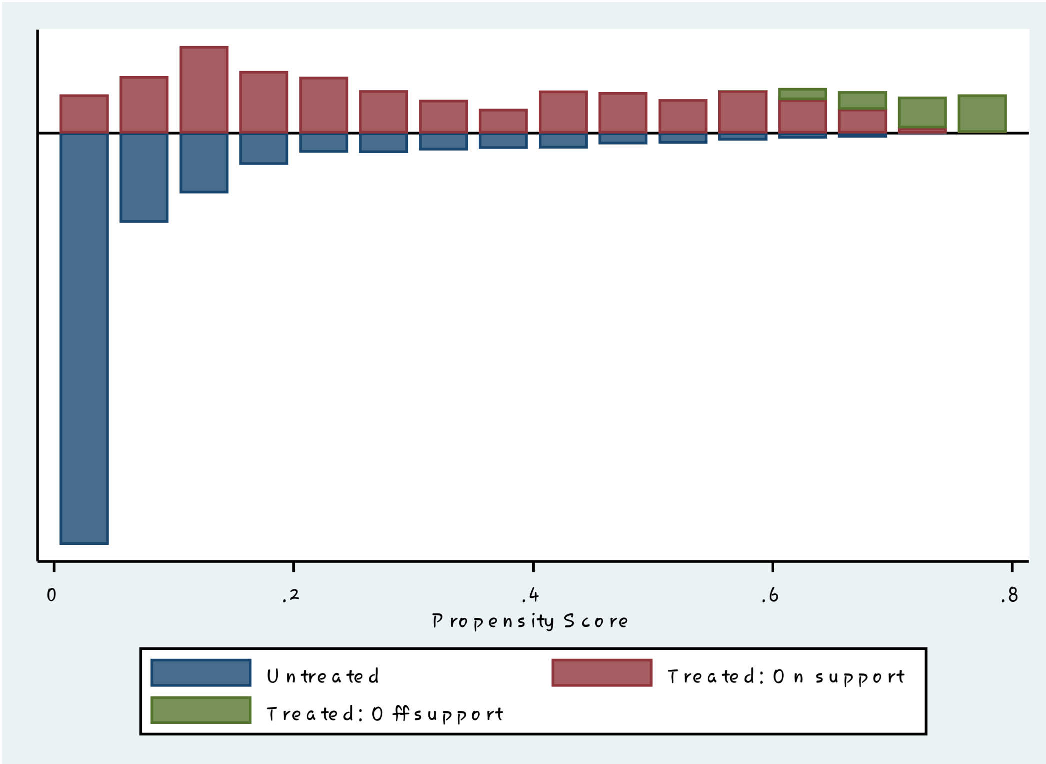

Figure 2: Distribution of Propensity Scores

Fig 2 is divided into three groups, the three groups used allow for distinguishing between observations that can be validly compared to the control (on-support adopters) and those that cannot (off-support adopters), ensuring that treatment effect estimates are based only on comparable households and preserving the validity of causal inference. Each group is represented by a different color: Color blue represents non-adopters(untreated), color red represents adopters (treated on support) and color green represents adopters outside the common support (treated off support). The treated (non-adopters) show the density of households that did not take up the innovation, serving as the control group. The treated (on support) group represent adopters whose propensity scores fall within the range of scores among non-adopters, meaning that for those households, a comparable match exists in the control group. The treated off support group includes adopters with propensity scores outside this range, reflecting that no comparable non-adopters exist. These households are excluded from the treatment effect estimation. From figure 1, different bars show varying heights indicating the relative frequency of households at each propensity score value within each group. So taller bars indicate more households with that propensity score.

4.4.2. Choice of matching Algorithm and matching.

Selection of effective matching algorithm for the propensity score matching (PSM) estimation was determined through a comprehensive evaluation of the key balance indicators, including the mean bias after matching, the pseudo R^2 post matching, and the number of matched observations retained within the common support region. The results, presented in the (Table 9), compared various matching approaches, including nearest neighbor without replacement, Radius, Kernel matching with different calipers (0.01, 0.05, 0.1, 0.25) and bandwidths of 0.01, 0.05,0.10, 0.20.

Among these algorithms, nearest neighbor with a caliper of 0.01 emerged as the optional choice. This algorithm achieved a mean bias of 3.1% after matching, well below the recommended threshold of 5%, indicating excellent covariate balance between adopters and non-adopters (Muja & Lowe, 2014). Additionally, the Pseudo R^2 after matching was reduced to 0.003, approaching zero, which signifies that the covariates no longer substantially explain the treatment assignment, further confirming effective balancing (Dehejia & Wahba, 2002).

Table 9: The choice of the optimal matching Algorithm

Matching Algorithm	Mean Bias after matching	Pseudo R^2 after matching	Matched Sample size
Nearest neighbor			
Cal 0.01	**3.1**	**0.003**	**17,384**
Cal 0.05	3.1	0.004	17,384

Cal 0.1	3.2	0.004	17,387
Cal 0.25	2.3	0.004	17,546
Kernel			
B-width 0.01	16.3	0.22	17,393
B-width 0.05	20.4	0.236	17,486
B-width 0.1	26.2	0.278	17,675
B-width 0.20	31.7	0.346	18,160
Radius			
Cal 0.01	5.6	0.015	17,665
Cal 0.05	8.7	0.032	17,815
Cal 0.1	11.4	0.06	18,032
Cal 0.25	20.5	0.214	17,546

Source: Author's computation

4.4.3. Assessment of the propensity scores and associated covariate balance.

The (Table 10), illustrates the degree of similarity in key baseline covariates between the control and treatment group, both prior to and following a statistical adjustment process using nearest neighbor without replacement (caliper 0.01). The aim of this adjustment is to create more comparable groups by pairing adopters of irrigation technology with the most similar non-adopters, discarding any matches that fall outside the specified caliper to minimize bias from poor pairings (Austin, 2009). A lower average difference in covariates following the matching process indicates a higher level of balance achieved, reflecting the effectiveness of the matching technique employed.

Selection bias is one of the challenges experienced during the matching process (Tucker, 2010). Initially before matching occurred, some of the covariates included in the model had a high bias between 9.4% to 188.1%. After applying with nearest neighbor matching with a 0.01 caliper, the percentage bias narrows significantly, reducing to between -5.0% and 5.3%, way below the accepted threshold of 20% (Nguyen et al., 2017). The reduction of the bias highlights that the unmatched samples exhibit considerably larger differences compared to the matched pairs. Additionally, the t-statistic indicates that before the matching process, six variables showed significant variations, whereas post matching, all the covariates demonstrated balance with no significant disparities. Overall, the balance assessment suggests that the propensity score matching approach was effective in reducing cofounding bias and creating a valid counterfactual for estimating the impact of irrigation uptake on maize productivity.

Table 10: Propensity score and the balancing of covariates.

Variable	Before matching N= 19,221				Nearest Neighbor (Cal 0.01) N= 17,384			
	Treated	control	%bias	T	Treated	Control	%bias	t
P-score	0.586	0.103	188.1	134.48	0.308	0.307	-0.4	-0.17
Credit access	0.501	0.306	40.7	23.13	0.441	0.436	1	0.32
Extension access	0.599	0.553	9.4	5.18	0.611	0.640	-5.9	-1.89
Location	0.510	0.450	12.1	6.74	0.456	0.445	2.1	0.67
Education	6.059	5.636	12.2	6.71	6.014	5.829	5.3	1.66
Farm size	2.252	1.502	152.9	93.98	1.815	1.831	-3.3	-1.61
Off farm income	220.43	1502.9	-103.8	-50.23	396.86	456.56	-4.8	-1.84
Household size	4.122	3.555	23	13.64	3.930	3.961	-1.3	-0.39

Source: Author's computation.

Another test that can be used to assess the quality of propensity Score matching is the chi square test presented in Table 11, from the findings provided, Pseudo R^2 which explains the power of the propensity score model reduced to 0.003 suggesting that the model no longer explains much of the treatment assignment after matching, which is desirable. Additionally, the Likelihood ration test, which assesses the collective impact of covariates was not significant and had a higher p-value (0.158). This shows that the treatment and control groups have similar distribution in covariates post matching. The results of the chi-square test shows that the covariates in the paired and un-paired groups have been balanced.

Table 11: Chi-square test to determine the joint significance of variables.

Sample	Ps R^2	LR chi^2	p>chi^2	B	R
Unmatched	0.458	8,804.35	0.000	197.1*	1.96
Matched	0.003	19.18	0.158	13.6	1.52

Source: Author's computations

4.4.4 ATE estimation of impact of irrigation technology adoption on maize productivity.

Maize serves as a cornerstone for addressing food security and economic stability for small-scale cultivators in many regions of Mozambique. To correctly approximate the influence of irrigation innovation on maize yields, it is crucial to ensure that the treated (adopters) and control (non-adopters) are comparable regarding both observed and un observed attributes of the sampled households. This balance is critical for eliminating selection bias and ensuring the reliability of the treatment effect estimate. The (ATET) which is the Average Treatment Effect on the control group estimates the differences in mean of maize yields obtained by the matched farmers that implemented irrigation technology and those that did not.

Table 12: Treatment effects on maize productivity.

Variable	Sample	Treated	Controls	Difference	S. E	T-stat
Maize Yield	Unmatched	791.699	265.358	526.341	12.536	41.99
	ATT	826.874	236.465	590.410	27.502	21.47

Source: Author's Calculations

The use of irrigation in farming is very important as it helps mitigate climate change impacts and provide water to farmers throughout the year increasing crop yields and enhancing household income. Our findings confirm this statement as they reveal that the impact of implementing irrigation innovation which is the Average Treatment effect on maize productivity was 590.41kg/ha. From our t-statistic this mean difference was significant at 1% level. These findings were corroborated by Ngango & Seungjee., (2021) in Rwanda in their study on the diffusion of small-scale irrigation systems and influence on land productivity who discovered that implementing irrigation enhanced maize yields by 193.38kg/ha using nearest neighbor matching, 197.14kg/ha for kernel based matching and 199.79kg/ha for radius matching. Additionally, (Dillon, 2011) on his study on impact of irrigation on poverty and production found positive and significant impact of irrigation on maize productivity. However, it's worth noting that contradictory results were discovered in Ghana by Adeoti., (2008), who found no significant association between the uptake of irrigation and productivity.

4.4.5. Sensitivity analysis.

To ensure the robustness of the estimated Average Treatment Effect on the Treated (ATT) in propensity score matching (PSM), it is very critical to assess the potential influence of the unobserved cofounding factors. Since non- experimental data precludes direct measurement of selection bias, sensitivity analysis offers a solution to assess the reliability of the matching estimators.

Sensitivity analysis is performed to ensure that the treatment effect estimated is not affected by hidden bias. As noted by Rosenbaum, (2002), we employed the Rosenbaum bounds method to assess the sensitivity of the average Treatment Effect (ATT) to hidden biases. From our findings, effect arising from implementation of irrigation on maize yield was consistent between the control and non- control group despite allowing the odds of treatment assignment to range up to the value of Gamma 3. The p-values remained statistically significant at different levels of Gamma. This implies that our model accounted for covariates that influence both maize yield and irrigation technology uptake. With using a value of Gamma as high as 3 which exceeds the threshold value of 2(100%) applied in other studies. The average treatment effected (ATT) was still robust, demonstrating that there was no evidence of being undermined by unseen elements. The above findings illustrate that ATT of 590.41kg/ha for those that implemented irrigation technology, is dependent on unobserved selection bias and shows a genuine effect of the irrigation technology uptake on maize productivity.

CHAPTER FIVE

5. CONCLUSION AND POLICY RECOMMENDATIONS

5.1 CONCLUSION.

Maize is a very important food security crop not only in Mozambique but Sub-Saharan African as a whole and it contributes greatly to the gross domestic product in the country. The crop plays a vital role in poverty eradication especially among small-scale cultivators but its potential has highly been affected by climate change. From our findings, there is a huge potential for irrigation in Mozambique which is still untapped and requires combined efforts to explore it. Realizing increase in productivity requires integrating technologies together with improvement in farming institutions and development of the workforce. Additionally, maize output increment is not only as a result of technology uptake but also through the effectiveness of implementing the technologies. This study exclusively focused on examining the drivers that affect smallholder farmers from taking up irrigation and the impact of adoption on maize productively carried out at a national level. The survey of this study was carried out in 145 predominantly rural districts of Mozambique composed of ten provinces including Maputo, Gaza, Manica, Sofala, Tete, Nampula, Zambezi, Inhambane, Cabo Delgado and Niassa. From the findings, the descriptive statistics found the mean age of the head of the house to be 34.63years. The average age of the households that adopted irrigation technology was 34.73years while those that did not adopt had a mean age if 34.61years.

The irrigation technology adopters were 20% whereby majority 25.1% of these adopters were located in Maputo province, 6% in Gaza and 8% in Inhambane province. Regarding their land use pattern, farming households had an average farm size of 3.12 hectares. while adopters and non-adopters had 2.25 hectares and 1.5 hectares respectively.

The empirical evidence from this research confirms that irrigation innovation uptake among small-scale cultivators was significantly influenced by household demographics, institutional support, and farm-level characteristics. The factors influencing the uptake of irrigation technology were established using logistic regression model. From the twelve explanatory variables predicted to influence the uptake of irrigation innovation, Household size, Farm size, access to extension services, credit access, education and region positively influenced the adoption of irrigation technology among smallholder farmers. While off-farm income negatively influenced adoption decisions. Furthermore, Age, hired labor, membership to a farmer group and gender were found to have no significance in influencing the uptake

The impact of irrigation technology uptake on maize productivity approximated using Propensity Score Matching (nearest neighbor algorithm), had a significant role in improving maize yields. The findings revealed that, adopting irrigation technologies improved the yields by 590.41kg/ha.

5.2 POLICY RECOMMENDATIONS.

Findings from this study imply that there is a serious need for government to improve access to credit access among farmers. To effectively address the chronic barriers to formal credit faced by smallholder farmers, priority should be put on the nationwide scaling and institutional integration of Village Saving and Loan Associations (VSLAs) as a core, low-cost, and sustainable strategy for enhancing rural financial inclusion.

To drive greater adoption of agricultural technologies, the government of Mozambique should strengthen extension services and digital advisory systems so that farmers can actually learn about, trust, and use new tools. This means investing in training and expanding the numbers of extension agents, equipping them with tools like mobile apps, and radios to reach remote areas, and building partnerships with universities and NGOs to deliver practical demonstration plots for technologies so that farmers gain practical skills.

To improve education among farmers, the government should adopt a practical, adult -centered approach that integrates agricultural knowledge, literacy, and business skills into accessible community-based programs. Many smallholder farmers have limited formal schooling, which constrains their ability to adopt new technologies, interpret market information, or engage with financial institutions. Expanding functional adult literacy programs delivered in local languages and embedded within agricultural content can significantly enhance farmers' capacity to understand extension advice, read input labels, track expenses, and engage with digital tools. Rather than separating literacy from farming, programs should combine reading, numeracy, and applied agricultural problem-solving so that learning is immediately relevant and income-generating

There is a critical need for secure land tenure arrangements in Mozambique to strengthen land security and enable scalable farm sizes, which are essential for improving the economic viability and widespread uptake of irrigation technologies among smallholder farmers.

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APPENDIX A

A.1 Akaike Information Criterion for model selection.

Iteration 0:   log likelihood = -13363.695
Iteration 1:   log likelihood = -10106.209
Iteration 2:   log likelihood = -10103.836
Iteration 3:   log likelihood = -10103.835
Iteration 4:   log likelihood = -10103.835

Logistic regression   Number of obs = 19,282
                                                        LR chi2(1)   = 6519.72
                                                        Prob > chi2   = 0.0000
Log likelihood = -10103.835   Pseudo R2   = 0.2439

y	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
x1	1.527311	.0238589	64.01	0.000	1.480549	1.574074
_cons	.0163125	.0171998	0.95	0.343	-.0173985	.0500235

. estat ic

Akaike's information criterion and Bayesian information criterion

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	19,282	-13363.69	-10103.84	2	20211.67	20227.4

Note: BIC uses N = number of observations. See [R] BIC note.

. *** Probit Model
. probit y x1

Iteration 0:   log likelihood = -13363.695
Iteration 1:   log likelihood = -10116.533
Iteration 2:   log likelihood = -10114.02
Iteration 3:   log likelihood = -10114.019

Probit regression   Number of obs = 19,282
                                                        LR chi2(1)   = 6499.35
                                                        Prob > chi2   = 0.0000
Log likelihood = -10114.019   Pseudo R2   = 0.2432

y	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
x1	.8973088	.0128601	69.77	0.000	.8721035	.9225142
_cons	.0103281	.0101611	1.02	0.309	-.0095873	.0302434

. estat ic

Akaike's information criterion and Bayesian information criterion

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	19,282	-13363.69	-10114.02	2	20232.04	20247.77

Note: BIC uses N = number of observations. See [R] BIC note.

. *** Ordinary Least Squares(OLS)
. regress y x1

Source	SS	df	MS
Model	1379.13541	1	1379.13541
Residual	3440.57998	19,280	.178453318
Total	4819.71538	19,281	.249972272

Number of obs = 19,282
F(1, 19280) = 7728.27
Prob > F = 0.0000
R-squared = 0.2861
Adj R-squared = 0.2861
Root MSE = .42244

y	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
x1	.2686159	.0030556	87.91	0.000	.2626268	.2746051
_cons	.5029012	.0030424	165.29	0.000	.4969377	.5088646

. estat ic

Akaike's information criterion and Bayesian information criterion

Model	N	ll(null)	ll(model)	df	AIC	BIC
.	19,282	-13993.14	-10743.4	2	21490.8	21506.54

A.2 Hosmer Lemeshow test for goodness of fit of the logit model.

Number of Observations	19221
Number of Groups	10
Hosmer Lemeshow Chi (8)	9.42
prob > chi2	**0.32**

A.3 Output for Variance Inflation Factor (VIF)

. vif

Variable	VIF	1/VIF
credit_acc~s	3.81	0.262419
Group_Memb~p	3.64	0.274633
location	1.45	0.690790
Off_Farm_I~e	1.41	0.710999
extension_~s	1.38	0.723250
Age	1.16	0.862376
Household_~e	1.13	0.884195
Farm_Size	1.12	0.894869
edu_cat	1.10	0.908767
Gender	1.02	0.979443
Information	1.01	0.994894
Mean VIF	1.66	

Appendix B.

B.1 Descriptive statistics.

Variable	Obs	Weight	Mean	Std. dev.	Min	Max
treated	19,281	3652243.48	.1851411	.3884221	0	1
Labour	19,281	3652243.48	1.922512	.2673719	1	2
Farm_Size	19,281	3652243.48	1.64165	.5226776	1	3
Male	19,281	3652243.48	.4722743	.4992436	0	1
Access_to_~t	19,281	3652243.48	.0774885	.2673719	0	1
extension_~s	19,281	3652243.48	.5699428	.4950967	0	1
labour	19,281	3652243.48	.3295272	.4700537	0	1
edu_cat	19,281	3652243.48	2.030991	.8759955	0	4
Group_Memb~p	19,281	3652243.48	.456838	.4981465	0	1
Age	19,281	3652243.48	34.71037	10.1966	22	78
Off_Farm_I~e	19,220	3643163.16	1386.074	1525.297	0	5000
Marital_st~s	19,281	3652243.48	2.543684	1.289604	1	7
Information	19,281	3652243.48	1.487953	.4998678	1	2

B.2 Logistic regression output

```
. logit treated access_to_credit Age2 age_group education_sq edu_cat Group_Membershi
> s Information Male Off_Farm_Income Farm_Size Household_Size i.region [pw= weight ]

Iteration 0:   log pseudolikelihood = -1744103.1
Iteration 1:   log pseudolikelihood = -544271.04
Iteration 2:   log pseudolikelihood = -319337.26
Iteration 3:   log pseudolikelihood =  -245600.9
Iteration 4:   log pseudolikelihood = -238736.72
Iteration 5:   log pseudolikelihood = -238488.79
Iteration 6:   log pseudolikelihood = -238487.95
Iteration 7:   log pseudolikelihood = -238487.95

Logistic regression                                     Number of obs = 19,220
                                                        Wald chi2(15) = 551.85
                                                        Prob > chi2   = 0.0000
Log pseudolikelihood = -238487.95                       Pseudo R2     = 0.8633
```

treated	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
access_to_credit	.2740252	.1416187	1.93	0.053	-.0035423	.5515927
Age2	-.0742953	.2141897	-0.35	0.729	-.4940994	.3455087
age_group	.2942132	.7503083	0.39	0.695	-1.176364	1.76479
education_sq	-.1106164	.0713165	-1.55	0.121	-.2503942	.0291614
edu_cat	.5819319	.2814992	2.07	0.039	.0302036	1.13366
Group_Membership	.0707628	.9095666	0.08	0.938	-1.711955	1.853481
Hired_labour	-.2039832	.2957488	-0.69	0.490	-.7836403	.3756738
extension_access	4.005772	.5263195	7.61	0.000	2.974205	5.037339
Information	1.316542	.9136479	1.44	0.150	-.474175	3.107259
Male	.1476149	.1431505	1.03	0.302	-.1329549	.4281847
Off_Farm_Income	-.0013249	.0000703	-18.84	0.000	-.0014628	-.001187
Farm_Size	3.503683	.2745529	12.76	0.000	2.96557	4.041797
Household_Size	.0777041	.0299864	2.59	0.010	.0189318	.1364764
region						
Central	10.86269	.7877441	13.79	0.000	9.31874	12.40664
Southern	3.348839	.5918294	5.66	0.000	2.188875	4.508803
_cons	-18.09943	1.375453	-13.16	0.000	-20.79527	-15.4036

```
. margins, dydx(*)

Average marginal effects                          Number of obs = 19,220
Model VCE: Robust

Expression: Pr(treated), predict()
dy/dx wrt:  access_to_credit Age2 age_group education_sq edu_cat Group_Membership Hired_labour extension_access
            Information Male Off_Farm_Income Farm_Size Household_Size 2.region 3.region
```

	dy/dx	Delta-method std. err.	z	P>|z|	[95% conf.	interval]
access_to_credit	.0049335	.0025635	1.92	0.054	-.0000908	.0099578
Age2	-.0013376	.0038618	-0.35	0.729	-.0089066	.0062314
age_group	.005297	.0135309	0.39	0.695	-.0212231	.0318171
education_sq	-.0019915	.0012817	-1.55	0.120	-.0045037	.0005206
edu_cat	.010477	.0050551	2.07	0.038	.0005692	.0203849
Group_Membership	.001274	.0163752	0.08	0.938	-.0308209	.0333689
Hired_labour	-.0036725	.0053356	-0.69	0.491	-.0141301	.0067851
extension_access	.0721196	.0069887	10.32	0.000	.0584221	.0858171
Information	.0237029	.0162117	1.46	0.144	-.0080715	.0554773
Male	.0026576	.0026151	1.02	0.309	-.0024678	.0077831
Off_Farm_Income	-.0000239	9.23e-07	-25.86	0.000	-.0000257	-.000022
Farm_Size	.06308	.0044111	14.30	0.000	.0544344	.0717256
Household_Size	.001399	.0005383	2.60	0.009	.0003438	.0024541
region						
Central	.5835848	.0279263	20.90	0.000	.5288502	.6383194
Southern	.0513805	.0088347	5.82	0.000	.0340647	.0686963

B.3 Results for Balancing of Covariates in PSM

```
. pstest Male access_to_credit extension_access Education educationsq Farm_Size Off_Farm_Income Household_Size, g
> both
```

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
Male	U	.50208	.46694	7,0		3,90	0,000	.
	M	.50145	.51018	-1,7	75,2	-0,51	0,609	.
access_to_credit	U	1,5934	1,4611	26,7		14,76	0,000	0,97
	M	1,4875	1,5777	-18,2	31,9	-5,32	0,000	1,02
extension_access	U	.59969	.55335	9,4		5,18	0,000	.
	M	.54043	.52356	3,4	63,6	0,99	0,322	.
Education	U	6,0593	5,6366	12,2		6,71	0,000	0,93*
	M	6,2781	6,103	5,1	58,6	1,42	0,156	0,88*
educationsq	U	48,277	44,148	8,6		4,73	0,000	0,97
	M	51,713	51,168	1,1	86,8	0,30	0,764	0,88*
Farm_Size	U	2,2526	1,5019	152,9		93,98	0,000	1,90*
	M	1,8232	1,8138	1,9	98,8	0,81	0,417	1,71*
Off_Farm_Income	U	220,43	1502,9	-103,8		-50,23	0,000	0,31*
	M	429,61	420,48	0,7	99,3	0,26	0,793	2,01*
Household_Size	U	4,1221	3,5552	23,0		13,64	0,000	1,52*
	M	3,9808	4,1012	-4,9	78,8	-1,33	0,185	1,08

* if variance ratio outside [0,94; 1,07] for U and [0,91; 1,10] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0,438	8423,64	0,000	43,0	17,6	188,3*	1,23	67
Matched	0,009	42,59	0,000	4,6	2,7	22,3	0,97	67

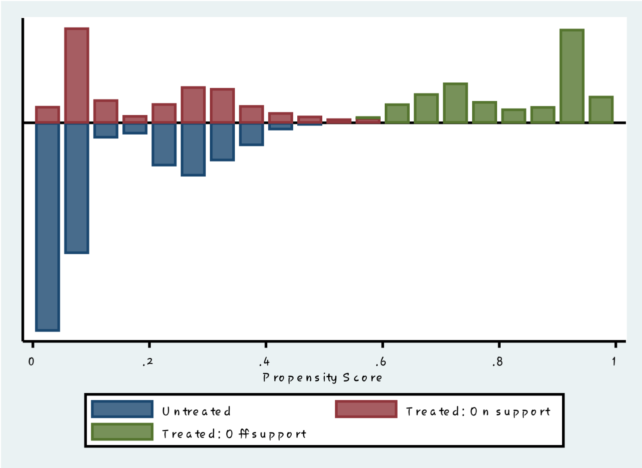
* if B>25% R outside [0,5; 2]

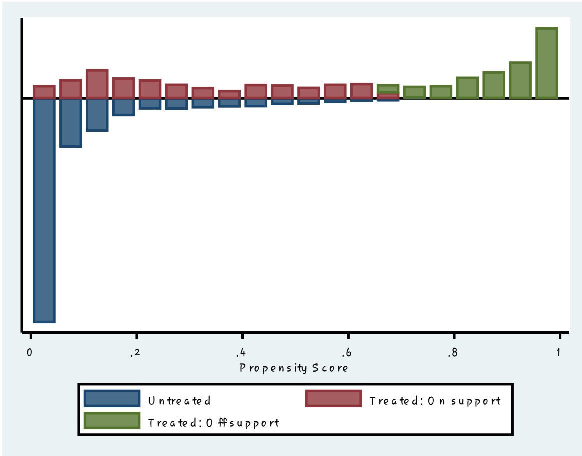
B.4 Output for treatment effect on maize productivity.

```
. psmatch2 treated access_to_credit Education Farm_Size Household_Size extension_access Off_Farm_Income region, ne
> ighbor(1) noreplace caliper(0.05) logit outcome(maize_productivity) common

Logistic regression                                     Number of obs =  19,221
                                                        LR chi2(7)    = 8813.27
                                                        Prob > chi2   =  0.0000
Log likelihood = -5208.5499                             Pseudo R2     =  0.4583

------------------------------------------------------------------------------
         treated | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-----------------+------------------------------------------------------------
access_to_credit |   .5735326   .0505202    11.35   0.000     .4745149    .6725503
       Education |   .0025545   .0071929     0.36   0.722    -.0115433    .0166523
       Farm_Size |   3.338586    .065101    51.28   0.000     3.210991    3.466182
  Household_Size |   .0685968   .0103007     6.66   0.000     .0484078    .0887859
extension_access |   .3960305    .055312     7.16   0.000      .287621      .50444
 Off_Farm_Income |  -.0008503   .0000271   -31.36   0.000    -.0009034   -.0007972
          region |   .6311289   .0345619    18.26   0.000     .5633889    .6988689
           _cons |    -9.4579   .1849844   -51.13   0.000    -9.820463   -9.095337
------------------------------------------------------------------------------

----------------------------------------------------------------------------------------
        Variable     Sample |    Treated     Controls   Difference         S.E.   T-stat
----------------------------+-----------------------------------------------------------
maize_producti~y  Unmatched | 791.699236   265.35838   526.340856   12.5361682    41.99
                        ATT | 826.874394   236.464703   590.409691   27.5020688    21.47
----------------------------+-----------------------------------------------------------
Note: S.E. does not take into account that the propensity score is estimated.

 psmatch2: |   psmatch2: Common
 Treatment |        support
assignment | Off suppo  On suppor |     Total
-----------+----------------------+----------
 Untreated |         0     15,379 |    15,379
   Treated |     1,708      2,134 |     3,842
-----------+----------------------+----------
     Total |     1,708     17,513 |    19,221
```

B.5 PSM graphs for different Algorithms.

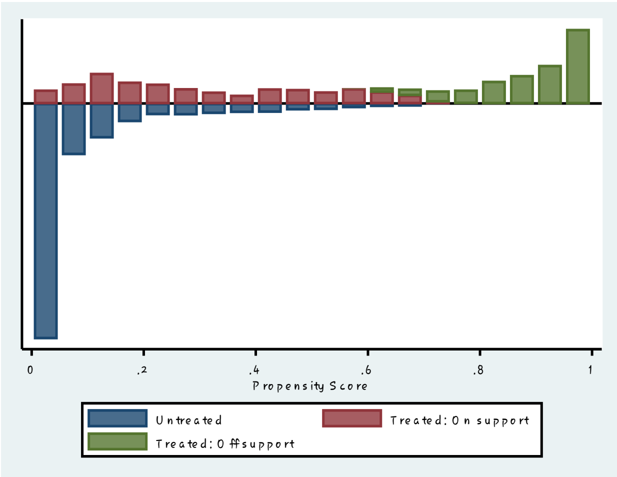
Kernel matching caliper 0.01 Caliper 0.05

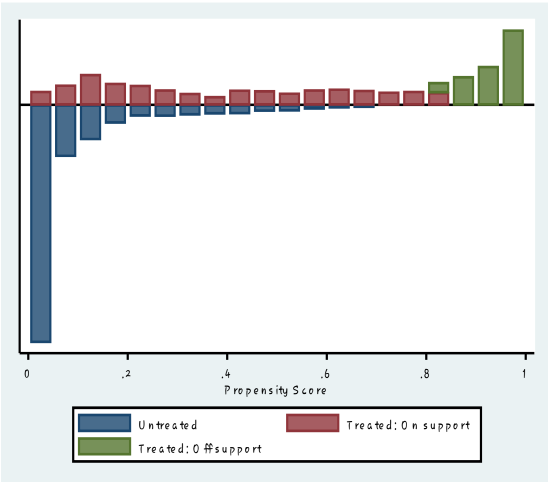




Nearest Neighbor matching caliper 0.01

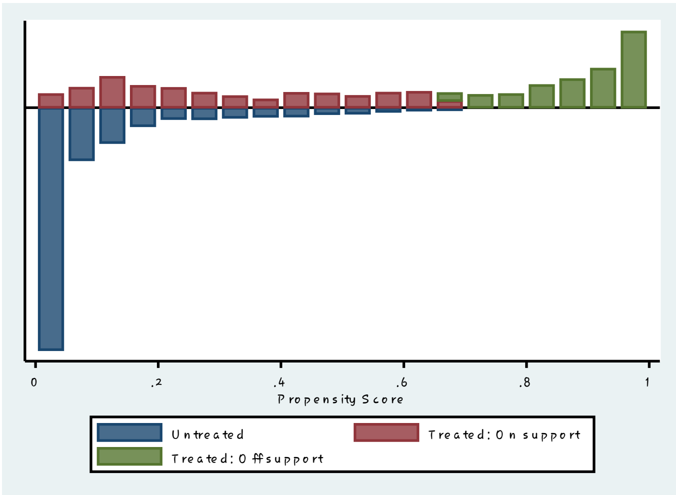
Caliper 0.05



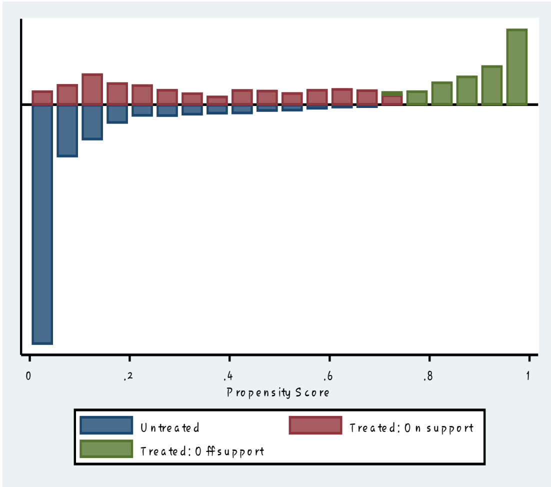


Radius Matching.

Band width of 0.01



Band width of 0.25



B.6 Results for Sensitivity analysis.

```
. rbounds maize_productivity , gamma(1(0.1)3)
```

Rosenbaum bounds for maize_productivity (N = 19282 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	186.354	186.354	181.341	191.234
1.1	0	0	173.257	200.1	168.834	205.598
1.2	0	0	161.907	214.945	157.579	220.538
1.3	0	0	152.159	229.281	149.343	236.287
1.4	0	0	144.066	244.584	140.162	250.651
1.5	0	0	137.121	256.922	133.4	262.719
1.6	0	0	130.523	269.403	127.41	275.138
1.7	0	0	125.063	281.391	122.193	290.145
1.8	0	0	119.96	295.165	116.725	302.369
1.9	0	0	115.057	307.763	112.496	315.236
2	0	0	110.519	319.192	107.761	327.338
2.1	0	0	106.394	331.416	104.136	341.573
2.2	0	0	103.182	343.924	100.385	353.628
2.3	0	0	100.05	356.428	97.9569	367.868
2.4	0	0	97.5125	370.294	94.58	380.19
2.5	0	0	94.3155	381.441	91.7125	391.863
2.6	0	0	91.6775	393.064	88.8125	403.009
2.7	0	0	88.74	403.68	86.751	415.208
2.8	0	0	86.7712	415.208	84.5195	426.002
2.9	0	0	84.6765	425.338	82.0975	437.719
3	0	0	82.3279	436.45	80.2213	449.428

```
* gamma  - log odds of differential assignment due to unobserved factors
  sig+   - upper bound significance level
  sig-   - lower bound significance level
  t-hat+ - upper bound Hodges-Lehmann point estimate
  t-hat- - lower bound Hodges-Lehmann point estimate
  CI+    - upper bound confidence interval (a=  .95)
  CI-    - lower bound confidence interval (a=  .95)
```