Spatial Dependence in Decision Making: Implications for Improved Rice Technology Adoption Decisions in Nigeria

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Declaration

I confirm that this is my own work and that the use of all material from other sources has been properly and fully acknowledged.

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Abstract

Improved agricultural technology plays a key role in the economic advancement of both the developed and developing countries. Notwithstanding, the rate of diffusion of the agricultural technological innovation in developing countries is of great concern. Specifically, in Nigeria adoption of improved farm technology has been at the front of this debate. In terms of their attitudes towards risk taking and temporal perspectives, farmers in the developing countries have been described as being risk averse and impatience. Yet, these attitudes in addition to neighbourhood or spatial dependence effects may influence the adoption of improved agricultural technology. This study therefore investigates the roles of risk preference and time preference as well as the spatial dependence effects in improved rice technology adoption decisions.

Combinations of experimental, qualitative and quantitative data obtained from the four agricultural zones in Ogun State Nigeria were used for the study. Rice farmers' risk preference and time preference are elicited using panel lotteries and front-end delay methods, respectively. Using a power function weights matrix that enable the examination of limit of spatial dependence, Instrumental Variable (IV) method was applied to examine the effects of spatial dependence on risky decision making as well as in intertemporal decisions. In addition, a structural model is estimated using Instrumental Variable (IV) probit model to examine first, the effects of risk preference and spatial dependence in adoption decisions; and second, the effects of time preference and spatial dependence in adoption decisions.

The results reveal that most sampled farmers are risk avoidant, have high subjective discount rates and low adoption rates. Relative to the non-adopters, the adopters of improved rice varieties are significantly more willing to take risky decisions and are oriented towards the long terms implications of being patience. In addition to socio-economic factors, the findings show that rice farmers' risk and time preferences are spatially correlated up to 60 km radius indicating rice farmers within this distance are more likely to have similar adoption pattern. The results obtained from employing instrumental variable probit reveal that farmers' specific factors, location, institutional factors and perceptions about improved rice technology attributes significantly determine rice farmers' adoption decisions. More importantly, risk and time preferences are not only endogenous but also significant factors explaining rice farmers' decisions to adopt improved rice technology.

It is evident that cluster plays significant roles in decision making, and thus matters in the diffusion of improved agricultural innovation. Decisions to adopt improved rice varieties are not only significantly influenced by less willingness to take risks but also short-sightedness towards present consumption (impatience). Therefore, specific attention should be paid to the heterogeneity in farmers' locations as well as their risk-taking ability and level of impatience which drive their attitudes when designing and implementing agricultural technological innovation.

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Dedication

To the memory of my late siblings: Taiwo Ambali, Alaba Ambali and Funmi Awonuga; uncle Dele Ajayi and sister-in-law: Ayo Ambali whose sudden departure from this earth shakes my PhD sojourn.

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Chapter One

1.0 Introduction

This chapter provides general background information on the roles of risk and time preferences as well as the spatial dependency among decision makers in the adoption of agricultural technological innovation. This is followed by the statement of problem relating to the factors affecting the adoption of such innovation in developing countries. It also explicitly states the specific objectives analysed as well as the hypotheses tested in the study. It concludes with the structure of the thesis.

1.1 Background of the Study

Agriculture and related activities are important sources of livelihood for most of the population of subsistence farmers in the global south. Players in this field (farmers, government and development partners alike) are making endless efforts to bridge the gap between food demand and food supply, especially in the developing countries where this gap is probably widest. Arguably, while food is in excess supply in some parts of the world, it is not only insufficient in supply in others but also inaccessible. Notwithstanding, the livelihood of over two-third of the sub-Saharan Africa (SSA hereafter) population depend on rain-fed Agriculture which significantly affect farmers' yield and income (Shah, Fischer, & Velthuizen, 2008; Ludi, 2009). This is particularly the case in Nigeria where the income of most rural households is largely dependent on farming. Therefore, achieving self-sufficiency in food production as well as self-reliance in income generation in developing countries requires giving specific attention to smallholder farmers who produce most of the food consumed in the world.

Low agricultural growth has been identified as a bane to the economic development in developing countries attributable to overreliance on unstable weather and climate, inconsistency in government policies, weak public institutions (extension services, imperfect financial and insurance markets) and low diffusion of agricultural technological innovation. Low diffusion of agricultural innovation may also be a consequence of smallholder farmers' attitudes toward the adoption of improved agricultural technologies.

Technological advancement is the main driver of economic development because meaningful economic development is unrealistic without revolutionising agriculture as evident from most advanced nations of the world. However, despite the importance of improved agricultural innovation in the agricultural development of most agrarian nations, the slow spread of the available improved farm technologies calls for concern. Specifically, this has been in the front of debate in Nigeria. Several factors have been attributed to the reasons for the adoption, dis-adoption and non-adoption of improved agricultural innovation. From the supply standpoint, adoption may be constrained by high transaction cost, non-involvement of farmers in developing improved farm technologies as well as low knowledge about the potential benefits of such improved farm practices especially in the face of grossly inadequate extension services. For example, Oladele (2006) attributed dis-adoption of improved maize and cowpea seeds among farmers in Southwest Nigeria to inadequate contact with extension agents. From the demand angle, factors such as perceptions, preferences and disposition of farmers toward agricultural innovation may hinder or delay the diffusion of innovation and subsequently agricultural development. On the other hand, some externalities such as climatic environment (Feder & Umali, 1993), as well as the existing spatial dependence and social interaction among farmers may enhance or deter the acceptance of agricultural technological innovation. In short, many adoption constraining factors are unobservable and some are not under the control of farmers especially the supply factors, yet investment decisions are made with the objective of increasing yield and income to enhance food security and welfare.

Literature suggests that factors affecting farmers' adoption processes may be intrinsic (for example, risk aversion) and extrinsic (for example, environmental factors). These factors may be categorised into farm and farmer specific characteristics, institutional factors, environmental factors, social learning effects and risk attitudes (Feder, Just, & Zilberman, 1985; Foster & Rosenzweig, 2010). The less examined factors, farmers' preferences for risk and time as well as the potential spatial dependency in such preferences are the crux of this study. Few empirical studies have demonstrated the significant roles played by risk aversion, impatience and neighbourhood influence in the acceptance or rejection of improved agricultural technology. Notwithstanding, these roles have been independently examined. For examples, Le Cotty, Maître d'Hôtel, Soubeyran, and Subervie (2017) reveals a negative impact of impatience on fertilizer adoption among maize farmers in Burkina Faso while Liu (2013) shows that risk and loss averse farmers are late Biotechnology (BT) cotton adopters in China. On the other hand, Läpple and Kelley (2015) submit that farmers living closely exhibit similar behaviour with respect to organic farm adoption in Ireland while Ward and Pede (2015) make a conclusion on the positive neighbourhood influence in hybrid rice adoption in Bangladesh. Variables like risk and time preferences are not directly observable which partly explains the reason for their omission in adoption model. In addition, no existing studies examine the endogeneity of risk and time preferences in adoption decisions' model. Adoption of improved agricultural technology may not only be correlated with farmers' preferences for risk and time, these important variables may be endogenously determined in the adoption model. In other words, most unobservable factors which constitute the disturbance errors in adoption model may be correlated with risk aversion as well as farmers' level of impatience. In short, adoption model estimated without accounting for the potential endogeneity problem could yield an estimate that measures only the magnitude of the degree of association with negative consequence on the policy suggestions based on such inference.

Farmers' pattern of adoption may be a reflection of the heterogeneity in risk and time preferences as well as the geographical area or location where they operate. Therefore, neighbouring effects may not only play significant role in the adoption decisions (as previously reported) but also in risky and intertemporal decisions. Studies which examined the spatial dependence or neighbourhood effects in adoption decisions conclude that farmers do influence their neighbours to accept improved agricultural technologies (Case, 1992; Holloway, Shankar, & Rahmanb, 2002; Krishnan & Patnam, 2014; Läpple & Kelley, 2015; Tessema, Asafu-Adjaye, Kassie, & Mallawaarachchi, 2016). Social learning effects have also been found to aid adoption and diffusion processes attributable to high communication that exists among farmers in a social networks (Bandiera & Rasul, 2006; Conley & Udry, 2010).

Decision making processes may be correlated in space and time. Insight into such spatial correlation or dependence in decision making is therefore important in many ways. First, neighbourhood or social interaction effects may reduce the cost associated with acquiring information about improved agricultural technology outside farmers' locations. Under good coordination, social network may substitute for extension services in developing countries like Nigeria where high social interaction and communication exist among individuals and farmers. Second, social learning effects along with other unobserved spatial characteristics such as socio-economic, local climatic, ecological and topographic conditions may manifest in farmers' risky and temporal investment decisions and subsequently affect decisions to adopt technological innovation. Furthermore, clustering may manifest in the real life as well as experimental decisions due to social interaction and other socio-economic factors inherent in farmers' environment. Therefore, neighbouring or spatial effects could be an influential device for the diffusion of agricultural technological innovation.

Farmers in the developing countries have been reported to be risk-averse and impatient towards time. Empirical evidence abounds on the significant effects of risk aversion on propensity to adopt improved agricultural technologies (Marra, Pannell, & Abadi Ghadim, 2003; Liu, 2013; Ward & Singh, 2014; Barham, Chavas, Fitz, Salas, & Schechter, 2014; Barham, Chavas, Fitz, Ríos-Salas, & Schechter, 2015). However, most previous studies did not only ignore the role of time preferences in adoption decisions but also pay less attention to the fact that spatial dependence may be inherent in risky and intertemporal decisions. Like most economic factors, risk aversion and subjective discount rates are random variables often measured at the point where a decision maker is indifferent using utility function which could be spatially correlated. For instance, intertemporal decision reflects a trade-off between present and future implying it is not only temporal but may also be spatial when measured over space.

In addition, it has been empirically demonstrated that farmers with higher level of impatience (high subjective discount rates) show less tendency to investment in Burkina Faso (Liebenehm & Waibel, 2014). Financial commitment made in rice production by a smallholder farmer today may double in worth within three months. However, status quo or present bias may encourage preferences for present consumption with huge negative consequences on farmers' wealth. Risk aversion and impatience have also been reported having significant negative impact on farmers' income in developing countries (Yesuf, 2004; Yesuf & Bluffstone, 2009; Tanaka, Camerer, & Nguyen, 2010; Nguyen, 2011; Liebenehm & Waibel, 2014). Findings have equally showed that these intrinsic factors have negative effects on poverty (Lawrance, 1991; Wik, Aragie Kebede, Bergland, & Holden, 2004; Yesuf & Bluffstone, 2009). Notwithstanding, little is reported about the heterogeneity in farmers' decision-making.

Understanding the heterogeneity in adoption decisions is important for policy formulation and implementation. This study therefore extends the existing knowledge in many ways. First, non-accounting for the endogeneity of risk and time preferences in adoption model may yield an estimate that may affect policy analysis because adoption is a decision-making under uncertainty which relates to risk, ambiguity and time. Spatial dependence effects incorporated into adoption decisions model may help in accounting for some variables like climatic, geographical, ecological and socio-economic conditions, which are often omitted in the adoption models. In other words, risk and time preferences may be correlated (endogenous) with other socio-economic factors that are not often accounted for in adoption model suggesting wrong application of model could yield misleading estimates. Second, farmers' attitudes are likely to vary across locations, suggesting that using only binary variables to control for locations may not provide sufficient information on the heterogeneity in adoption decisions. Third, past behavioural studies attempted to examine the determinants of risk and time preferences without recourse to the spatial dependency in farmers' decision-making. Such spatial correlation may not only reflect the existing social interaction or networking among farmers but explain patterns of adoption (cut across the agricultural zones or boundaries) and guide policy direction with respect to the diffusion of agricultural innovation. Fourth, most rice farmers in Nigeria may be acquainted with the potential benefits of high yield rice varieties (HYV), yet uncertainty associated with such improved technology may affect their choice of investment. Patterns of adoption may be a reflection of the heterogeneity in farmers' preferences for risk and time which also affects their utility function and subsequently sub-optimal decisions (Ward & Singh, 2014). Therefore, omission of risk preferences and time preferences as well as spatial dependence in adoption decisions' model has created a gap which this study fills.

Furthermore and specifically to Nigeria, most past agricultural development policies and programmes aimed primarily at increasing agricultural productivity for self-sufficiency in food production achieve little success since most farmers' intrinsic as well as environmental factors are neglected in policy making. In addition, most past policies are top-down driven which casts doubt on their effectiveness. Thus, it is imperative to examine both the intrinsic and extrinsic factors which are correlated with farmers' adoption decisions. In the light of the above, this study attempts to broadly examine the correlation between real-life decisions (adoption and decisions relating to risk and time) as well as providing valuable insights into some indispensable variables (such as spatial dependence or correlation) that may guide the direction of efforts at ensuring the acceptance of improved farm (rice) technologies especially in the developing countries.

1.2 Statement of Problem

Improved agricultural technologies have many benefits including the potential for higher yield (increased productivity) and labour saving. They may also mitigate the effects of climatic shocks (Dar & Laxmipathi Gowda, 2013). Such technologies are essential for sustainable intensification because they may increase yield without increasing farm size with less environmental problem. Following the drive for green revolution in Asia, some empirical studies submitted that improved agricultural technologies have a significant positive impact on income and welfare in developing countries (Rahman, 1999; Mendola, 2007; Kijima, Otsuka, & Sserunkuuma, 2008; Udoh & Omonona, 2008; Becerril & Abdulai, 2010; Kassie, Shiferaw, & Muricho, 2011). Increased agricultural growth has also been identified as a solution to food insecurity problems in SSA (Mainuddin & Kirby, 2009; Godfray, Beddington, Crute, Haddad, Lawrence, Muir, Pretty, Robinson, Thomas, & Toulmin, 2010; Barrett, 2010; Pinstrup-Andersen & Watson II, 2011; Rada, Rosen, & Beckman, 2013). Notwithstanding, productivity growth in rice production in this region is constrained by extreme weather conditions such as drought and flood. Therefore, these background risks have significant negative impact on the livelihoods of rural farmers whose income largely depend on rain-fed agriculture.

Rice is an important food security crop especially in developing countries. Specifically in Nigeria, rice is cultivated in virtually all the geo-political zones mostly by smallholder farmers. Rice production in this country is however confronted with varying degrees of constraints ranging from the socio-economic to institutional factors (lack of access to credit, market and accessible roads). Over dependence on rain has dire consequences on farmers' income[1]. Nigeria is a leading rice producer in Africa but surprisingly a leading importer in the world due to her increasing population and low rice yield. Since low rice productivity results in low income per unit of land, importation has served as alternative option to bridge the supply-demand gap with the country spending billions of dollars annually on importation. In the past, the Nigerian

[1]For instance, the average rice yield in SSA from the irrigated lowland (3.5 tonnes/ha) is higher than for rain-fed lowland (2.2 tonnes/ha), mangrove swamp (2 tonnes/ha) and rain-fed upland (1 tonne/ha). Moreover, about 7 million hectares of rice areas in SSA are prone to drought and flood implying most Nigeria rice areas are prone to weather threats, being the largest rice producer in SSA (Africa Rice Centre, 2015). Agricultural environment is associated with varying degrees of uncertainties including fluctuation in weather which affects farm outputs, market imperfection, to variability in prices of inputs and outputs.

Government and development partners have introduced and implemented several productivity and efficiency enhancing policies and programmes. These among others, include Green Revolution, Operation Feed the Nation (OFN) and Agricultural Development Programme (ADP). However, since most of these policies are top-bottom driven, the answer to the question about whether these policies have made significant impact remain mixed.

The quest for increasing rice yield against all odds prompted the introduction of many improved varieties to Nigeria most of whom are supported by international organisations. For instance, some of the HYVs under cultivation in Ogun State include the new rice for Africa (NERICA), FARO 44, FARO 50, FARO 52 ITA 150, WAB 189 and WITA 4 (Saka, Okoruwa, Lawal, & Ajijola, 2005; Saka & Lawal, 2009). These authors reported significant yield difference between the adopters and non-adopters of improved rice varieties. However, it is not only unclear whether rice farmers increase the adoption rates over time but also the reasons for adoption, non-adoption or dis-adoption behaviour have not been adequately investigated. Many factors are attributed to the reasons for the low spread of improved agricultural innovation in developing countries. These may include farmers' size of holding, low level of education or literacy, physical and institutional factors such as road, location, access to credit and market as well as extension services (Feder *et al.*, 1985) . Access to good road networks, for example may aid access to information and thus encourage the use of improved farm techniques. Farmers' perceptions of technology attributes have also been found to play significant roles in adoption decisions (see for examples (Adesina & Zinnah, 1993; Adesina & Baidu-Forson, 1995; Kallas, Serra, & Gil, 2010)). However, smallholder farmers have no control over many factors especially the production environment as well as unobservable ones but exercise some level of control over their preferences including decisions relating to risk and time.

Notwithstanding the above identified constraints, preferences for risk and time as well as the spatial dependence associated with decision making among farmers may explain reasons for adoption, an investment decision under uncertainty. Indeed, farmers may know or may not know the probability distribution associated with the yield of HYV suggesting risk and ambiguity are important factors in the decisions to grow such technologies. However, given that most farmers in the developing world may not have the opportunity to transfer their challenges to the third party due to imperfect credit market and lack of access to insurance (Yesuf, 2004), taking risky decisions or showing preference for delayed or temporal outcomes may have a significant impact on their livelihood. Although heterogeneity has been observed in farmers' risk attitudes, adoption of agricultural technological innovation is not the focus of most studies (Harrison, Humphrey, & Verschoor, 2005a; Nguyen & Leung, 2009; Harrison, Humphrey, & Verschoor, 2010; Nguyen, 2011; Bocqueho, Jacquet, & Reynaud, 2014)). Liu (2013) and Ward and Singh (2014) attempted to bridge this gap but their studies focus on *ex post* and *ex ante* technology, respectively. This study differs from these two studies in two respects. First, it examines farmers' attitudes with respect to the existing improved agricultural technology. Second, it considers the roles of time preferences and spatial dependence in adoption decisions. Some attempts have also been made to examine the roles of ambiguity in adoption decisions (Barham *et al.,* 2014; Ward & Singh, 2015). This present study focuses on the roles of risk, time and spatial dependence in adoption decisions. Farmers in most developing countries may have strong preference for immediate consumption, which is attributable to many factors including poverty and low access to infrastructure and information yet a few studies have attempted to examine the effects of impatience on adoption decisions. Farmers' level of impatience, like risk aversion, may be geographically correlated suggesting the possibility of having important policy implications for the acceptance of technological innovation.

In summary, the roles of spatial dependence in decision making relating to risk and time have not been exploited in the literature. Spatial dependence effects may reflect farmers' adoption pattern implying social interaction and communication may aid the adoption and diffusion of agricultural technological innovation. However, many factors relating to agricultural production environment are unobservable or latent and thus often omitted in the analysis or not accounted for by most previous studies. Some of these factors including socio-economic, geographical and climatic conditions as well as infrastructural facilities may explain the degree of heterogeneity in farmers' adoption patterns. Some of these factors are accounted for by incorporating the spatial lags of the risk and time preferences in the adoption model as instrumental variables. In addition, adoption decisions may be affected by perceived riskiness of improved technology as well as the uncertainty associated with its future expected yield.

Particularly in Nigeria, most rice farmers operate under uncertainty with drought and flood constituting the main risky and uncertain events in rice production. Exposure to extreme weather events would not only reduce farmers' income but also increase importation tendency. With the present Nigerian Government commitment to reducing importation of rice into the country, increasing the rates of adoption of drought-resistance and yield-enhancing rice varieties remains a viable strategy for the actualization of increased rice productivity as well as raising farmers' income. Therefore, the motivation for the current study to examine the roles of spatial dependence in rice farmers' decisions relating to risk and time with the implications for improved rice varieties' adoption decisions in Nigeria.

From the foregoing, it is important to provide answers to the following questions. What factors determine rice farmers' risk preferences (risk avoidance)? Are rice farmers' risk preferences spatially determined or correlated? Does risk preference significantly explain rice farmers' adoption decisions? What factors determine rice farmers' time preference (impatience)? Are rice farmers' time preferences spatially determined? Does time preference significantly explain rice farmers' adoption decisions? These are the questions this study addresses with the intention of providing policy options that would guide policy makers, governments and development partners. Although this study focusses on rice farmers' attitudes toward risk and time and adoption behaviour in Nigeria, the impact of the findings may extend to other developing countries with similar setting. Emanating from the motivation provided in the background of the study, and the research questions, the following specific objectives are analysed in this study.

1.3 Objectives and Hypotheses of the Study

This study specifically addresses or examines:

i. spatial dependence or correlation in rice farmers' risk preferences;
ii. effects of risk preferences (risk avoidance) on rice farmers' adoption decisions;
iii. spatial dependence or correlation in rice farmers' time preferences and
iv. effects of time preferences (impatience) on rice farmers' adoption decisions.

Four hypotheses were tested in this study to achieve the above stated objectives. These hypotheses are stated in the alternative forms as follows:

Hypothesis one: *there is spatial dependence in rice farmers' risk preferences*. Spatial dependence measures spatial relationship between random variables. Since risk attitude parameter is generated randomly among subjects over space, it calls for examining correlation among this variable. Put differently, like time series data, arguments abound in the literature on the potential endogeneity problem associated with spatial lag models. Therefore, if this exists, spatial correlation has implications not only in policy making but also on the choice of model such as application of Instrumental Variable (IV) model (IV hereafter) rather than Ordinary Least Squares method (OLS hereafter) which may yield an inconsistent estimate for such spatially lagged models. Indeed, endogeneity and spatial dependence in risk preferences may be attributed to different sources including measurement error and omission of important variables. It may also be due to the geographical clustering the reflection of the existing socio-economic conditions.

Hypothesis two: *risk preference is endogenous and has a significant effect in rice farmers' adoption decisions*. Since risk preference or attitude is often estimated from the utility function, it is expected to be an exogenous variable. It may however be endogenously determined in adoption decisions' model. In other words, risk preferences may not only significantly explain reasons for adoption and non-adoption, but may also be correlated with the error term in the adoption decisions' model, due largely to measurement error (in risk preference), simultaneity problems as well as the omission of relevant variables in the adoption model. Although measurement error in the dependent variable (adoption decision) may only increase the variance of the error, that of explanatory variable causes an endogeneity problem. In facts, correlation of an important covariate with the error term motivates the application of Instrumental Variable probit model (IV probit hereafter) model. Therefore, in addition to testing the effect of risk preference in adoption, the endogeneity hypothesis is examined.

Hypothesis three: *there is a spatial dependence or correlation in rice farmers' time preferences*. Time preferences relate to the preference for immediate consumption relative to future consumption. Like risk aversion, discount rate is often measured at the point where a decision maker (DM hereafter) is indifferent between choices. This suggests that subjective discount rates are random variables. They are equally generated over space in this study. Indeed, spatially lagged model is noted for the potential endogeneity problem. Thus, motivation for the application of IV model. Like risk preferences, farmers' intertemporal decisions may show some correlation with one another due largely to the geographical setting as well as the climatic and socio-economic conditions that exist where farmers live.

Hypothesis four: *time preference is endogenous and significantly explains rice farmers' adoption decisions*. The parameter, discount rate which characterizes individual time preference is often estimated from the utility function. Therefore, the *a priori* expectation is that this variable is subjective or exogenous. It may however be an endogenous variable in adoption decisions model. That is, it may be correlated with the error term. It is not only important to hypothesize the effect of time preference in adoption or investment decisions, but also necessary to examine whether time preference is correlated with the disturbance error in the adoption decisions' model. Therefore, IV probit is used to address this endogeneity problem. In summary, the endogeneity hypotheses are necessary to control for the potential measurement errors in the risk and time variables, omitted variable bias as well as the simultaneity nature of the adoption decision models which are estimated in two stages due to the spatial lags as instrumental variables (risk or time model, first and adoption decisions, second).

1.4 Organisation of the Study

This thesis is divided into seven chapters. **Chapter One** provides background information on the issues addressed in the study, highlighting the objectives, the hypotheses tested as well as the questions answered by the study. **Chapter Two** presents the literature reviewed in relation to the state of rice sector in Nigeria, conceptual framework, empirical evidences on the predictors of adoption of improved agricultural technology, theories of decision making under uncertainty as well as extensive literature relating to methods applied in the study. The research methods (data collection and analytical methods) are extensively explained in **Chapter Three** while **Chapter Four** is devoted to the descriptions of the data. **Chapter Five** presents the results of the effects of risk preference and spatial dependence on adoption decisions. These are presented in a paper format, consisting of background information, literature review, methods, results and discussion and conclusion. In this chapter, the role of spatial dependence in risky decisions is presented first followed by the effects of risk preference on HYV adoption decisions. The results of the effects of time preference and spatial dependence on adoption decisions are presented in **Chapter Six.** These are also presented in a paper format, consisting of background information, literature review, methods, results and discussion and conclusion. Also in this chapter, the role of spatial dependence in intertemporal decisions is presented first followed by the effects of time preference on HYV adoption decisions. Lastly, **Chapter Seven** summarizes the findings and highlights the contributions to knowledge as well as the policy implications emanating from the study.

Chapter Two

2.0 Review of Literature

This chapter begins with the review of the literature on the state of Nigerian agriculture with specific attention being paid to the rice sector. The conceptual framework explaining the link between the potential factors affecting farmers' decisions to adopt improved agricultural technology, is presented next. This is followed by the overview of the theories of decision making under uncertainty which have been previously and broadly used to explain farmers' risk attitudes. In addition, a brief account of intertemporal choice theory is presented while its implications on farmers' adoption decisions are presented. The session on the literature on methods used to elicit risk and time preferences follow while the modelling approaches relating to spatial dependence, adoption decisions' analytical model as well as instrumental variable estimation methods conclude the chapter.

2.1 The State of Nigerian Agriculture and Rice Sector

Agriculture has been in dwindling state for many decades in Nigeria where about two-third of the population whose livelihood largely depends on it survive on less than a dollar per day (World Bank, 2012). The decline in the share of agricultural gross domestic product (GDP) from an average of 70 percent in the 1970s to about 21 percent in 2014 could be attributed to low agricultural growth rate of 5.5 percent (Central Bank of Nigeria, 2014). Although Agriculture contributes the least among non-oil sectors, the above source reveals that crop sub-sector makes significant contribution, 88.38 percent out of the 21 percent Agricultural GDP confirming the relevance of crop production in the Nigeria economy. Notwithstanding, a cursory look at the Nigeria national rice yield suggests the need for the country to intensify more efforts on the rice sector. Despite her dominant role as a leading rice producer in the West Africa sub-region, Nigeria is one of the leading rice importer in the world attributed largely to her low yield per hectare of land cultivated as presented. Indeed, available statistics from the FAOSTAT suggests that Nigeria national rice yield lag behind countries like Uganda, Togo and Sierra Leone. A brief discussion about the past agricultural policies is presented next.

Like most developing countries, Nigeria is a food insecure nation despite her enormous land and human resources. Some of the challenges to food crises and food insecurity in the global south identified by Holt-Giménez and Peabody (2008) include the mismanagement of green revolution, free trade agreement and introduction of structural adjustment programmes (SAPs). Although the green revolution encourages adoption of hybrid grain seeds including rice, wheat and maize, the argument put forward is that it forces farmers to cultivate marginal lands and fragile forest thereby discouraging the cultivation of local varieties and resulting in the destruction of agro-biodiversity due to the heavy use of fertilizers and herbicides. More so, free trade is partly responsible for the non-attractiveness and lack of competitiveness of the farm outputs of the peasant farmers in the global markets. Subsequently, the domestic production is strongly discouraged. Additionally, the desire to access the World Bank and International Monetary Fund loans through the SAPs compel most governments to dismantle the existing food commodity board, privatize government-owned institutions (companies) and services; and remove the tariff barrier on imported food items. Specifically in Nigeria, the SAPs (introduced in 1980s) and other practices have great consequences on the income and welfare of most smallholders.

Many agricultural policies and programmes have been established and implemented in the past to enhance food production and food security in Nigeria. Comprehensive reviews are well documented in academic publications (Adebayo & Ojo, 2012; Akerele, 2013). Adebayo and Ojo (2012) conclude that Nigeria currently lack sustainable food policy because most past policies are based on top-bottom approach; achieve little success and lack adequate support from all stake-holders. They offer suggestion on the need to give specific attention to peasant farmers by providing them with improved and affordable farm practices to enhance food security. It should be noted that among many programmes, only the National Cereals Research Institute (NCRI) established in 1975 specially focuses on rice. One of its important mandates is to conduct research into the improvement of rice in Nigeria. With ten sub-stations across the country, the positive effects of the research on the rural farmers are yet to be realized. While emphasizing the roles of peasant farmers in ensuring a food secure nation, Attah (2012) suggests the need for investment in rural development, access to improved farm technologies, increased budgetary allocation to Agriculture as well as educating the rural population who constitute a substantial farming proportion.

Rice is an important staple food for both the poor and the rich in the country yet Nigeria is largely dependent on importation to feed her growing population due partly to the low agricultural productivity growth. Specifically, the constraints associated with rice production and productivity in Nigeria could be viewed from macroeconomic and microeconomic perspectives, or institutional (government policy) and rice production factors. Some of the constraints identified by Daramola (2005) still remain contentious issues. Recent statistics from the Food and Agriculture Organisation of the United Nations (FAO)[2] buttress these challenges. From the macroeconomic standpoint, many factors are responsible for the unattractiveness of rice production as a farm business in Nigeria. These, among other factors identified by Daramola (2005) include high interest rate on loans, high cost of imported farm equipment, and instability in government policies. For example, inconsistency of government policies encourages illegal importation of cheaper rice mostly from Thailand and Vietnam. Decaying infrastructure and weak government institutions also play significant roles in this respect. Infrastructure like roads is generally lacking or at moribund state, thereby contributing to the high cost of production and transportation. There are also inadequate irrigation facilities. Similarly, the land tenure system which favours the rich constitutes a big impediment to rice production. There is poor funding to research institutes, which causes, for example, poor extension services in disseminating the available improved farm practices to farmers. Non-standard seed certification and produce measures are contributory factors to these problems.

Most studies including Awotide, Diagne, and Omonona (2012) conclude that improved rice technology contributes significantly to farmers' productivity. Notwithstanding, from the micro-economic perspective, most farmers prefer status quo (local variety) to alternative improved technology. They rely on local processing and packaging methods which makes the seeds unclean relative to imported rice. In addition, the uneven nature of the finished grain makes it less attractive and less competitive relative to imported rice. Most rural rice farmers also have little or no knowledge about consumers' preferences and taste. Although rice is cultivated in most of the ecological zones of Nigeria, its output is not encouraging relative to the outputs of other food commodities. Lack of irrigation has a significant effect on the National rice yield which is estimated approximately at 1.81 tonnes/hectare (FAO, 2015). The Nigerian rice area, estimated at 3.7 million hectares constitutes about 10.6 percent of the total cultivated arable land (35

[2] FAO highlighted the challenges confronting the Nigerian crop sector to include lack of irrigation, low access to credit, high cost of farm inputs and low use of improved technologies. This information is sourced from Nigeria at a Glance, Food and Agriculture Organisation of the United Nations. Available at: http://www.fao.org/nigeria/fao-in-nigeria/nigeria-at-a-glance/en/. Sourced on: 04/12/2017.

million hectares)[3] suggesting rice is an important food security crop in Nigeria. In short, rice production is constrained by vagaries of weather connoting that farmers should embrace stress-resistant improved seed varieties as part of remedying the challenges and ensuring food security.

The macro and micro economic challenges encourage the production of other crops like cassava, maize and vegetables, which command higher prices locally. The wide demand-supply gap in rice output contributes largely to the import dependency and thus poses big challenges to meeting the demand of the growing Nigeria population[4]. For instance, an estimated $150 million is envisioned by the past administration (2011-2019) to be spent on rice importation (36 million metric tonnes (MMT)) annually in order to meet the increasing rice demand by 2050 (Adesina, 2013). In fact, recent publication in the Nigerian national daily newspaper reveals that one trillion Nigerian naira (USD 2 billion) is spent yearly on rice importation[5]. Notwithstanding other socio-economic factors, low diffusion of agricultural technological innovations (higher yielding rice varieties) may contribute to low yield and import dependency in Nigeria.

As part of efforts to revolutionize the rice sector in SSA, the Africa Rice Centre developed upland and lowland NERICAs to enhance rice production and yield. Other improved varieties have also been developed in the past, yet the reasons for low adoption rate remain mixed. Recent study suggests that food crop production technologies like improved seeds are available, affordable and user and gender friendly in Nigeria (Obayelu, Okuneye, Shittu, Afolami, & Dipeolu, 2016). However, this study did not examine the intrinsic factors that may hinder the adoption processes.

Improved or higher yielding rice varieties available in the study area, Ogun State include NERICA, FARO 44, FARO 50, FARO 52 ITA 150, WAB 189 and WITA 4. Are rice farmers adopting these improved rice technologies? Why do some farmers adopt and others do not? These questions deserve some answers. Research indicates that technology and extension gaps exist among rice farmers in Ogun State, Nigeria (Oladele

[3]According to FAO (note 2), rice provides employment to millions of small-holder farmers who sell about 80 percent of their produce. However, about 77 percent of Nigeria rice area is rain-fed out of which 47 percent is lowland, 30 percent is upland.(Monitoring African Food and Agricultural Policies (MAFAP), 2015).

[4]Rice demand rate (8 percent) has been exceeding supply rate (6percent) in West Africa for decades. Thus, most countries in SSA especially Nigeria depend on import to bridge the gap between demand and supply (Africa Rice Centre, 2008).

[5] In spite of the human and land resource endowments of Nigeria, the country relies so much on rice importation to feed her increasing population. As part of the efforts to bridge the rice supply-demand gap, Ogun State government recently launches MITROS rice mill and MITROS rice. Information about this information as well as the amount reportedly spend on rice importation is sourced from https://www.vanguardngr.com/2017/12/ogun-rice-revolution/. Assessed on 19/05/2018.

& Somorin, 2008). Farmers' adoption or investment interests may be motivated by different factors, both observable and non-observable ones. For instance, farmers in Kwara State Nigeria prioritize personal objectives over income or profit objectives (Adewumi & Omoresho, 2002). Nonetheless, both intrinsic and extrinsic factors may be responsible for the decisions to grow the limited available improved rice varieties in Nigeria.

A brief overview on the well-known NERICA may provide insights into some of the challenges confronting the adoption of improved agricultural technologies in SSA. The aforementioned production constraints and failure of the green revolution technologies motivated the world expert breeders under the West African Rice Development Authority (WARDA), currently known as Africa Rice Centre (or Africa Rice) to develop NERICA. Africa Rice is one of the fifteen centres of the Consultative Group for International Agricultural Research (CGIAR), currently having twenty-five-member States including Nigeria. NERICA is an improved rice variety that resulted from the crossing of the toughness Africa rice (*Oryza glaberrima*) and high yielding Asian rice (*Oryza sativa*). Like most improved rice varieties, it has some attributes that strengthened it against environmental and agro-climatic challenges as well as meeting both the producers' and consumers' preferences. Put differently, its two main attributes: biological and agrochemical cumulate to five main features: higher yield (50-200 percent yield increase), early maturity (30-50 days), resistance to local stress, good taste and high protein content (Nwanze, Mohapatra, Kormawa, Keya, & Bruce-Oliver, 2006). It has also been reported to be widely adopted in some West African countries with positive outcomes yet the slow pace of the adoption and diffusion after two decades of introduction in Nigeria called for investigation.

NERICA was first tested on the field in 1994[6] after which stakeholders in the breeding and distribution adopted Participatory Varietal Selection (PVS) sponsored by the African Rice Initiative (ARI)[7] to aid the dissemination of these improved rice varieties among farmers in SSA. Record shows that after recording some successes in four countries: Cote d'Ivore, Ghana, Guinea and Togo, the good news was spread to all

[6] Details information about NERICA and its diffusion is documented in the New Rice for Africa: A Compendium. Available on: http://www.africarice.org/publications/nerica-comp/Nerica%20Compedium.pdf and http://www.africarice.org/warda/guide-compend.asp. Assessed on 23/03/2015.

[7] More information about NERICA dissemination and sponsors is available in Africa Development Bank: http://www.afdb.org/fileadmin/uploads/afdb/Documents/Project-and-Operations/Multinational New_Rice_for_Africa__NERICA__Dissemination_Project.pdf . Assessed on 23/03/2015.

Africa Rice Member States in 1999. A consortium was equally established in 2001 to enhance its widespread and rapid diffusion in the rice growing areas of Africa. The successes of the first varieties motivated the development of varieties suitable for marginal lands in 2004. Thus, seventeen upland and eleven lowland varieties are reported to have been cultivated in over 700,000 hectares as at 2009 in over thirty SSA countries (Diagne, Midingoyi, Wopereis, & Akintayo, 2011). In Nigeria, nine States reportedly participated in the three-year PVS trials programme in 1999. This increased to eleven States in 2002 and twenty-one States in 2004. Two major initiatives are adopted for its dissemination in Nigeria. The first is the Presidential Initiative on Increased Rice Production, Processing and Export launched in 2003 by the Federal Government of Nigeria. The second is the African Development Bank (ADB) funded ARI's Multinational NERICA Rice Dissemination Project (MNRDP). Notwithstanding, the area under NERICA in Nigeria was estimated at about 244,293 hectares as at 2009 (Diagne *et al.*, 2011). This constitutes about 35 percent of the area cultivated to it in SSA but relatively small considering Nigerian rice land areas.

Wopereis, Diagne, Rodenburg, Sié, and Somado (2008) argue in support of the success of NERICA in Africa. The story is however different in Nigeria where many farmers show negative attitudes toward its adoption. For instance, the actual adoption rates in three Nigerian States was estimated at 19 percent and 35 percent attributable to awareness and seed constraint, respectively (Dontsop Nguezet, Diagne, Okoruwa, Ojehomon, & Manyong, 2013). Arguably, the seed constraint has been partly addressed in most countries. For example, Diagne *et al.* (2011) report a rapid increase in seed production under ARI from 2,733 tonnes in 2005 to 13,108 tonnes in 2008. Furthermore, the recent Federal Government efforts at reducing some of the demand-side constraints associated with the adoption of improved agricultural technology gave birth to the Anchor Borrower's Programme (ABP) on November 17, 2015 to ease credit constraints. Therefore, the effects of both demand and supply factors on rice farmers' adoption decisions are not disputed yet some variables are not directly observed. This is the focus of this study.

Low diffusion of agricultural technological innovation or adoption rates are associated with many constraints yet intrinsic factors such as attitudes toward risk taking as well as willingness for immediate consumption or myopic views about future outcomes and benefits that may accrue from adopting modern technology, could explain some of the reasons why some farmers are not willing to switch from conventional rice varieties to improved varieties. These factors are the subject of investigation in this study. The next section focuses on the inter-relationship between factors that may affect farmers' adoption processes and decisions.

2.2 Conceptual Framework

Adoption and diffusion are two related concepts in agricultural technological innovation. Broadly, adoption is a processes of accepting innovation. In the context of divisible agricultural technology, adoption has been described as farmer's attitudes towards a new technology while diffusion is aggregate adoption (Sunding & Zilberman, 2001). In their definition, Feder *et al.* (1985) opine that adoption is the "extent of the acceptance of innovation after farmers are fully informed about the technology and its potential benefits". Although the above definition allows measurement of intensity of adoption, poor record keeping among farmers especially in the developing countries makes it practically impossible to assess the intensity of adoption of divisible technology. Improved rice varieties fall in the class of divisible agricultural technologies, which are innovations that may be adopted separately over time.

Adoption is a complex process that takes place over space and time suggesting one theory may not adequately capture all the actions or processes involved in the adoption of technological innovation. Therefore, there is the need to provide a comprehensive structure on the interaction between several factors that may explain adoption decisions or processes. As earlier noted, these factors may be intrinsic and extrinsic. Previous studies have devoted a lot of efforts in identifying factors that extrinsically determine the decisions to accept and use agricultural technological innovation. This study groups these extrinsic adoption factors into farmers' personal and socio-economic characteristics, environmental factors, community and institutional factors while the intrinsic factors are mainly preferences, awareness and perceptions (**Figure 1**). In short, while some factors are external or environmental in orientation, some are within the purview of farmers indicating farmers may exercise some level of control over them. The likely linkage between some selected variables and adoption decisions are presented next.

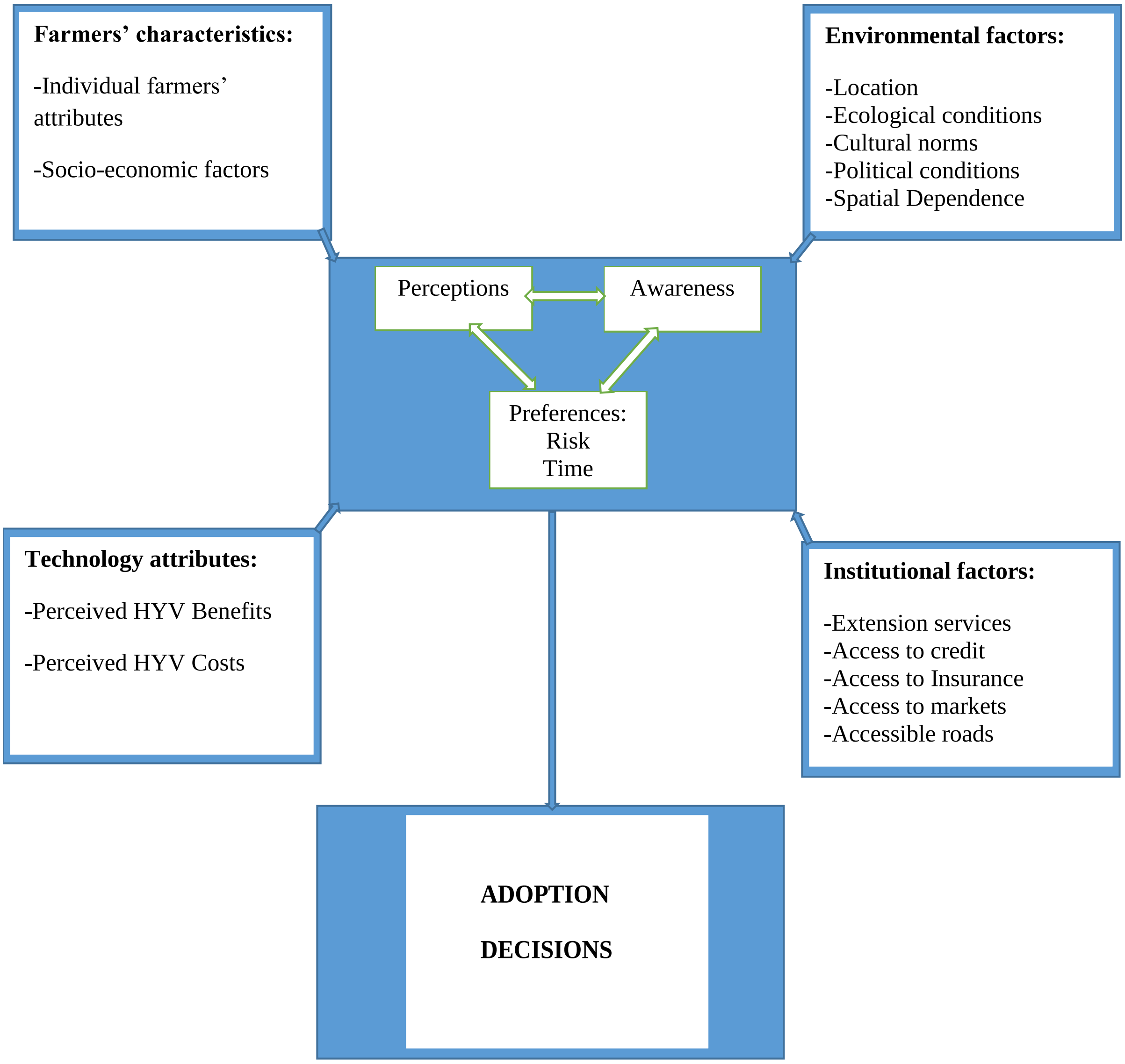

Figure 1: Conceptual Framework

First, farmers' personal and socio-economic attributes such as level of education, age, farm size, gender and experience are extrinsic factors that determine their day-to-day behaviour and interaction. For example, farmers living closely or in the same location may have similar level of education. Informal interaction may manifest in rice farmers' day-to-day farming decisions. Put differently, educational, cultural values and norms may constitute a barrier in one hand and gateway to awareness, perception and preference in another hand. These attributes may also reflect in the size of holding and subsequently determine their decisions relating to investment and consumption. Empirical studies have attempted to examine the effects of farm and other farmers' specific factors affecting adoption decisions with farm size constituting almost a universal variable (Feder *et al.*, 1985). Läpple, Renwick, and Thorne (2015) revealed the positive impact of education and farm size on adoption decisions while age is negatively related to HYV.

Second, environmental factors like climatic, ecological, topographic conditions may affect farmers' adoption learning processes and subsequently adoption decisions. These unobserved variables may reflect in spatial dependence. In their studies, Goodchild (1992) and Anselin (1989) emphasized that spatial dependence is the tendency for close locations or individuals to influence one another, corroborating Tobler (1970) that individuals living closely are more related than distant individuals. Indeed, observations from province or state or region are generally characterized by spatial heterogeneity. Thus, spatial correlation in individual farmers' decision-making may reflect their pattern of adoption. Farmers residing in remote villages, for instance, may have less or late information about improved agricultural technology partly due to low access to formal education, similar local climate, and lack of access to modern infrastructure like road networks. These farmers may therefore form similar attitudes toward the adoption of HYV.

In terms of locations, the zonal division in the study area, for example reflects or captures the climatic conditions and cultural relationship between individual farmers. For instance slight variation is observed in the rainfall pattern in the zonal divisions in Ogun State Nigeria (Apantaku, Lawal-Adebowale, & Omotayo, 2004). The agricultural zones include Abeokuta, Ilaro, Ikenne and Ijebu-Ode. The northern part of Abeokuta zone is derived savannah vegetation while the southern part is rain forest. The Ilaro zone is bounded by Abeokuta zone in the east. The vegetation is derived savannah in the north and rain forest belt and mangrove swamp in the south. Ikenne is the closest zone to Abeokuta zone which it bounded in the west. The vegetation is mainly rain forest belt. Ijebu-Ode zone is a combination of both rural and urban. The northern part is mainly rain forest belt while the southern part is mangrove swamp. Farmers living in the core rural zones or areas may behave differently from their urban zones counterparts by forming different attitudes toward risk and time and subsequently adoption decisions. It is worthy of note that most spatial factors highlighted above are often ignored in the adoption models due to the difficulty in measurement. Therefore, inclusion of spatial dependence or spatial lag captures these unobservable factors in the adoption model. Farmers living closely may either have similar adoption patterns, growing local rice varieties or adopting HYV. Conversely, rice farmers located farther beyond a point may behave differently.

Third, institutional factors play important roles in the development and acceptance of technological innovation in developing countries (**Figure 1**). For example, extension services, access to credit and insurance markets and accessible roads may affect farmers' level of awareness and subsequently attitudes toward adopting HYV. Availability of accessible road will not only increase farmers' access to information but also improve the desire to accepting innovation and aid easy market access. Empirical studies report the importance of access to extension services in the acceptance of innovation (Emmanuel, Owusu-Sekyere, Owusu, & Jordaan, 2016). It is however evident that extension services are very poor and inefficient in many developing countries. Technological innovation is developed for farmers' acceptance, yet the limited numbers of extension workers hinders the diffusion of innovation in most developing countries.

Lastly, the perceived cost and benefits associated with agricultural technological innovation may influence farmers' decisions (see (Obayelu, Ajayi, Oluwalana, & Ogunmola, 2017) for a review). For example, Areal, Riesgo, and Rodríguez-Cerezo (2011) study reveals that European farmers' attitudes toward adoption of GM herbicide-tolerant crops are mainly determined by economic factors such as expected income and potential for the reduction in weed control cost. Other economic factors such as inflated transaction costs of improved agricultural technology may hinder innovation acceptance in addition to the perceived benefits in terms of potential yield and income. The cost of acquiring information and purchasing improved agricultural technology (seeds) may also constitute impediments to the adoption of the technology in question.

Although the above factors may constitute barrier to rice farmers' adoption of HYV, intrinsic factors such as preferences for risk and time are influential factors in farmers' decisions. Intrinsically, awareness, perceptions and preferences are central to adoption processes and decisions (as shown in **Figure 1**). [8]Awareness relates to knowledge or a state of being aware about improved agricultural technology. It relates to getting facts, information and familiarity with HYV. Perception is a belief or opinion held by a farmer about improved agricultural technology. It is the way of understanding and interpreting the perceived benefits and costs associated with HYV such as high yield

[8] The definitions of awareness, perception and preferences are obtained from Cambridge dictionary

and shorter growing cycle. Preference relates to ordering of alternatives based on the perceived utility. All these factors are easily understandable but difficult to measure suggesting the reason for their omission in most empirical studies. Notwithstanding, variables like education can serve as proxies for awareness or knowledge. This current study focuses on the effects of farmers' risk and time preferences on adoption decisions.

Attitudes, choices, preferences and perceptions are important variables in decision-making. Attitudes could be defined as disposition with regard to a fact (Hillson & Murray-Webster, 2007). Attitude can also be regarded as a position a farmer holds with respect to improved farm technology. On the other hand, choices are actions taken in decision-making (Wilkinson, 2008). Perception relates to understanding of a situation or improved farming practices. Correspondingly, perceptions drive attitudes (Hillson & Murray-Webster, 2007) while attitudes determine preferences (Wilkinson, 2008). Farmers' perceptions of technology attributes may determine their adoption preferences. Therefore, the above four elements may reflect in risk and time preferences. The extent of risk taking ability or willingness to taking risky decisions by individuals constitutes risk preferences (Charness, Gneezy, & Imas, 2013) while desire for present outcome over delayed outcome relates to time preferences (Frederick, Loewenstein, & O'donoghue, 2002). Overall, preferences are more appealing because they relate to optimal choices in decision-making.

Intrinsic factors have received less attention in the adoption literature. Indeed, perceptions about the attributes of new and improved technology may influence rice farmers' attitudes and subsequently adoption decisions. HYV is often associated with attributes like higher yield, shorter duration, good resistant, among others relative to conventional varieties (Adesina & Zinnah, 1993). Moreover, rice farmers may be interested in the likely benefits and costs associated with new and improved technology. These have consequences on the way such technology is perceived and subsequently accepted. Simply put, most farmers in the developing countries may have preferences for high income which may serve as motivation for adopting HYV.

As noted earlier, both awareness and perceptions drive attitudes which determine preferences. Positive attitudes may increase the probability of adopting HYV. Yet awareness, perception, preference and adoption decisions may be influenced by the interactions among farmers. Some farmers may not be interested in accepting innovation even when such innovations are available and accessible. In such instance, intrinsic factors like risk aversion or risk avoidance may play a key role in adoption behaviour. This suggests omission of preferences and spatial dependence may lead to bias estimation of the determinants of adoption decisions.

Since adoption is a learning process, awareness may affect farmers' knowledge and subsequently decisions to adopt HYY, yet farmers often communicate and interact in informal settings. The level of interactions may determine to some extent, adoption decisions of rice farmers' neighbours because after being aware of improved agricultural technology, farmers learn about its potentials, decide on the timing and method of adoption. This suggests that the level of information a farmer has may not only influence their perceptions of the new and improved technology but also the attitudes towards accepting it. In brief, knowledge about improved agricultural technology may be obtained through spatial and social interaction while the level of awareness may influence farmers' beliefs and subsequently adoption decisions.

In summary, risk avoidance or aversion to risk implies strong preference for the sure or less risky outcomes. This may translate to low preference for HYV which is risky but offer higher yield. Moreover, rural farmers or farmers located in rural agricultural zones may be more biased towards the status quo than their counterparts in urban areas or agricultural zones. Yet, status quo bias or strong preference for the present may be a consequence of interaction or communication among rice farmers because farmers may be equally likely to be as risk averse as their neighbours. Put differently, risk aversion or risk avoidance and impatience may be spatially related. Such spatial effects may reflect in rice farmers' heterogeneity in adoption decisions and patterns.

2.3 Predictors of Adoption of Improved Agricultural Technology

Following the pioneer hybrid corn adoption study conducted in the USA by Griliches (1957), many attempts have been made to examine factors affecting improved agricultural technology adoption decisions under uncertainty. Most of the foremost papers examine the determinants of farmers' adoption decisions (Feder, 1980; Feder, 1982; Feder *et al.*, 1985; Feder & Umali, 1993; Saha, Shumway, & Talpaz, 1994; Abadi Ghadim & Pannell, 1999). Other studies focus on adoption learning (Lindner, Fischer, & Pardey, 1979; Lindner, Pardey, & Jarrett, 1982; Leathers & Smale, 1991; Marra *et al.*, 2003; Abadi Ghadim, Pannell, & Burton, 2005; Barham *et al.*, 2015). While farm size, land tenure, climatic environment, credit constraint, education and awareness are the main factors identified as the driving forces behind adoption decisions, the submission under learning is that farmers usually improve their prior beliefs about innovative technology over time. Empirical evidence on the predictors of improved agricultural technology adoption decisions are categorized in this study into farm and farmers' specific factors, institutional and community factors, risk and time preferences, social network/learning and spatial dependence effects. These are briefly explained in line with empirical studies mainly from the developing countries.

Farm and Farmers' Specific Factors

The first socio-economic factor considered is land. Access to land is important in adoption decisions. The effects of land may relate to institutional factors as well as climatic and economic factors. Land holding may be constrained by credit access especially among the smallholder farmers who lack tangible collateral. For example, the land tenure system in Nigeria favours the rich, as revealed by this study that most sampled farmers rented land for rice production. Some empirical studies have identified socio-economic factors affecting improved agricultural technology adoption and its intensity in developing countries. Empirical evidences from Africa reported a positive correlation between adoption rates and farm size (Nkonya, Schroeder, & Norman, 1997; Alene, Poonyth, & Hassan, 2000; Dadi, Burton, & Ozanne, 2001; Saka & Lawal, 2009; Adedeji, Nosiru, Akinsulu, Ewebiyi, Abiona, & Jimoh, 2013). Adoption of improved agricultural technology may depend on whether a technology is land saving or labour-intensive. Farmers in advanced countries, for instance, often adopt land saving technologies such as green-houses while farmers in developing countries use yield enhancing and soil conserving or soil enhancing technology such as seed, manure and inorganic fertilizer.

Broadly, education, availability of labour, age and gender are human capital commonly used to explain adoption decisions in different contexts. For instance, awareness and education have been found to influence agricultural technology adoption in Africa (Kebede, Gunjal, & Coffin, 1990; Nkonya *et al.*, 1997; Tiamiyu, Akintola, & Rahji, 2009). Moreover, migrant farmers are reported to be early adopters while younger farmers have higher tendency to adopt improved cassava varieties in Southwest Nigeria (Polson & Spencer, 1991). Labour intensive technology such as improved rice varieties require higher labour supply. Therefore, most smallholder farmers in the developing countries rely on household members to carry out farming operations in the face of limited and expensive hired labour. Nkonya *et al.* (1997) identified farm size, education and extension in Tanzania. Education, household labour and timely availability of improved maize seeds are also singled out in Ethiopia (Alene *et al.*, 2000). Furthermore, farm size, distance to market, region and perception of input price enhance the adoption of fertilizer and herbicide in Ethiopia (Dadi *et al.*, 2001) although Fufa and Hassan (2006) identified age, expectation of rainfall and perception of fertilizer price in the same country.

Specifically, in Nigeria, farm size and extension visits have been identified as some of the factors affecting the adoption of improved rice varieties in South-Western region (Saka *et al.*, 2005; Saka & Lawal, 2009). In Northern Nigeria, one study concludes that yield, labour cost and membership of association significantly explain improved soybean seed adoption decisions (Ojiako, Manyong, & Ikpi, 2007). Another study also identifies education, extension visits, farming experience, land ownership, credit use and farm holding as determinants of NERICA adoption decisions in Savannah zone (Tiamiyu *et al.*, 2009). Similarly, the study by Adedeji *et al.* (2013) shows that farming experience, age, extension visit and farm size determine NERICA adoption in Ogun State. Low NERICA adoption rates in three Nigerian States of Osun, Niger and Kano are attributed to awareness and seed constraints (Dontsop Nguezet *et al.*, 2013). Seed constraints may not be a universal factor, yet awareness may not be an issue especially in some Western Nigerian states where social interaction is a way of life. In summary, most past adoption studies in Africa and the developing world omit the roles of risk and time preferences in their analyses.

Institutional and Community Factors

Institutional factors like access to credit, market and good road networks may encourage the acceptance of improved agricultural technological innovation. For instance, credit constraints have been identified as one of the factors hindering the adoption of improved agricultural technology (see for examples (Feder *et al.*, 1985; Feder & Umali, 1993; Lee, 2005)). Smallholder farmers may not have access to credit from financial institutions due to lack of collateral. Low-income level, resulting from small farm size may constitute an impediment to farmers’ access to production inputs including decisions to adopt HYV because improved agricultural technology may require additional cost or financial commitments even though most farmers often processed seed locally and stored for replanting. On the other hand, large farms may take advantage of high income from farming to access credit and subsequently adopt HYV.

Access to production inputs and outputs is important for the acceptance of technological innovation. For example, distance to road is reported to limit market access and decreases the adoption of cover crop (maize *mucuna*) in Honduras (Neill & Lee, 2001). In most developing countries including Nigeria, local markets are often flooded with food commodities during the harvest season due largely to lack of good transportation infrastructure and storage facilities. In fact, many farmers live in rural areas and accessed the city markets on regular intervals but were often constrained by bad road networks. It has been empirically demonstrated that institutional factors play a significant role in the acceptance of agricultural technological innovation. Alene *et al.* (2000) for instance, pointed out the positive effect of extension services on improved maize seed adoption in Ethiopia while Anley, Bogale, and Haile-Gabriel (2007) reported the positive and significant effect of extension on conservative technology in the same country.

Risk and Time Preferences

Risk aversion behaviour has been previously observed as one of the factors hindering the acceptance of improved agricultural technology. Specifically, farmers in developing countries are reportedly risk-averse (Humphrey & Verschoor, 2004; Harrison *et al.*, 2005a; Galarza, 2009; Yesuf & Bluffstone, 2009; Harrison *et al.*, 2010; Tanaka *et al.*, 2010; Ihli, Chiputwa, & Musshoff, 2013) and loss-averse (Liu, 2013; Ward & Singh, 2014). Some studies however assumed behaviour is homogenous, that is, only risk aversion could explain farmers' risk attitudes (Kebede *et al.*, 1990; Knight, Weir, & Woldehanna, 2003; Engle-Warnick, Escobal, & Laszlo, 2007). Studies that examine the heterogeneity in farmers' risk attitudes however, did not focus on adoption decisions (Harrison *et al.*, 2005a; Nguyen & Leung, 2009; Harrison *et al.*, 2010; Nguyen, 2011; Bocqueho *et al.*, 2014). Liu (2013) and Ward and Singh (2014) studies which attempted to bridge this gap examine *ex post* and *ex ante* technology, respectively. In addition, the role of time preference in adoption decisions is not the focus of most previous studies.

Risk aversion has been attributed to be one of the reasons for the low adoption rates of improved agricultural technology in the developing countries. For instance, Kebede *et al.* (1990) and Knight *et al.* (2003) reported a negative relationship between risk aversion and adoption decisions in Ethiopia. In their study, Engle-Warnick *et al.* (2007) affirmed that ambiguity aversion matters more in technology adoption in Peru. Moreover, in reviewing the drivers of agricultural technological innovation, Lee (2005) posited that ability to take risky decisions influences technology adoption. On the other hand, consumption risk due to crop failure was reportedly reducing fertilizer adoption in Ethiopia by Dercon and Christiaensen (2011). In addition, Liu (2013) revealed that more risk averse and loss averse farmers were late biotechnology cotton adopters while those who overweighed small probabilities constituted early adopters in China. Similar study reach a conclusion that risk aversion reduces the adoption of pesticides among Chinese farmers (Liu & Huang, 2013). In India, Ward and Singh (2014) and Ward and Singh (2015) results indicate that risk and loss aversion decrease willingness to adopt improved rice varieties. Conversely, Barham *et al.* (2014) found low impact of risk aversion on soy adoption in USA. The *ex post* and *ex ante* modern technology adoption assessed respectively by China and India studies limits their comparability to this study which examines rice farmers' behaviour with respect to currently growing rice technologies or improved rice varieties.

A few studies have simultaneously examined farmers' risky and temporal attitudes in developing countries (Tanaka *et al.*, 2010; Tanaka & Munro, 2014; Liebenehm & Waibel, 2014). While future consumption optimizers may be willing to take risky adoption decisions, the *laissez faire* or impatient farmers may be reluctant. More also, since farming involves making commitment today with the expectation of future outcome, farmers who undertake risky production decisions today are more likely to experience yield gain and earn more income in the future. In other words, strong preferences for traditional seed varieties (status quo bias) may imply low interest in HYV and future wealth. Furthermore, early adopters may have income advantage over late adopters due to learning by doing. Some pertinent questions require answers. Why do some farmers adopt, and others did not? Why are some farmers not willing to increase adoption rates over time? Answers to the above questions may be embedded in the preferences for risk and time as well as spatial dependence among rice farmers.

Perceptions about the Attributes of Improved Technology

As noted in the conceptual framework, attitudes, perceptions and preferences are closely related concepts. These variables are however, often ignored by most studies due largely to the difficulty in measurement. Indeed, farmers' perceptions of improved technology attributes have been reported as one of the factors affecting improved agricultural technology adoption decisions (Adesina & Zinnah, 1993; Adesina & Baidu-Forson, 1995; Sall, Norman, & Featherstone, 2000; Kallas *et al.*, 2010). Some of the key attributes often tested relate to the producers' and consumers' preferences or marketable traits such as yield, stem, duration, taste and ease of cooking.

Social learning/Networks and Spatial Dependence

Many studies have attempted to explain the roles of social networks and learning effects in the adoption of improved agricultural technology. In the developing countries, inefficient extension services as well as imperfect markets usually encourage farmers to rely on social networks as alternative sources of information. Some appealing studies which examine the effects of social learning on adoption of innovation are briefly presented as follows. In their review studies, Foster and Rosenzweig (2010) and Foster and Rosenzweig (1995) emphasized the important roles of social networks and learning from other farmers in technology adoption in India. In studying the pattern of adoption of improved rice varieties in Madagascar, Moser and Barrett (2006) revealed that farmers who learn from extension agents and other farmers have higher probability to adopt system of rice intensification. In their study, Conley and Udry (2010) found positive effects of learning from other farmers in a social networks in pineapple production among farmers in Ghana. However, Baerenklau (2005) reported that neighbourhood influence is less relevant relative to risk preference and endogenous learning among dairy farmers who adopted intensive farming technique in USA.

Lots of arguments have been put forward that like most economic variables, agricultural data are random. Therefore, ignoring such spatial dependence and heterogeneity in micro-economic data may motivate application of wrong policy. Following this assertion, a number of studies have attempted to examine the spatial pattern among farmers, including precision farming (Weiss, 1996). Spatial clustering and geographical proximity may play key roles in the technology adoption stimulation. Studies that examined spatial issues in adoption decisions concluded that neighbourhood effects matter in decision making (Case, 1992; Holloway *et al.*, 2002; Holloway, Lapar, & Lucila, 2007; Wimalagunasekara, Edirisinghe, & Wijesuriya, 2012; Krishnan & Patnam, 2014; Wollni & Andersson, 2014; Ward & Pede, 2015; Tessema *et al.*, 2016). In studying factors affecting the adoption of sickle (used for rice grain harvesting) in

Indonesia, Case (1992) observed the neighbourhood influence among rice farmers. In their study, Krishnan and Patnam (2014) reported that relative to extension services, neighbours have long time and greater effects on the adoption of improved maize seed and fertilizer in Ethiopia. Similarly, Tessema *et al.* (2016) observed neighbourhood influence in the adoption of conservative tillage in Ethiopia. Notwithstanding, the above cited studies did not examine the roles of risk and time preferences in adoption decisions. To fill this gap, this study considers both exogenous and endogenous variables by directly controlling for risk and time preferences and indirectly incorporating spatial dependence (spatial lags) in the adoption model.

2.4 Decision Making under Uncertainty: Concepts, Theories and Applications

DM as an economic unit generally make decisions in relation to production, financial, health and other welfare indicators. Specifically, these decisions are often argued to be made under uncertainty. Therefore, risk, ambiguity and uncertainty are the three closely related concepts in decision making. However, there is no agreed definition on these three terms. Starting from Knight's distinctions between risk and uncertainty in 1921, the argument on the difference between these three terms is yet to be concluded. While some school of thoughts are of the view that risk and ambiguity are forms of uncertainty, others hold contrary opinion. In general terms, a DM is said to take a risk when he faces a situation of known probability distribution of an outcome; an ambiguous or uncertain situation when the probability of an outcome is unknown (Klibanoff, Marinacci, & Mukerji, 2005). This study did not dispute the roles of ambiguity or uncertainty in decision making as previously emphasized by past studies (Klibanoff *et al.*, 2005; Engle-Warnick *et al.*, 2007; Barham *et al.*, 2014). It was however, more interested in the roles of risk aversion and impatience in farmers' adoption processes and decisions.

DM may and may not know the probability of an event occurring. For example, farmers may not know the probability associated with the yield of the planted seeds (traditional or improved). Put differently, like most DM, farmers often face with the situation of unknown probability of outcome, for example, the probability of rain falling may never be perfectly predicted however, farmers may rely on previous farming experience as well as the frequency of the past rains to adequately predict the likelihood of rain as well as (best or worst) farm outputs, given the extreme weather conditions. Therefore, an ambiguous or uncertain situation may be quantified or explained with subjective probabilities. This study is limited to risk since risk is more quantifiable. Arguably, uncertainty is a time variant because farmers may consider future benefits (willing to smooth consumption over time) in making temporal choices. Thus, risk and time preferences are key factors that affect farmers' investment, financial and other economic decisions. Brief descriptions of the theories that have been applied to explain DM behaviour in different contexts are presented next.

The utility theory originally proposed by Daniel Bernoulli is the bedrock of choice's theories. The Cardinal school of thought believes utility could be measured in monetary term. However, advances in the literature suggest that utility is a weight assigned to outcomes in decision-making process. This decision utility called revealed preference is often measured from individual's choices (Wilkinson, 2008). Farmers usually make decisions between risky prospects. For example, whether to adopt improved farm technologies or to continue growing traditional technology. Such decisions which are made mostly to maximize the expected utility are risky due to the "expectation or known probability of outcomes". Risk has also been perceived in the past as an uncertainty which associated with the probability of harmful effects. However, advances in the literature suggest that risk combines threats and opportunities (Hillson & Murray-Webster, 2007). Risk has also been described as an event which associates with objective probability while ambiguity is characterized by subjective outcomes (Klibanoff *et al.*, 2005).

In general, decision making under uncertainty is a choice between different prospects. These prospects may be described as series of outcomes with associated probabilities (Wilkinson, 2008). Choices made between prospects or decisions made to adopt or not to adopt reveal the preferences of individual farmers toward outcomes (positive or negative). This revealed preference may reflect optimal choices which theories seek to explain. Therefore, theories predict phenomena or concepts. Decision-making theories under risk are generally classified into expected utility theory (EUT) and non-expected utility theory (non-EUT), while intertemporal choice theory relates to time preferences. This Section is devoted to risk while the next Section presents the concept/theory of intertemporal decisions.

Following von Neumann and Morgenstern (1947), EUT initially proposed by Daniel Bernoulli in 1738 has been widely used to explain revealed preferences with objective probabilities (see Equation 2.1). From Equation 2.1, p_i is the objective probability, U is the utility function while x_i is the payoff. EUT characterizes individual behaviour by increasing concave utility function but decreasing marginal utility (MU). This decreasing MU of income called risk aversion is usually measured using constant relative risk aversion (CRRA) or constant absolute risk aversion (CARA). One common feature of the EUT is the estimation of utility function with recourse to the wealth or income of a decision maker as reference point. This poses some challenges on its applications especially in the developing countries where most households have no stable or quantifiable income. Pratt (1964) provides some of the earlier application of utility function.

EUT which is based on many axioms (completeness, independence of irrelevant alternative, transitivity and continuity) is associated with a number of advantages. It differentiates between risk exposure and risk attitudes using utility function and probability (Chavas, Chambers, & Pope, 2010). It has however been criticized with two major anomalies which violate independent axiom. The first relates to the common consequence effect which is a tendency to choose certain outcome over probable outcome (see (Allais, 1953)). The second is the common ratio effect which was demonstrated with lotteries of equal ratio of probability (see (Kahneman & Tversky, 1979)). EUT has also been criticized for presuming the universality of risk aversion behaviour (Wilkinson, 2008). In short, attitude is a complex concept which may not be explained using a single parameter. Notwithstanding these limitations, EUT has been widely applied in agriculture. For instance, Lin, Dean, and Moore (1974) argue that farmers seek to maximize expected utility rather than profit while Young (1979) acknowledged its role in agricultural management. In addition, most authors applying the binary models such as probit and logit as modelling tools in agricultural decisions such as adoption of improved agricultural technology assumed farmers' behave according to EUT.

$$\sum_{i=1}^{n} p_i U(x_i) \tag{2.1}$$

The well acknowledged limitations of EUT motivated the proposal of some alternative theories. The popular among these are the decision weighting theories. These include prospect theory (PT) proposed by Kahneman and Tversky (1979), rank-dependent utility (RDU) propounded by Quiggin (1982) and cumulative prospect theory (CPT) credited to Tversky and Kahneman (1992). These theories assume subjects do convert objective probabilities to subjective probabilities before making decisions. While these theories are not free from limitations, many authors have argued in favour of these later theories for not treating behaviour a homogenous concept (see Camerer (1998) and Starmer (2000). Some of the distinctions between the EUT and decision weighting theories are presented next.

PT differs from EUT in terms of probability weighting, value functions and loss aversion. PT allows for framing by using non-linear weights to evaluate probabilities. In other words, the central idea of the PT is that subjects do subjectively weights the probabilities (p_i) by maximizing $\sum_{i=1}^{n} \pi(p_i)v(x_i)$ (Kahneman & Tversky, 1979). Where π is the transformation of cumulative probabilities and v is the value function. The probability weighting function is also assumed to be well behaved around the ends with the weights of one equals to one and weights of zero equals to zero, respectively. In addition, the increasing utility function satisfies a value function equals zero ($v(0) = 0$) at the reflection point. It therefore presents s-shaped value functions that are concave above the reference point and convex below the reference point. Moreover, the value functions are steeper for losses than gains implying disutility of a loss is stronger than the utility of a similar gain, a phenomenon generally called loss aversion. PT has however been criticised for ignoring small probabilities for example, shocks which are usual occurrence in agriculture (Bocqueho *et al.*, 2014).

RDU cumulates probabilities as against separable probability assumed by the PT ($RDU = \sum w_i U(x_i)$, where w_i is the cumulative probababilities. This anticipated utility ranks the outcomes $x_1, \ldots x_n$ from worst (x_1) to best (x_n). Overall, RDU explains the tendency to overestimate and underestimate probabilities associated with good or bad outcomes. It therefore has applications in investment and arguably may solve the problem of stochastic dominance in PT.

Afterwards, the CPT was proposed to combine the framing of gain and loss of PT with the cumulative decision weights of RDU. CPT however differs from PT by applying the principle of diminishing sensitivity (DS) to weighting and utility functions. According to this principle, the impact of change in probability decreases as we move away from the boundary resulting in an inverted S-shape weighting function. CPT has been used to explain risk and uncertainty, and thus empirically plausible (Loomes, Moffatt, &

Sugden, 2002; Mason, Shogren, Settle, & List, 2005; Tanaka *et al.*, 2010; Liu, 2013; Bocqueho *et al.*, 2014; Ward & Singh, 2014).

Decision making theories have been generally applied in agriculture in different contexts. Specifically, decision weighting theories have some implications in technology adoption decisions yet very few studies have attempted to relate them with adoption behaviour (See Liu, 2013, Ward and Singh, 2014, 2015). For instance, risk-seeking attitude in the domain of losses may imply wealth (adopters or risk takers may have higher income) while the risk-averse behaviour in the domain of gains may be an indication of losses (non-adopters or non-risk takers may not accumulate wealth). There is also some empirical evidence supporting the stability of risk attitudes over time (Love & Robison, 1984; Harrison, Johnson, McInnes, & Rutström, 2005b). However, risk aversion behaviour may change. For example, Bocqueho *et al.* (2014) posit farmers may change from risk aversion to risk seeking after a loss of income. Notwithstanding, behaviour is not universal and may be explained with or without theories

Related concepts may be employed to explain farmers' adoption decisions. For example, endowment effect implies willingness to accept good things is greater than willingness to pay for them (Thaler, 1980). It is a phenomenon which explains how individuals ascribe high value to the good or product in their possession. In the risk concept, sure payoffs or outcomes may be favoured relative to highly risky or uncertain outcomes. In the context of improved farm investment decisions, farmers may attach more value to the yield obtained from the current local varieties relative to the potential yield from the proposed improved HYV. In other words, farmers may be willing to pay more to retain their acclaimed 'sure yield'. Put differently, rice farmers may not be willing to pay higher price (take the risk of gaining or losing) to adopt HYV despite its high yield advantages.

In addition, loss aversion measures sensitivity to losses assuming dissatisfaction received from losses is greater than the utility received from similar gains (Kahneman & Tversky, 1984; Tversky & Kahneman, 1991). A risk averse farmer may be a loss averse farmer or vice versa. Accordingly, adopters may not be willing to dis-adopt local rice varieties if they are sensitive to losses. More importantly, status quo bias implies preference for the current state which reduces individual desires for buying and selling (Samuelson & Zeckhauser, 1988; Kahneman, Knetsch, & Thaler, 1991). It may be likened to strong preferences for present consumption relative to delayed outcomes. In the farming context, farmers may exhibit strong preference to the local rice varieties or traditional farm practices. Thus, rice farmers' biasness towards local rice varieties may prevent the acceptance of HYV or reduce their adoption tendency. To sum up, in addition to risk taking ability, endowment effect may affect individual farmers while sensitivity to losses as well as biasness towards local rice varieties may have negative consequences on their adoption decisions.

Notwithstanding the importance of decision making theories in Agriculture, all attitudes may not be explained using parameters. As stressed by Thaler (1980), "observed behaviour of an economic agent may not be consistent with the economic theory". Moreover, subjects may seek to maximize the expected utility or expected payoffs or behave in line with decision weighting theories. Thus, a non-parametric approach is adopted in this study to explain rice farmers' risk attitudes in Nigeria. In other words, while many studies have attempted to explain individual behaviour or attitudes with recourse to theories, it is important to note that theories may not explain all human attitudes or behaviour, a "complex" phenomenon.

In this study, the term "risk avoidance" is introduced in place of risk aversion because the parameter of utility function is not estimated due to the nature of the risk elicitation method employed. Since rice farmers are faced with the situation where the probabilities of outcomes are known, a highly risky event (payoff) is often associated with low probabilities while a less risky event (payoff) is attributed with higher probabilities. Therefore, a farmer who chooses payoffs with high probabilities (0.6-1.0) is a "risk avoidant" farmer. Otherwise, the farmer may be regarded as showing high willingness to risk taking. This does not preclude acknowledging the decision making theories as well as the existing studies that have applied these theories.

2.4.1 Applications of EUT and non-EUT in Developing Countries

As noted in the previous Section, different theories have been put forward by different authors to explain the risk attitudes of the economic agents or DM using lab and field experiments. **Table 1** summarises some of the empirical studies in developing countries which characterize risk attitudes in line with different theories. Most empirical studies from both the developed and developing countries which applied Holt and Laury (2002) (HL thereafter) risk elicitation method evidently supported the view that individuals behave in line with EUT. For example, behaviour is linked to the utility maximization in developed countries (Harrison, Lau, & Rutström, 2007; Andersen, Harrison, Lau, &

Rutström, 2008; Barham *et al.*, 2014). Similar findings among farmers in the developing countries include Rwanda (Jacobson & Petrie, 2009) and Ethiopia, Uganda and India (Harrison *et al.*, 2005a; Harrison *et al.*, 2010). On the other hand, Yesuf and Bluffstone (2009) apply Binswanger's method in Ethiopia and reported risk aversion attitude among subjects while Ihli *et al.* (2013) compare HL and Brick's method in Uganda but found that farmers acted in accordance with the expected utility theory. While some studies attempted to compare EUT with PT (gain domains with at least three parameters), others argue only risk aversion could explain farmers' risk attitudes.

Hey and Orme (1994) found no superiority between EUT and non-EUT although evidence from the laboratory (Camerer, 1989; Camerer & Ho, 1994) and field (Bocqueho *et al.*, 2014) supported non-EUT in developed countries. In developing countries, Humphrey and Verschoor (2004) rejected hypothesis in favour of PT in Uganda. Accordingly, risk and loss aversion attitudes are observed among farmers who exhibit S-shape probability weighting function. Similarly, Galarza (2009) found evidence in support of CPT (gain domain) among cotton farmers in Peru but mixed results with respect to probability weighting. Moreover, studies by Nguyen and Leung (2009) found PT appealing in Vietnam and reported less risk aversion attitudes among subjects.

In addition, Tanaka *et al.* (2010) rejected hypothesis in favour of CPT in Vietnam and found evidence in support of inverted S-shape probability weighting. Accordingly, rich farmers are less risk and loss averse. Correspondingly, Liu (2013) found most Chinese cotton farmers to be risk averse, behave according to CPT and exhibit an inverted S-shape probability weighting. One limitation of this study is assuming hundred percent adoption rates as risky prospects. In a similar study, Ward and Singh (2014) found evidence against EUT (support CPT) in India while examining risk attitudes toward proposed improved rice technology. Hence, non-EUT is currently more appealing in the literature. The list of the empirical studies on the applications of theories of decision making could not be exhausted. However, not all risk attitudes could be explained using parameters which limit the applications and comparability of most cited literature to this study.

2.4.2 Intertemporal Choice: Concepts, Theories and Applications

There are two related concepts underpinning intertemporal choice: time discounting and time preference. While attempts have been made to distinguish between these two concepts, they have been used interchangeably in many cited empirical studies. Other terms often used include but not limited to delay discounting and temporal discounting (Doyle, 2013). The distinction between time discounting and time preference is quoted as follows:

"*We distinguish time discounting from time preference broadly to encompass any reason for caring less about a future consequence, including factors that diminish the expected utility generated by a future consequence, such as uncertainty or changing tastes. We use the term time preference to refer, more specifically to the preference for immediate utility over delayed utility*" (Frederick *et al.*, 2002, p. 352)

The above distinction is important to putting this study in context. Given the nature of this study, the term time preference is preferred, although time discounting is employed to refer to the methods of discounting intertemporal choice or time preference. In short, intertemporal choice relates to given up present consumption for future consumption. This type of economic behaviour has important implications on the health, wealth and happiness of individuals and subsequently on the economic agents in the society at large (Frederick *et al.*, 2002).

Historically, Adam Smith is the first economist to acknowledge the effects of intertemporal choice on the wealth accumulation of nations in his book entitled "The Wealth of a Nation", first published in 1776 (Smith & McCulloch, 1838). The intertemporal choice theory was originally proposed by John Rae in the Sociological Theory of Capital in 1834 (Rae, 1905). This Scottish economist identified two promoting factors and two inhibiting factors that affect individual wealth see (Frederick *et al.*, 2002; Wilkinson, 2008). The promoting factors are the desires by individuals to accumulate wealth and ability to foresee the likely benefits of the future outcomes associated with the economic decisions made at any point in time. On the other hand, the inhibiting factors relate to uncertainty about life and desire for enjoyment. While the formal encourages savings for future consumption, the latter encourages immediate consumption. How do rice farmers see the future? Are farmers willing to smooth consumption over time? Going by intertemporal choice, the necessary condition for accepting HYV is that the future outcome (yield) must higher than the present outcome (conventional yield). Put differently, it implies improved rice technology constitutes new optimal plan (increase farmers' income) if it offers more yield.

There are number of follow-up theories and concepts to intertemporal choice. According to the positive theory of capital credited to an Austrian economist, Bohm-Bawerk (1888), present goods are associated with higher subjected value and higher price than future goods suggesting that the degree of individual impatience depends on income stream and the time shape. Bohm-Bawerk (1888) attributes the degree of impatience among individuals and nations to three factors: future supplies or goods are generally more than present supplies or goods; future goods are less valued compared to present goods attributable to lack of foresight; and present goods are used to initiate production for the future consumption. In consolidating intertemporal theory, time preference is defined as a preference for early or present income over a deferred income (Fisher, 1930). This preference for early income over deferred income results in impatience. Therefore, the theory of interest proposed by Fisher (1930) identified four characteristics of income that affect the individual level of impatience. These include the size of the income of individual, the distribution of the income, the composition of the income as well as the degree of risk or uncertainty associated with the income. Besides, Fisher argued that in addition to the above factors, personal factors such as foresight, control over oneself, the habit of individual, expectations in life, and whether an individual shows concerns for the lives of others and fashion freak, determine the level of impatience of an individual. The four characteristics of income are briefly explained in relation to farm or adoption decisions.

Size of Income of Farmers: It is assumed that low income or poverty increases the degree of impatience. In other words, low income may translate to higher preference for the present over future income. Many farmers in developing countries are low income earners attributable to their size of land holdings. Low income is therefore an important attribute of poverty. Poverty may increase the desire for present consumption relative to exercising some degree of patience for future consumption. Put differently, pressure of present needs may blindfold farmers from seeing the future benefits associated with improved seeds or varieties or benefits that could accrue from savings. For example, any amount of money invested in rice production today may be worth more than double in three months. Present income is important for both present and future, yet the desire to keep life going may constitute temptation for present consumption. Strong desires for present consumption could also be attributed to lack of foresight and self-control. For instance, poor or low-income rice farmers may only think about immediate survival rather than future income that may act as security for livelihood.

The Time Shape of the Income of Farmers or Distribution of Income: As stressed by Fisher, increasing or high income may imply patience or encourage saving for the future while decreasing or low income may encourage high impatience, and vice versa. This is because time is often associated with uncertainty. For instance, wealthy rice farmers may be less impatient by choosing payoffs associated with future time. In other words, such farmers may have strong desires for saving for the future. On the other hands, poor rice farmers may be under temptation for immediate consumption attributable to their low level of income.

The Composition of Income: The degree of individual rice farmers' impatience may be associated with the worth of their income. That is, the benefit offers by the present and future income. For instance, 12,000 (Nigerian naira) may be valued differently depending on the level of income of individual farmers. While this amount of money may be worth less on the farm assets of a wealthy farmer, it may significantly contribute to the farm assets of a very poor farmer.

Degree of Risk and Uncertainty Associated with the Income: The risk level faced by individual rice farmer may increase or decrease impatience. While low income may encourage impatience, future income is often associated with uncertainty and may influence the level of farmers' impatience. Risk and uncertainty may encourage saving or immediate consumption since little is known about the future compared to the present. Furthermore, life events such as sickness, accident, death may make future riskier relative to the present. These life events may therefore cause higher impatience. Uncertainty may also encourage rice farmers to save for rainy days suggesting greater future risk may result in greater saving for the future.

While the above four attributes of income are important in explaining individual level of impatience, they are not directly observed. The difficulty associated with eliciting these attributes along with their measurement challenges explain their inclusion in econometric models.

2.6 Methodological Issues

Different elicitation methods have been proposed and applied to examine risk and time preferences of individuals. Most elicitation methods are designed to test theories. A brief overview of the features of existing methods is highlighted below in addition to the justification for the choice of methods applied by this study.

2.6.1 Risk Preferences Elicitation Methods

Different approaches have been advanced to elicit the risk attitudes of a DM in both the developed and developing countries. Risk attitudes depend largely on domain and contexts. Notwithstanding, the approaches used in the literature range from save-risky or good-bad single choice to multiple price lotteries to self-reported or stated preference methods. Risk preference elicitation methods could be generally classified into laboratory or field based (Harrison & Rutstrom, 2008; Charness *et al.*, 2013). Most laboratory methods including balloon analogue risk task (BART) proposed by Lejuez, Read, Kahler, Richards, Ramsey, Stuart, Strong, and Brown (2002) requires computer skill and expertise which makes them practically impossible to use for smallholder farmers who generally have low level of education. Arguably, the BART requires a bit of time for comprehension and implementation. Moreover, the random lottery pair (RLP) put forward by Hey and Orme (1994) though plausible for no natural ordering, it places too much information on the probabilities. This study therefore limits the discussion to the risk elicitation methods applied in the developing countries[9]. Some field risk experimental methods as well as the utility theories applied are summarized in **Table 1**. The pros and cons of the elicitation methods are summarized next.

Binswanger (1978), Binswanger (1980) and Binswanger (1981) are among the foremost papers that examine farmers' risk attitudes in the developing country of India. The elicitation method enforces making one choice from an ordered set of eight lotteries. In other words, farmers' risk attitudes are elicited using multiple price list (MPL) whose two outcomes (lotteries A and B) are associated with 50 percent probability each. The payoff associated with the first choice of both lotteries are equal in value, the payoff for lottery A decreases while that of lottery B increases as we move down the row. Thus, both the expected value and the variance increase down the row. In general, a risk averse subject is expected to choice from the top six rows, a risk neutral (row seven)

[9]The readers are refer to the Charness *et al.* (2013) who provided a comprehensive review on the risk preferences elicitation methods including the advantages and disadvantages. Harrison and Rutstrom (2008) equally acknowledge the different ways of eliciting risk attitude especially in the laboratory.

while a risk loving subject chooses the last row. Although Binswanger's single choice lottery is simple and may be easily comprehended by less educated subjects, it suffers from many setbacks and shortcomings some of which have been empirically demonstrated. It is designed to explain EUT and thus assumes risk aversion as the only parameter that could explain utility function. It is therefore not free from the anomaly of certainty effects. Lastly, fixing probability to 0.5 makes probability weighting or warping difficult if not impossible to explain.

Over the years, Binswanger's lottery has undergone a lot of modifications. Some of its variants include 50-50 chance gamble (Eckel & Grossman, 2002; Eckel & Grossman, 2008) and "bad-good" lottery (Yesuf, 2004; Yesuf & Bluffstone, 2009) where subjects make single choice from ordered six lotteries. One popular variant to Binswanger's is the multiple price list (MPL) credited to Holt and Laury (2002) (HL thereafter). Indeed, HL popularizes the MPL by eliciting risk preference from ten binary choices which are ordered by probabilities. In other words, HL varies probabilities and fixed the payoffs. Afterward, Brick, Visser, and Burns (2012) varied payoffs but fixed the probabilities under the assumption that subjects get confused with varied probabilities. The main advantage of the HL format of the MPL method is riskiness (both payoffs associated with options A and B are risky with varied probabilities). It also has wide range of applications; widely tested in both the developed and developing countries. The main limitation is the imposition of monotonic switching although this is done for ease of analysis. It may also suffer from framing effect since it may encourage subjects to choose middle rows (Harrison & Rutstrom, 2008). Lastly, the lotteries only capture risk aversion in the gain domain.

The desire to examine the heterogeneity in risk attitudes prompted the introduction of mixed lotteries (three series' MPL lotteries) initially in 2006 (Tanaka, Camerer, & Nguyen, 2006). This was popularized in 2010 (Tanaka *et al.*, 2010). This method differs from HL in terms of probabilities and losses. Indeed, three parameters corresponding to the risk aversion, probability weighting and loss aversion are estimated from the method. Under this method, subjects are expected to make multiple binary choices between two risky options. The strengths of this elicitation method are many. It has been demonstrated to conform to CPT and EUT and widely adapted to different currencies (Nguyen & Leung, 2009; Nguyen, 2011; Liu, 2013; Bocqueho *et al.*, 2014; Liebenehm & Waibel, 2014). However, arguably, this elicitation method may not be simple to comprehend although it has been applied among subjects in the developing countries. This method also imposes monotonic switching; the design is a bit complex and requires estimating many parameters to explain risk attitudes.

Table 1: Risk Elicitation Methods and Applications of Decision Making Theories in Developing Countries

Authors	Theories	Elicitation Methods	Countries
Jacobson and Petrie, 2009	EUT	MPL	Rwanda
Harrison *et al.* (2005a) Harrison *et al.* (2010)	EUT	MPL	Ethiopia, Uganda and India
Brick et al, 2012	EUT	*MPL	South Africa
Binswanger (1980, 1981)	EUT	Single choice MPL	India
Yesuf and Bluffstone (2009)	EUT	Modified Biswanger's single choice 'bad-good' lotteries	Ethiopia
Yesuf (2004)	EUT	Modified Biswanger's single choice 'bad-good' lotteries	Ethiopia
Humphrey and Verschoor (2004)	PT	Decision Problems	Uganda
Galarza (2009)	CPT	MPL	Peru
Nguyen and Leung (2009)	PT	3 series MPL	Vietnam
Nguyen (2011)	PT	3 series MPL	Vietnam
Tanaka *et al.* (2010)	CPT	3 series MPL	Vietnam
Liu (2013)	CPT	3 series MPL	China
Ward and Singh (2014, 2015)	CPT	3 series MPL	India
Bocqueho *et al.*, 2014	CPT	3 series MPL	France
Sabater-Grande and Georgantzis, 2002	EUT	Panel Lotteries	Spain

Note: MPL = Holt and Laury (2002) fashion of multiple price list risk elicitation methods
*MPL = MPL with fixed probability and varied payoffs
3 series MPL = Tanaka et al 2010 fashion of multiple price list risk elicitation method

Source: Author's Compilation, 2016

There is an argument in the literature that risk attitudes self-reported by individuals may produce an accurate prediction of risky behaviour. The popular among the self-reported risk elicitation method is that proposed by Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011). Individual risk attitude is elicited on a scale of 11 (including zero) with 1 being completely unwilling to take risk while 10 is completely willing to take risk. This perceptual risk elicitation method has been argued to be relevant in the experimental setting just like other methods. While this method may aid preference revealing, it casts doubt on the possibility of capturing the diversity in risk attitudes.

Given the limitations of most one-dimensional, parameter-based lotteries, the panel lotteries proposed by Sabater-Grande and Georgantzis (2002) (SGG thereafter) provides alternative. The initial SGG lottery consists of one treatment (which has four panels) with each panel containing ten options. The main feature of the SGG lotteries is eliciting risk attitudes with a choice between positive outcome and null outcome. The lotteries are designed in a way that the topmost option is safest (with 100 percent probability) while the last option is riskiest (10 percent probability). The panels make comparing risk attitudes across stake possible. The lotteries have been extended to four treatments: small gain, small loss, large gain and large loss (García Gallego, Georgantzís, Jaramillo-Gutiérrez, & Parravano, 2012). This later version of the SGG is adopted by this study. However, the current study modify the nomenclatures to small gain one (SG1), small gain two (SG2), large gain one (LG1) and large gain two (LG2), respectively because all the four treatments are in the gain domains. Thus, in the new SGG lotteries, sixteen panels result in sixteen observations unlike the HL where only one observation (the switching point) is often relied on to estimate the risk aversion parameter.

The panel lotteries have many advantages over many previously reported elicitation methods. First, it is easy to comprehend especially among less educated subjects because it involves selecting one option among ten different lotteries with clearly defined probabilities. Second, it captures two dimensions of individual risk attitudes: willingness to taking risky prospects or decisions and sensitivity of individual to variations in returns to risk (García Gallego *et al.*, 2012). Third, it does not require parameter estimation. Fourth, it does not impose monotonic switching. Furthermore, it does not require complex theoretical assumptions; subjects may seek to maximize expected utility or payoffs; it has been applied in different contexts and currencies. Lastly, the simplicity and bi-dimensional nature of the panel lotteries make it attractive to this study. Unlike the MPL, the SGG lotteries do not impose monotonic switching. Thus, it may not suffer from anchoring bias.

While the original SGG lotteries were presented in the Spanish currency, peseta, which lost its legal tender on March 1, 2002, all the follow-up studies presented their experiments in Euro following the introduction of Euro as the official currency of the European Union (Georgantzís & Navarro-Martínez, 2010; García-Gallego, Georgantzís, Navarro-Martínez, & Sabater-Grande, 2011; García Gallego *et al.*, 2012; Attanasi, Georgantzís, Rotondi, & Vigani, 2018). In view of the fact that risk attitudes depend on contexts and elicitation methods used, a comparative study was recently conducted between SGG, HL and self-reported[10].

Two main methods have been used to estimate the parameters of risk preference in the literature. One involves estimating risk attitude parameters using switching point revealed by subjects. The other involves a joint estimation of all the parameters based on latent choice structural model using maximum likelihood estimation (MLE) technique. MLE method is initially proposed by Harless and Camerer (1994) while Andersen *et al.* (2008) and Harrison and Rutstrom (2008) build on the structural model. The advantages of joint estimation are many. First, it may give accurate attitude parameters. Furthermore, it uses all the information in the data set, generates standard error and allows for statistical test and comparison across studies. Structural model is usually based on the utility functions, CRRA or CARA. The standard utility function, CRRA has been used to estimate the risk aversion coefficient associated with the choice made under the SGG lotteries (see (García-Gallego *et al.*, 2011; Attanasi *et al.*, 2018). Notwithstanding, this study did not parameterize rice farmers' risk attitudes, instead it relies on the probabilities revealed by individual farmers.

2.6.2 Time Preferences Elicitation Methods

Different methods have been advanced to elicit the time preferences of individuals[11]. Some of the foremost methods use consumption data obtained through survey (Hausman, 1979; Viscusi & Moore, 1989; Dreyfus & Viscusi, 1995). The complexity in estimating discount rate is the main limitation of this method. The second approach, which has gained some popularity, is the experimental method (see Frederick *et al.*

[10] Attanasi *et al.* (2018) provides a distinction between SGG, HL (MPL) and self-reported risk elicitation methods. Supported with empirical evidences, they reported that subjects showing risk averse attitudes under the HL are equally averse to risk under SGG. However, subjects classified as risk neutral and risk loving were under HL were risk averse under SGG.A significant positive correlation is also reported between the risk ordering under HL and SGG and between SGG and self-reported risk method.

[11] Frederick *et al.* (2002) provide a comprehensive survey on different time preference elicitation methods applied by economists and psychologists in both the developed and developing countries. It is also important to stress that the choice of time elicitation method depends largely on the context and purpose of the research.

(2002) and Wilkinson (2008)) for details. The experimental approaches could be categorized into four. The first is the *choice tasks* which involve making binary choices between present and future rewards. Anchoring effect (bias) is the main limitation of this method. The second is the *matching tasks* which involve asking subjects open-ended questions to state a future amount that would make them indifference to present reward, and vice versa. This method may aid high magnitude effects. Furthermore, *rating tasks* relates to rating outcomes (like or dislike) in different time periods. The main disadvantage of the rating tasks is that it yields related results. Lastly, *pricing tasks* assess subjects' willingness to pay to receive outcomes (monetary or non-monetary) or otherwise in the future. This method allows time manipulation but it is highly subjective since subjects may state outrageous values that could be difficult to analyse. Economists favour the first two methods due to their relative advantages.

The anchoring bias associated with the choice tasks may be overcome by varying both time horizon and rewards. For example, Harrison, Lau, and Williams (2002) fixed proximate delayed (one month) rewards and varied future rewards. This method has been applied to non-farm population in Denmark (Andersen *et al.*, 2008; Andersen, Harrison, Lau, & Rutström, 2014). Although their method includes time delay, the two rewards are too close that subjects may be tempted to always choosing proximate rewards. Conversely, Benhabib, Bisin, and Schotter (2004a) and Benhabib, Bisin, and Schotter (2010) apply matching methods in the USA. The matching tasks allow the estimation of different discount rates for all subjects. Nevertheless, complexity in protocol design and analysis are the obvious problems of the matching methods.

Generally, there is high tendency for subjects to favour present monetary rewards when confronted with present and future amount. However, rewards associated with different future dates (front-end delay) may reduce this tendency (Andersen *et al.*, 2008). Additionally, two distinct future dates may result in low discount rates (Frederick *et al.*, 2002). Thus, Tanaka *et al.* (2010) vary present and future rewards without time delay. In contrast, Tanaka and Munro (2014) consider front-end delay in their design. In the later method, both the present and future rewards are predetermined but varied with different time horizon. The main strength of this approach include capturing of preference reversal, flexibility and easy comprehension. Giving these advantages, this study applies the front-end delay method to elicit rice farmers' time preferences.

2.6.3 Time Discounting Methods

Quite a number of theories and concepts have been proposed to explain how an economic agent or DM behaves with respect to time or discount future income, saving and consumption. The popular among these theories is the intertemporal choice theory credited to John Rae (Rae, 1905). This has been used to explain economic behaviour in different contexts. Rae's theory is elaborated in the Positive Theory of Capital by Bohm-Bawerk (1888), and further consolidated in the Theory of Interest by Fisher (1930). Keynes equally established an economic relationship between saving and income in the general theory of employment, interest and money (Keynes, 1936). Keynesian model assumes that marginal propensity to consume is less than the average propensity to save. This simplicity assumption that saving increases with income which may have negative consequence on consumption and thus the economy has generated lots of criticisms (Sablik, 2016). These motivated alternative theories and concepts including lice cycle income hypothesis which assume individuals seek to smooth consumption throughout their lifetime (Modigliani, 1954). The contradiction with this hypothesis is that individuals may save more in their prime age as against what the life cycle income hypothesis argued.

Turning back to the intertemporal choice theory, Fisher opines that consumers seek to maximize lifetime satisfaction when making a choice between present and future consumption. Fisher's principle has also experienced a lot of modifications. One of its popular variant is the Discounted Utility Model (DUM hereafter) proposed by Samuelson (1937). DUM has been used to model intertemporal choices in different contexts using exponential function. DUM is however associated with two main anomalies: *magnitude effect* and *preference reversal*. In other words, DUM assumes a constant discount rate. However, discount rates may vary over time and across different intertemporal stakes (Wilkinson, 2008). To illustrate, individuals may prefer 12,000 (USD) in 21 days over 10,000 (USD) in 20 days but also prefer 10,000 (USD) now over 12,000 (USD) tomorrow. Psychologists and perhaps economists have proposed hyperbolic and quasi-hyperbolic discounting models to handle such time reversal behaviour (Strotz, 1955; Loewenstein & Prelec, 1992; Laibson, 1997; Kirby, 1997; O'Donoghue & Rabin, 1999). Other methods have been put forward to account for different behaviour relating to intertemporal decision-making. Doyle (2013) surveyed and documented over twenty delay discounting methods adopted by psychologists and economists.

Although both hyperbolic and quasi-hyperbolic models account for present bias, some studies rejected hypotheses in favour of hyperbolic discounting (Benhabib *et al.*, 2004a; Benhabib & Bisin, 2005; Benhabib *et al.*, 2010). Like exponential model, hyperbolic discounting model estimates the discount rate using the future value (F), present value (P) and time (t), $h = \left(\frac{F}{P} - 1\right)/t$. h is the discount rate relating to hyperbolic discounting. On the other hand, quasi-hyperbolic discounting model accounts for present bias. $qh = [ln(BF/P)/t]$. qh is the discount rate from the quasi-hyperbolic model and B is the present bias parameter. It is worth noting that the quasi-hyperbolic discounting collapses to exponential function when the present bias parameter equals to one.

Another concept that has often been used mostly among psychologists to explain decision-making is impulsivity. Arguments abound on the fact that individuals usually make decisions without deep thought about the consequences of such decisions. While applications cut across different disciplines (Evenden, 1999; Bickel, Odum, & Madden, 1999; Whiteside & Lynam, 2001; Dalley, Fryer, Brichard, Robinson, Theobald, Lääne, Peña, Murphy, Shah, & Probst, 2007), its application is limited among agricultural subjects.

Since no discounting method is free from limitations, exponential discounting method has been used in different contexts by economists and social scientists as tools for policy evaluations. Moreover, the choice of the discounting method depends to a great extent on the goal of the research. Exponential discounting method has also been applied among agricultural farm agents (Tanaka *et al.*, 2010; Tanaka & Munro, 2014). Exponential function could be discrete or continuous. Its applications are well documented in economic growth and development. The compounding growth model generally applied could be expressed as; $F = P(1 + r)^t$. Where F is the future value, P is the present value, r is the discount (growth) rate and t is the compounding periods. Discounting for a number of times per annum aids the use of the geometric form: $F = P\left(1 + \frac{r}{n}\right)^{nt}$. n is the number of discounting per year. If n increases infinitely, then the geometric form could be expressed in exponential form as $F = Pe^{rt}$, $r = \left[log\left({}^{F}/_{P}\right)/t\right]$. This continuous exponential discounting method is employed by this study. In summary, discounting model aids the understanding about how individuals trade off present income or consumption for future income or consumption, and vice versa.

Different methods have been used to examine the correlation between attitude parameters and socio-economic variables. The econometric models applied in the literature depend largely on the elicitation methods adopted by the researchers as well as the objective of the study. Good examples include the application of OLS (Tanaka *et al.*, 2010; Liu, 2013) and interval regression model (IRM) (Yesuf, 2004; Ihli *et al.*, 2013; Tanaka & Munro, 2014). Tanaka *et al.* (2010) apply logistic model to jointly estimate the determinants of time preferences using the joint time discounting model proposed by Benhabib, Bisin, and Schotter (2004b). In another study, after estimating the subjective discount rate using the rate of time preference (RTP), Yesuf (2004) applies IRM to identify the covariates of time preferences among Ethiopian subjects. OLS may not yield consistent estimates, IRM allows the estimation of average parameters yet the coefficients may be interpreted as marginal effect (Tanaka & Munro, 2014). However, both OLS and IRM restrict utility function to single parameter (Harrison & Rutstrom, 2008). Risk and time preference parameters have also been jointly estimated based on the assumption that risk experiments may impose temptation for immediate consumption yet the future rewards associated with the time experiment remove this temptation (Andersen *et al.*, 2008; Harrison & Rutstrom, 2008). The model is based on the dual self-model of impulse control (Fudenberg & Levine, 2006). There are other applications of joint estimation of attitude parameters in agriculture using structural models (Nguyen & Leung, 2009; Harrison *et al.*, 2010; Nguyen, 2011). This study adopts an approach which differs from most cited studies. After estimating rice farmers' subjective discount rates using continuous exponential discounting method, spatial autoregressive regression (SAR) model is applied to examine the determinants of rice farmers' risk preference and time preference. The different modelling approaches to spatial dependence effects are briefly highlighted in the next session.

2.6.4 Modelling Spatial Dependence Effects

Spatial dependence is motivated by many reasons including time dependence, omitted variables, spatial heterogeneity especially in panel data, externalities and uncertainty (LeSage & Pace, 2009). Motivations can also be either theory-driven or data-driven (Anselin, 2002). This informs the choice of the model. For example, empirical applications have sought the use of time-lag model. The time lags of the dependent variable are justified by behavioural theoretical models (LeSage, 2008). Spatial autoregressive regression (SAR) model which is a variant of time lag spatial model is used for cross Sectional data. This model combines spatial autoregressive structure with the conventional regression model. The spatial Durbin model (SDM) arose from the omitted variable motivation. It is an extension of the SAR model. In addition, spatial error model (SEM) reflects dependence in the disturbance process by assuming correlation arises indirectly through the errors in the decisions.

This study is partly interested in examining whether correlation exists between a farmer decision and that of her neighbours. Since this is the first of its kind in testing this hypothesis, related literature is reviewed and presented here. Different approaches have been advanced in the literature to capture spatial dependence effects in adoption decisions. While some studies use social capital as proxy for information access (see for examples (Di Falco & Bulte, 2011; Teklewold, Kassie, & Shiferaw, 2013)), others rely on social learning network (Marglin, 1963; Conley & Udry, 2010). Social learning may be considered a component of spatial dependence yet it does not capture other spatial factors like climatic condition or soil characteristics. Different approaches have been used to address this limitation. For examples, Neill and Lee (2001) used distance from road while Guerin and Guerin (1994) adopted contact with neighbouring farmers. In addition, in examining spatial heterogeneity in adoption, Fuglie and Kascak (2001) used regional variation while Feder and Umali (1993) based their analysis on climatic environment. Recent studies applied weights or distance function in examining spatial issues in adoption (Case, 1992; Holloway *et al.*, 2002; Krishnan & Patnam, 2014; Läpple & Kelley, 2015; Tessema *et al.*, 2016).

Spatial weights are generally specified in two ways. One method is based on symmetric neighbour definition which could be defined based on contiguities or distance thresholds while the other method is asymmetric k-nearest neighbours. In the symmetric contiguity weights matrix, $\boldsymbol{W}$ is created with a code of one for close neighbours and zero otherwise. The symmetric matrix, $\boldsymbol{W}$ may also be based on the distance between individual observation points (Anselin, 2002).

Several limitations are associated with both methods. First, the question of who share boundaries arise for contiguity while the number of neighbours to include or distance to use is the main issue in k-nearest neighbour method. Second, for both methods, non-neighbours may be defined as neighbours because the researchers select the cut off distance (Anselin, 2002). Lastly, binary contiguity matrix may not capture all the spatial interaction between closer neighbours**.** Different specifications have been used in applied studies. For examples, Kim, Phipps, and Anselin (2003) applied SAR and contiguity method and considered individual within 4 km centroid as neighbours. Conversely, Roe, Irwin, and Sharp (2002) applied inverse distance function specification with 200 miles constituting the limit of spatial dependence. Similarly, Bell and Bockstael (2000) applied inverse distance function and reported 600 metre as the limit of spatial dependence while Areal, Balcombe, and Tiffin (2012), using a Bayesian approach based their specification on power distance function and reported 240 km as spatial dependence limit. Krishnan and Patnam (2014) applied SDM using k-nearest neighbours assuming five nearest neighbours as cut-off point. On the other hand, Läpple and Kelley (2015) used inverse distance weights matrix while Ward and Pede (2015) based their specification on one over squared distance. A recent study by Tessema *et al.* (2016) sought the application of SDM where the weights matrix is defined based on the social group with zero for non-members, and 0.25 to power of two for members.

This study applies power weights function to define the weights matrix and estimated the spatial dependency in risk and time preferences among rice farmers using instrumental variables method. The different analytical methods that have been previously used to model adoption decisions in the literature are presented next.

2.6.5 Adoption Decision Analytical Models

Adoption decisions' models can be dynamic or static. The dynamic model captures the timing and extent of technology use (Abadi Ghadim & Pannell, 1999). However, dynamic model requires huge data including production inputs and outputs as well as temporal record on adoption which could only be realized through record keeping. Static model may be discrete or continuous. Discrete and continuous static adoption models are flexible and often applied assuming the farmers' main objective is to maximize utility. In addition, continuous model is used to capture optimal land shares of improved technology. In modelling discrete adoption model, the decision making unit (DMU) is often assumed to behave according to the expected utility. This objective of utility maximization motivates the use of univariate and multivariate logit and probit models because ordinary least squared (OLS) may yield biased and inefficient estimates for limited dependent variables (Feder & Umali, 1993).

The binary logit and probit models have been widely applied for binary outcome adoption variables in different contexts. Applications include reduced tillage adoption in the USA (Rahm & Huffman, 1984), adoption of fertilizer and herbicide in Ethiopia (Kebede *et al.*, 1990) as well as improved rice varieties' adoption in Nepal (Shakya &

Flinn, 1985). Nevertheless, the dichotomous adoption decision models do not differentiate between partial and full adoption. There is also a tendency of producing biased and inconsistent estimates and thus over-estimate adoption decisions (Amemiya, 1984). While adoption of multiple technologies motivates the use of multivariate probit (Ahmed, 2015), adoption and dis-adoption behaviours are often modelled using bivariate probit (see for example, (Neill & Lee, 2001)).

The quest for examining both decisions to adopt and intensity of technology use prompted the applications of Tobit model for improved agricultural technologies (Nkonya *et al.*, 1997; Baidu-Forson, 1999; Alene *et al.*, 2000; Dadi *et al.*, 2001; Fufa & Hassan, 2006), conservation farming practices (Anley *et al.*, 2007; Arslan, McCarthy, Lipper, Asfaw, & Cattaneo, 2014). While studies like Dadi *et al.* (2001) applied Heckman selection model, some studies used double hurdle model (Tambo & Abdoulaye, 2012; Anik & Salam, 2015; Hassan, Baiyegunhi, Ortmann, & Abdoulaye, 2016). Although the two-stage adoption models allow the estimation of intensity of adoption, intensity of usage of improved technology may not be measured due to unavailability of data, especially in the developing countries where record keeping is a major challenge.

Survival/duration/hazard model previously used by Kiefer (1988) to estimate the determinants of unemployment has recently gained attention in the adoption literature. Using timing of adoption as dependent variable, survival model has been used to model timing of adoption of improved agricultural technology in the USA (Fuglie & Kascak, 2001; Barham *et al.*, 2014) and China (Liu, 2013), among others. The strengths include measurement of probability of adoption and flexibility. It may however overestimate adoption decisions for new entrant farmers. More so, it does not capture intensity of adoption.

As indicated above, extensive studies exist and have provided argument that adoption decisions may be binary, multivariate or simultaneous which reflects decisions and intensity of adoption. Multivariate analysis is the appropriate approach when farmers face multiple adoption choices. Moreover, the possible simultaneity in the adoption decisions as well as its intensity may be accounted for using two-stage estimation methods. Indeed, the decision to adopt HYV may not be random as it may depend on the level of awareness among farmers. This may result in self-selection, thus it is important to account for sample selection bias. In addition, three-stage estimation method has been proposed and applied to account for awareness, decision and intensity (Saha *et al.*, 1994). Yet, difficulty in the measurement of farmers' level of awareness and intensity of technology usage are the main constraint to the application of the three-stage model. Therefore, the appropriate modelling approach depends to a considerable extent on the availability of data as well as the goal of the study.

A simultaneous adoption model (instrumental variable (IV) probit model or a binary outcome model with a continuous covariate) is considered in this study to test the hypotheses of endogeneity of risk and time preferences in adoption decisions. These models have a continuous dependent variable in the first stage and a binary outcome dependent variable in the second stage. Given the utility assumption and that most sampled rice farmers either grow HYV or traditional rice variety, rice farmers' decision to adopt HYV was expressed in the framework of discrete choice model. In addition, to address the potential endogeneity problem, spatial autocorrelation was examined in risk and time preferences in the first stage. As indicated earlier, the decision to adopt or not to adopt is modelled in line with farm and farmers' specific characteristics, institutional/community factors, perceptions about the attributes of improved technology as well as risk and time preferences. The next Section gives an account of the reason for applying IV method.

2.6.6 Instrumental Variables Estimation Method

The instrumental variable (IV) method has a long history as an econometric tool for addressing the potential endogeneity problem associated with economic models. Historically, the application of IV method is dated back to 1928 where it was applied by Phillip G. Wright in demand-supply model to estimate the effects of import tariff on animal and vegetable oils and fats in the USA (Stock & Watson, 2012, p. 334). Following this, IV has since been applied to both situation where the dependent variable is continuous or binary. Endogeneity occurs when unobservable variables in the disturbance term are correlated with the hypothesized endogenous variables (spatial lags as well as risk and time preferences, in this study). Like OLS, binary models may produce biased and inconsistent estimates when at least one explanatory variable is endogenous or correlated with the error. The goal is therefore to obtain the exogenous variation in the dependent variable. Instrumental variable is required to achieve this.

An instrument must be significantly correlated with the endogenous variable but not the error term. However, one fundamental issue that makes its application relatively difficult is the choice of instruments. Among many applications, Angrist and Keueger (1991) used quarter of birth as instrumental variable for education in their wage Equation (for unobserved ability) as an attempt to estimate the return to schooling while Card (1993) adopted geographical proximity for the same purpose. In critiquing the choice of month of birth as instrumental variable, Bound, Jaeger, and Baker (1995), argue that weak relationship between instrument and the error term may result in inconsistent estimate of the IV. Although many empirical studies exist on the applications of IV models with continuous dependent variable, a few studies are available in the case of binary outcome dependent variable (see (Clarke & Windmeijer, 2012)). It is also worth noting that applications of IV with binary outcome dependent variable is limited in the adoption literature. More so, both continuous and binary variables have been widely used as instruments in the literature. The instruments used in this study as well as the justification for their choices are detailed in the next chapter.

Chapter Three

3.0 Data and Estimation Methods

This chapter begins with a brief description of the study area followed by the explanation on the nature of risk and time experiments, data collection procedures as well as the analytical methods applied on the collected data. **Figure 2** summarizes the procedures followed in this study. First, panel lotteries and front-end delay time decision experiments were designed respectively to examine rice farmers' risk preferences and time preferences. In addition, variables relating to farm and farmers' socio-economic and demographic characteristics, perceptions about improved technology attributes and institutional factors were obtained during the survey. In the intermediate stage, the data collected were descriptively analysed and summarized using tables, frequencies and percentages in addition to calculating the distance between individual farmers using their location coordinates (longitude and latitude). The distance was used to construct the weights matrix used in the spatial and adoption decision models. Finally, econometric models including instrumental variable (IV) model and instrumental variable (IV) probit model were respectively applied to examine the spatial dependence effects in risk and time preferences and identify rice farmers' determinants of adoption decisions.

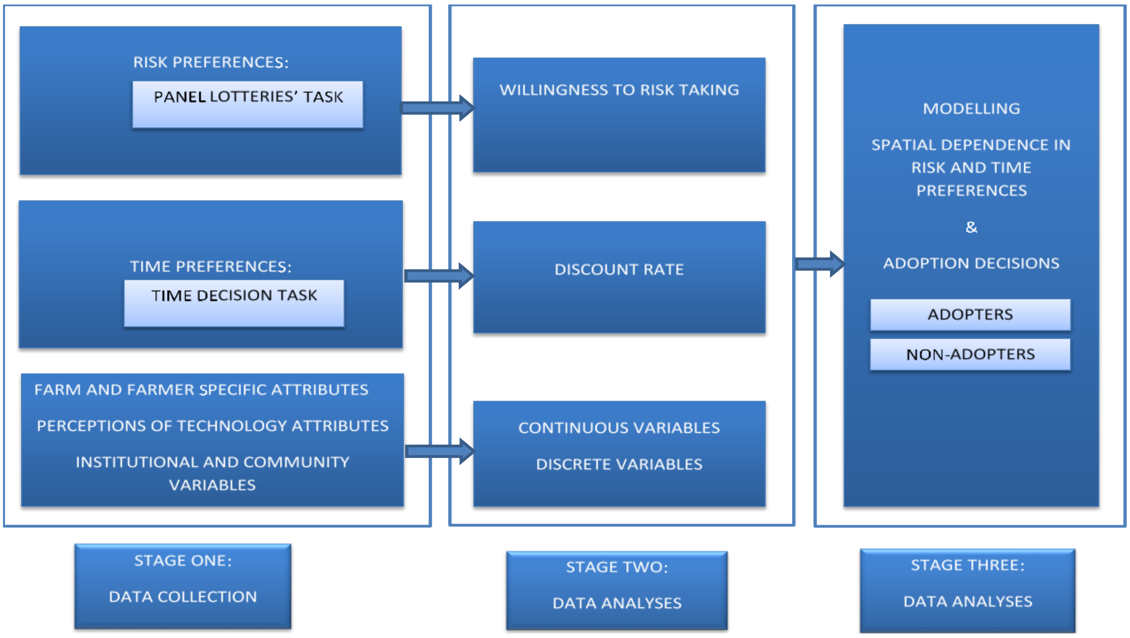

Figure 2 : Research Method Framework
Source: Author's Design, 2017

3.1 The Study Location

This study applies the data collected from the survey conducted in Ogun State, South Western Nigeria[12] between March and May, 2016. The country is situated approximately between longitude 3 degrees and 14 degrees and latitude 4 degrees and 14 degrees (see **Figure 3**). The total land area is estimated approximately at 923,770 sq.km (356, 668 sq. million or 92.38 million hectares) covering land area of 910,770 sq. km and coast line of 853 km.

The Nigerian population is estimated at 140,003,542 in 2006 by the National Population Commission. At a growth rate of approximately 2.44 percent per annum, the population is projected to grow from 186,053,386 million people in 2016 to about 392 million people in 2050[13]. Cultural and ethnic diversity is one of the unique features of the country which is blessed with over 250 ethnic groups, over 500 languages and dialects. More uniquely, Nigeria has three major tribes: the Hausas which dominate the northern part; the Igbos are in the eastern part while the Yorubas are the main inhabitancy of the western region. In terms of religion, the population of the country is approximately fifty percent Muslims, forty percent Christians and ten percent traditional worshippers including free-thinkers.

In terms of climate, Nigeria has relatively hot temperature, usually varies from 22 to 36 degree centigrade. Nigeria typically has two main seasons; rainy and dry seasons. The rainy season may last for seven months, usually from April to October while November to March constitute the dry season. The dry season usually starts with a very low temperature and chilly air around December. The estimated annual rainfall ranges between 1200 mm to 3000 mm. The rainfall pattern is bi-modal, usually at first peak in June followed by a short break in August and reaches the second peak in October.

[12] The information presented in this study on the geography, climate and vegetation of Nigeria is sourced from: http://www.nigeriahc.org.uk/about-nigeria. Assessed on 25/02/2017.

[13] Nigeria population is one of the fasted growing population in the world. Detailed information on the projected Nigerian population is sourced from http://www.indexmundi.com/nigeria/demographics_profile.html. Assessed on 25/02/2017.

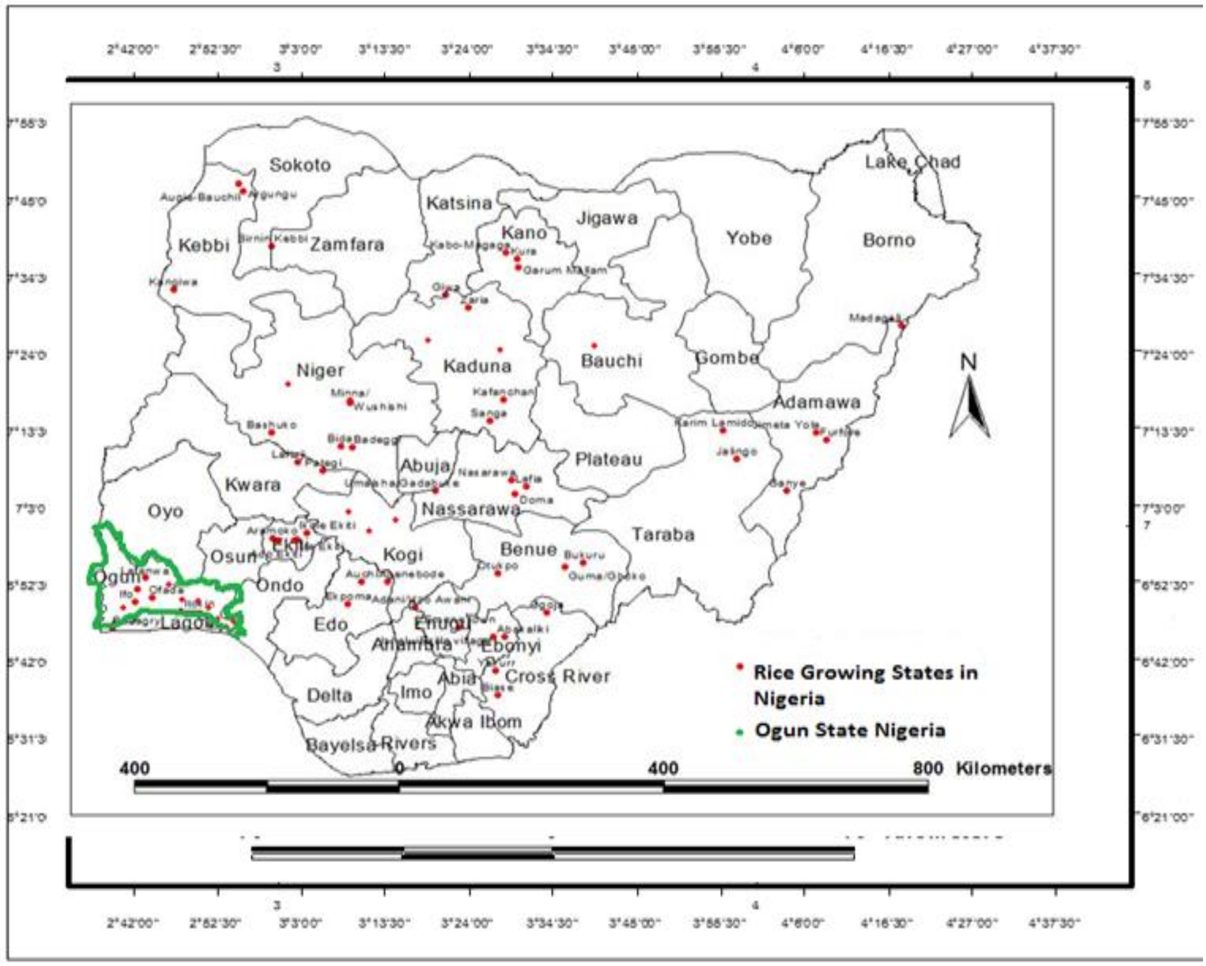

Figure 3: Map of Nigeria Showing the Study Location, Ogun State

Source: Designed by Agricultural Media Resource and Extension Centre, Federal University of Agriculture, Abeokuta, Nigeria and Edited by the author.

It is important to provide some information that motivates the selection of the study location. Ogun State is one of the six States in the South-Western Nigeria[14] (see the green mark in **Figure 3**). The State, is popularly referred to as Gateway State, which stems from sharing boundaries with many States including Ondo State in the East, Oyo and Osun States in the North; in the West by Republic of Benin and in the South by Atlantic Ocean and Lagos State, the commercial hub of the country. The State is multicultural but dominated by the Yoruba ethnic group. The major sub-ethnic groups include the Egbas, Yewas/Aworis, Ijebus and Remos. The total land area covered by the State is approximately 16,409.26 square kilometres. It also lies approximately between latitude 2^{o} 30 N and 4^{o} 37 N and longitude 5 ^{o} 30 E and 7 ^{o} 30 E as shown in **Figure 4**. This suggests the State is in humid tropical lowland region. Like many States in

[14] Ogun State was created from the old Western region of Nigeria in February 3, 1976. Details about socio-ecological attributes of Ogun State were obtained from the Ogun State website via http://www.ogunstate.gov.ng/about-ogun-309/ogun-state-profile.html. Accessed on 22/01/2015.

Nigeria, Ogun State has two main seasons (rainy and dry). The norther part of the State is drier relative to the southern part. This is evident as the average annual rainfall is approximately 1470 mm in the South and 1200 mm in the North. Moreover, the monthly temperature varies between 23^0C in July to 32^0C in February. Relative humidity has a range between 76 percent (during the dry season) and 95 percent (during the raining season). Thus, the climatic condition is relatively good for all living things (crops and animals). This favourable climate enhances the production of food crops and livestock rearing all year round. With its fertile soils, Ogun State is one of the leading rice producing States in South-Western Nigeria[15]. In fact, both the Federal and State Governments are committed to reducing rice importation thus Ogun State is one of the favoured States encouraged for increased domestic rice production.

There are twenty (20) local government areas (LGAs) that constitute the administrative units of the State. Yet for administrative convenience and agricultural purposes, the State is divided into four agricultural zones (ADP zones) by the World Bank sponsored Ogun State Agricultural Development Programme (OGADEP hereafter). Each zone coincides with the four major sub-ethnic groups (Egba, Ijebu, Remo and Yewa/Awori). The zones are further divided into blocks. The blocks are like LGAs of the administrative structure of Nigeria consisting of many farming communities and towns. Blocks are further divided into smaller units, the cells. The cells are therefore the small towns or villages where farm operations are carried out.

The agricultural zonal division in Ogun State reflects the socio-economic and climatic conditions among farmers. For example, the northern part of Abeokuta zone is derived savannah vegetation while the southern part is rain forest. Being the State capital, Abeokuta zone houses many financial and other government institutions. The Ilaro zone which bounded Abeokuta zone in the east has a derived savannah vegetation in the north and rain forest belt and mangrove swamp in the south. Ilaro zone is in the far eastern part of the State. It is rural in nature relative to Abeokuta zone. Ikenne is the closest zone to Abeokuta zone which it bounded in the west. The vegetation of this zone is mainly rain forest belt. Ikene is also a rural zone relative to Abeokuta zone. Ijebu-Ode

[15]Ogun and Ekiti are target States for increasing rice production in Western Nigeria. With government efforts at reducing rice importation, it is imperative for farmers to embrace improved innovation while government should support them with incentives such as low interest rate credit, access to improved rice varieties, etc. Information about the potential of Ogun State and Ekiti State being important rice producing States is obtained from http://agronigeria.com.ng/2013/04/02/we-dont-need-imported-rice-paddy-nigeria-fg-assures/. Accessed on 12/08/2015.

zone combines both rural and urban features. The northern part is mainly rain forest belt while the southern part is mangrove swamp.

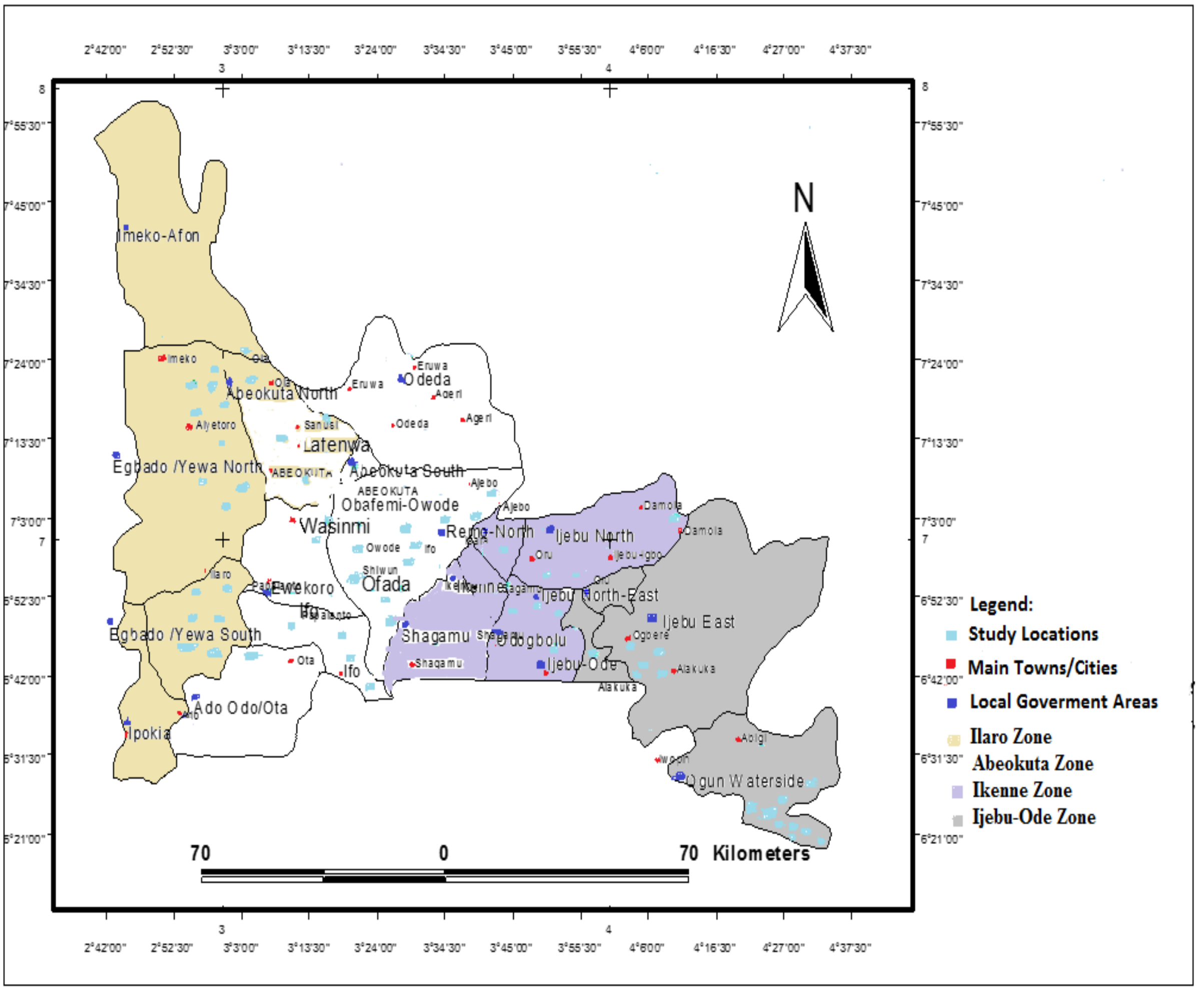

Figure 4: Map of Ogun State Showing the Study Area

Source: Designed by Agricultural Media Resource and Extension Centre, Federal University of Agriculture, Abeokuta, Nigeria. Edited by the author.

The current administration in Ogun State recently inaugurated and launched the MITROS rice factory and MITROS rice to encourage production and consumption of domestic rice in Nigeria[16]. With different packages ranging from 1 kg to 50 kg, it is intended to be affordable for local consumption. These efforts were lauded by the Governor of the Central Bank of Nigeria who promised a continuous support to grass root farmers through one digit interest rate. Notwithstanding the giant stride by the

[16] Nigeria is reportedly currently having 12 million rice farmers who produce less than 10 million metric tonnes per year. These farmers have a potential to produce 50 million metric tonnes annually if they depend on improved production and processing methods. This information is sourced from https://www.premiumtimesng.com/regional/ssouth-west/253235-ogun-launches-rice-sell-n11500.html. Assessed on 19/05/2018.

government, research into the extrinsic and intrinsic reasons for the adoption and non-adoption of the existing rice varieties would provide insights that would guide policy formulations on rice in Nigeria. The experiments adopted as well as the methods of data collection are presented next.

3.2 Experimental Designs and Procedures

This study conducted two different experiments to elicit rice farmers' risk and time preferences. The first task is bi-dimensional panel lotteries risk elicitation method which explains behaviour without the need for parameter estimation. The second experiment is the application of time preference elicitation method involving varied rewards and time horizon. This allows the estimation of subjective discount rates which determine the level of impatience among rice farmers.

3.2.1 The Risk Experiment

This study employs panel lotteries to examine rice farmers' willingness to risk taking or their level of risk avoidance. As earlier indicated, the panel lotteries have four treatments as presented in **Table 2** and **Appendix B: Questionnaire.** One of the unique features of the elicitation methods is that each panel has ten separate lotteries from which farmers only choose one option. The lotteries also allow the examination of the sensitivity of individual farmers to the varied size of the payoffs. The panel lotteries are adapted from the García Gallego *et al.* (2012) with modifications to the nomenclatures as defined in Equations 3.1 to 3.4. Note that as at the time of the experiment, 1 Euro is equivalent to 225 Nigerian naira.

For small gain one (and other stakes), individual subject has a probability (P) of winning a payoff (X), the amount of Naira shown in front of each treatment or nothing otherwise. Both the payoffs and the probabilities vary across the rows in each panel. Please note that the probabilities are the same for each panel of each treatment. The payoffs increase while the probability associated with winning a reward decreases as one moves from row (option) one to row (option) ten.

Rice farmers who are less willing to take risky decisions or avoid risky decisions are more likely to choose from the first few rows (top five options) while risk neutral and risk loving subjects may prefer payoffs that are closer to the bottom (last five rows). It follows that avoidance of zero earning, that is not picking higher rewards, implies risk aversion or risk avoidance. In other words, subjects whose utility functions are uniformly concave may choose extreme options; sure choices (when probability is 100 percent) while those with uniformly convex utility functions may choose the last or risky option (when the probability is 10 percent). In addition, the panel nature of the lotteries exposes subjects to the entire range of the probabilities and monetary rewards. In fact, rice farmers who are highly unwilling to take more risky options in the first and second panels of each treatment are attracted to risky decisions in the third and fourth panels which have relatively higher rewards. In this task, choosing one (1) option out of the ten (10) options in each panel results in sixteen (16) observations per subject. Only one of the panels in each treatment determines the earnings[17]. However, this task was not incentivized for two reasons: first, due to relatively high rewards involved and second it prevents non-rice farmers from participating in the experiment. Note that the term risk avoidance is used in place of risk aversion in this study since the parameter of the utility function is not estimated. The payoff associated with each probability in the SG1 treatment is constructed using Equation 3.1.

$$EV_{ij}(SG1) = P_{ij}X_{ij} = C + \left(1 - P_{ij}\right)t_j, \quad X_{ij}(SG1) = \frac{C + \left(1 - P_{ij}\right).t_j}{P_{ij}} \quad (3.1)$$

Where $EV_{ij}(SG1)$ is the expected value of the lottery $(SG1)$. $X_{ij}(SG1)$ is the payoff associated with the $(SG1)$. i varies from 1 to 10 corresponding to the lottery row; j varies from 1 to 4 representing panels 1, 2, 3 and 4 respectively, P is the winning probability which varies from 1 to 0.1. C is a constant which is fixed at ₦225.00 for each of the panel in the $SG1$. This is the Naira equivalent (as at 2015) of the one Euro used in the original SGG lottery. Therefore, all the four panels under $SG1$ begin with a sure amount (225). This is responsible for a linear large increment in the expected values down the vertical rows. t_j = 0.1, 1, 5, 10 is a panel-specific risk premium corresponding to panel 1, 2, 3, 4, respectively. The risk premium is responsible for the increment in the expected values as we move from panel one to four. Subsequently, other treatments are calculated from the SG_1. That is, $SG2$ is SG_1 less 225 ($SG2 = SG1 - 225$) as defined in Equation 3.2. On the other hand, $LG1$ is obtained by multiplying the $SG1$ by a constant, $LG1 = SG1 * 100$ as defined in Equation 3.3. This is done to bring about large increment in the small gain one in order to examine variation in subjects' risk attitudes across stakes. Lastly, $LG2$ is expressed as $LG1$ less 22,500, ($LG2 = LG1 - 22{,}500$) as illustrated in Equation 3.4.

[17] Detailed information about the risk task design and presentation is presented in **Appendix B: Questionnaire**.

Mathematically,

$$X_{ij}(SG2) = X_{ij}(SG1) - 225 \quad (3.2)$$

$$X_{ij}(LG1) = \left(X_{ij}(SG1)\right)100 \quad (3.3)$$

$$X_{ij}(LG2) = \left(X_{ij}(LG1)\right) - 22{,}500 \quad (3.4)$$

The average payoffs associated with the SG1 are 659.8, 661.2, 668.9 and 678.6 respectively for panels 1, 2, 3 and 4. The SG2 has an average payoff of 434.8, 436.2, 443.9 and 453.6 for panels 1, 2, 3 and 4, respectively. On the other hand, the LG1 is associated with the average payoff of 65,980, 66,120, 66,890 and 67,860 respectively for panels 1, 2, 3 and 4 while the LG2 has an average payoff of 43,421, 43,595, 44,367 and 45,331 associated with panels 1, 2, 3 and 4 respectively.

in the Study area as at the time the experiment was conducted, the average rewards associated with the small gain one and small gain two are below the average minimum farm labour wage rate of 1,500 (Nigerian naira). On the other hand, the rewards associated with the large gain one and large gain two are above the wage rate at that time. Both rewards (small and large) are presented to farmers to reflect their farm income and the reality of the economic situation in the study area. At times, farmers may run at loss on their farm business (zero profit), on another time they may make profit at margin or be at equilibrium or make huge profit. Indeed, rice farmers show full understanding about the payoffs and their consequences on farm investment decisions as well as day-to-day farm earnings. In addition, this variation in average rewards assists in the examination of the real risk attitudes of farmers as well as sensitivity to change in rewards (farm profit).

Table 2: Risk Panel Lotteries' Payoffs

Panel Lotteries for Four Treatments (currency in Nigerian naira)										
P	1	0.9	0.8	0.7	0.6	0.5	0.4	0.3	0.2	0.1
$X\ (SG1)$										
Panel 1	225	251	282	322	376	451	563	751	1,126	2,251
Panel 2	225	251	282	322	376	451	564	753	1,129	2,259
Panel 3	225	251	283	324	379	455	570	762	1,145	2,295
Panel 4	225	252	284	326	382	460	578	774	1,165	2,340
$X\ (SG2)$										
Panel 1	0	26	57	97	151	226	338	526	901	2,026
Panel 2	0	26	57	97	151	226	339	528	904	2,034
Panel 3	0	26	58	99	154	230	345	537	920	2,070
Panel 4	0	27	59	101	157	235	353	549	940	2,115
$X\ (LG1)$										
Panel 1	22,500	25,002	28,128	32,148	37,507	45,010	56,265	75,024	112,540	225,090
Panel 2	22,500	25,012	28,150	32,186	37,567	45,100	56,400	75,234	112,900	225,900
Panel 3	22,500	25,056	28,250	32,358	37,834	45,500	57,000	76,167	114,500	229,500
Panel 4	22,500	25,112	28,375	32,572	38,167	46,000	57,750	77,334	116,500	234,000
$X(LG2)$										
Panel 1	0	2,502	5,628	9,648	15,007	22,510	33,765	52,524	90,040	202,590
Panel 2	0	2,512	5,650	9,686	15,067	22,600	33,900	52,734	90,400	203,400
Panel 3	0	2,556	5,750	9,858	15,334	23,000	34,500	53,667	92,000	207,000
Panel 4	0	2,612	5,875	10,072	15,667	23,500	35,250	54,834	94,000	211,500

Source: Authors' Compilation, 2015

3.2.2 The Time Experiment

Given the advantages of elicitation method involving time delay (front-end delay), this study employs a variant of method applied by Tanaka and Munro (2014) to elicit rice farmers' time preferences. Rice farmers were presented with two monetary plans (A and B) shown in **Table 3**. While plan A presents both present and future (intermediate) rewards, plan B presents only future rewards. In the first and third series, present rewards were fixed while the future rewards varied to determine the point of indifference. In series two and four, the rewards associated with Plan A were varied while that of Plan B fixed. This is also done to determine the indifference point. Similar patterns apply for the remaining series. The switching task is adopted under the time experiment, rather than the risk task because the switching point does not only allow the identification of the point of indifference among farmers but also aids the estimation of the subjective discount rates for individual subject. This approach has also been widely used by other studies. In time discounting, individual is likely to have strong preference for immediate or present payoff if there is a marginal difference between the payoffs. Increasing the payoffs associated with the future increases the tendency of behaviour switch. This point at which individual switches is called the point of indifference in economics which are useful in economic analysis.

The minimum and maximum payoffs in the time task are 2,000 and 18,000, respectively. The minimum payoff is approximately equivalent to the labour wage rage in Nigeria as at the time the experiment was conducted. The maximum payoff is presented to farmers to achieve two aims: first, it is large enough to examine their level of patient with time and second, unlike the risk time, the experiment tests uncertainty but does not involve probability. There are 32 rows in the time experiment[18]. This task is hypothetical due largely to logistics. Non-incentivized equally prevents non-rice farmers from participating in the experiment. The order of presentation of the experiment as well as data collection method are presented in the next Section.

[18] See **Appendix B: Questionnaire** for the details about designs and presentation of Experiment Two.

Table 3: Time Preference Elicitation Payoffs

Row	Plan A	Plan B
Series 1		
1	Receive 10,000 today	Receive 12,000 in 2 months
2	Receive 10,000 today	Receive 14,000 in 2 months
3	Receive 10,000 today	Receive 16,000 in 2 months
4	Receive 10,000 today	Receive 18,000 in 2 months
Series 2		
1	Receive 8,000 today	Receive 18,000 in 2 months
2	Receive 6,000 today	Receive 18,000 in 2 months
3	Receive 4,000 today	Receive 18,000 in 2 months
4	Receive 2,000 today	Receive 18,000 in 2 months
Series 3		
1	Receive 10,000 in 4 months	Receive 12,000 in 6 months
2	Receive 10,000 in 4 months	Receive 14,000 in 6 months
3	Receive 10,000 in 4 months	Receive 16,000 in 6 months
4	Receive 10,000 in 4 months	Receive 18,000 in 6 months
Series 4		
1	Receive 8,000 in 4 months	Receive 18,000 in 6 months
2	Receive 6,000 in 4 months	Receive 18,000 in 6 months
3	Receive 4,000 in 4 months	Receive 18,000 in 6 months
4	Receive 2,000 in 4 months	Receive 18,000 in 6 months
Series 5		
1	Receive 10,000 today	Receive 11,000 in 1 month
2	Receive 10,000 today	Receive 12,000 in 1 month
3	Receive 10,000 today	Receive 13,000 in 1 month
4	Receive 10,000 today	Receive 14,000 in 1 month
Series 6		
1	Receive 9,000 today	Receive 14,000 in 1 month
2	Receive 8,000 today	Receive 14,000 in 1 month
3	Receive 7,000 today	Receive 14,000 in 1 month
4	Receive 5,000 today	Receive 14,000 in 1 month
Series 7		
1	Receive 10,000 in 5 months	Receive 11,000 in 6 months
2	Receive 10,000 in 5 months	Receive 12,000 in 6 months
3	Receive 10,000 in 5 months	Receive 13,000 in 6 months
4	Receive 10,000 in 5 months	Receive 14,000 in 6 months
Series 8		
1	Receive 9,000 in 5 months	Receive 14,000 in 6 months
2	Receive 8,000 in 5 months	Receive 14,000 in 6 months
3	Receive 7,000 in 5 months	Receive 14,000 in 6 months
4	Receive 5,000 in 5 months	Receive 14,000 in 6 months

Source: Author's Compilation, 2015

Note: Figures are in Nigerian naira

3.2.3 Data Collection Methods and Experimental Instructions

The data used for this study came from the individual interview of rice farmers over fourth six (46) different locations (towns and villages) across Ogun State, Nigeria between March and May, 2016. The questionnaire, which was electronically administered is composed of two main Sections: risk and time preferences' experiments and the socio-economic characteristics of the respondents (see **Appendix B: Questionnaire**). The later Section comprises factors that may explain farmers' adoption decisions, including socio-demographic variables, perceptions about improved rice varieties attributes as well as institutional and community variables. The questions relating to the socio-economic variables were open and close ended while preferences (risk and time) were elicited using the choice experiments described above.

A total number of three hundred and twenty nine (329) rice farmers were interviewed during the survey period. The respondents were drawn from the main rice growing towns and villages across the four Ogun State Agricultural Development Programme (OGADEP zones). **Table 4** presents the OGADEP structure in Ogun State. Efforts were made to draw farmers at the cell levels in the State. It is however worth mentioning that most of the villages and towns visited are not located on the OGADEP structure which shows only few farming communities in the State. While the researcher's initial intention was to select farmers based on OGADEP structure, this idea was frustrated due to the fact that many cells in the OGADEP structure are not among the predominant rice producing areas in the State; most rice growing villages and communities selected are within the large cells but difficult to delineate. In addition, there is an absence of a comprehensive list (sampling frame) consisting all rice farmers' in the State. Therefore, the researcher made efforts to contact extension agents who provided useful information on the locations where rice is mainly grown since rice farmers are the target respondents. Notwithstanding, the number of blocks selected from Abeokuta, Ilaro, Ijebu-Ode and Ikenne include 1/3, ½, 1/3 and ½, respectively. In addition, efforts were made to sampled representative data across the four OGADEP zones in the State. Over all, both male and female rice farmers were randomly sampled during the survey.

Table 4: OGADEP Zonal Structure

ZONE	BLOCKS	CELLS
ABEOKUTA	Olorunda*	Olorunda, Idi-emi, Ijale, Papa, Imala
	Ilewo	Ilewo, Ibara-Orile, Isaga, Orile-Joga
	Opeji	Alaabata, Sanusi, Opeji, Ijo-Agbe, Obete, Araromi
	Ilugun	Kila, Olugbo, Ilugun, Odeda, Ikereku, Olodo, Efan, Osiele
	Ifo	Ifo, Akinside, Egbeda, Ijoko, Coker, Ajibode, Iju-Atan, Ososun, Iyesi, Orudu
	Wasimi*	Wasimi, Oba-Oko, Itori, Onigbedu, Oworu, Ajegunle, Arigbajo, Papalanto
ILARO	Oke-Odan	Oke-Odan, Ipokia, Ihumbo, Alari, Ifonyintedo, Ipaja, Ilase, Agosasa
	Ado-Odo*	Ado-Odo, Ilaro, Iwoye, Owode, Ere, Agbara, Idolehin, Igbesa
	Sawonjo*	Sawonjo, Ibese, Igbogila, Imasayi, Igan, Ohunbe, Ijoun, Oja-Odan
	Imeko	Imeko, Ayetoro, Shaala, Idofa, Agboro, Idi-Ayin
IJEBU-ODE	Isoyin	Isoyin, Atan, Ijebu-Ode, Itamapako, Ilese, Ogbogbo
	Ala	Ala, Ibefun, Imosan, Ogbo, Odogbolu, Aiyepe
	Ijebu-Igbo*	Odiya, Ita-Egba, Osunbudepo, Agunboye
	Ago-Iwoye	Ago-Iwoye, Oru, Farm settlement, Odosenlu
	Ijebu-Ife	Ijebu-Ife, Itele, Imobi, Ogbere, Imushin, Ikija, Fowosere
	Ibiade*	Ibiade, Iwopin, Ayila, Efire, Ilushin, Ode-Omi, Abigi, Ayede
IKENNE	Isara	Iperu, Isara, Orile, Oko, Imagbon, Ilaro
	Simawa	Simawa, Ogijo, Odelemo, Oke-Ata
	Someke*	Owode, Ajura, Kobape, Oba, Mokoloki, Iro, Ibafo
	Obafemi*	Obafemi, Kajola, Ajebo, Aiyerose, Ogunmakin, Adigbe

Source: Author's Computation based on prior Information from OGADEP, 2015

*indicates the selected rice growing blocks.

Procedures and Order of Presentation in Data Collection

As part of the research process, before embarking on the field trip, the experiments as well as socio-economic variables intended to be captured on the field were coded on the Excel spread sheet and later linked to the smart android phone. Prior to the commencement of the survey, the researcher trained a team (three) of post-graduate students who were recommended by the two professors at the Federal University of Agriculture Abeokuta as enumerators who then assisted in the data collection. The training which was done in late February, 2016 last for approximately two hours. In this training, enumerators were illustrated with the risk and time experiment record sheets which are used as guide in addition to the information on how the smart phone software (technology) would be used for data collection. Indeed, the use of the technology motivates the post-graduate students to wanting to see how it works on the field.

As noted above, rice farmers were individually interviewed by contacting them at different locations including home and farms. The risk experiment is conducted first, followed by the time experiment and lastly questions were asked on the socio-economic factors. All data, including experimental and socio-economic variables were electronically collected using open data kit (ODK collect) with the aid of two smart android phones. In addition, the technology aids the recording of the GPS coordinates (latitude and longitude) of individual rice farmers. Notwithstanding, poor or absence of mobile networks in most villages visited prevented the direct records of the coordinates. Consequently, the locations (towns or villages) of each sampled farmer were manually recorded. This record was later used to obtain the coordinates from the website: http://www.mapcoordinates.net/en.

Rice farmers were assured about the confidentiality of the information supplied, that it is meant for research purpose only in line with the University of Reading ethical clearance obtained shortly before the field work. This was done by showing them a copy of the ethical clearance. In addition, each farmer which were met individually was informed about the voluntary nature of the survey and that he or she is free to withdraw from the experiment or survey at any time. Respondent mind was equally prepared on the need to use smart phones to record the information since most sampled farmers were never familiar with such technology for data collection. As noted above, subjects were presented first with the panel lotteries starting from panel one to panel four of SG1. The sequence follows the presentation of panels one to four of SG2, LG1, LG2, respectively, and series one to eight of the time experiment, respectively. This was done after brief instructions about the experiments as well as how to make choices. In addition, each subject is shown with a bag containing ten mixed blue and red balls which represent the winning and losing probability in the risk experiments and bag containing thirty two balls that indicates the number of rows in the time experiment. Overall, no respondent indicated interest in withdrawing from the experiments and survey. The experimental instructions are summarized next.

Instruction for Small gain one ($SG1$) *treatment*

After welcoming rice farmers with brief explanation on the importance of the survey, experiments and the likely impact of the study, instructions were read out to individual farmers as follows. The following four panels have ten options each, the winning prize or payoff in each panel is the amount of Naira shown under the heading “amount”. The blue balls represent the chances of winning with the ten blue balls imply hundred percent chances (sure) while one blue ball means ten percent chance of winning a payoff. Conversely, the red balls imply loss. You earn nothing if they do not win the lottery. Your earning would be determined by tossing a four-sided die. In other words, only one panel would be used for payment. That is, any of the number 1, 2, 3 or 4 which occurs from a toss of four-sided die determines the payment panel. For instance, if you choose option seven and one appears during die toss, you will win ₦563 if any of the balls 1, 2, 3 or 4 is drawn from the bag and nothing otherwise. Lastly, the record sheet was shown to farmers to make their choices which were recorded electronically.

Instruction for Small gain two ($SG2$) *treatment*

The following four panels have ten options each. The winning prize in each panel is the amount of Naira shown under the heading “amount”. The blue balls indicate the chances of winning; ten blue balls imply hundred percent chance (sure) while one blue ball means ten percent chance. Conversely, the red balls imply loss. If you do not win the lottery, you will earn nothing. Your earning would be determined by tossing a die. That is, only one panel would be used for payment. Any of the number 1, 2, 3 or 4 that occurs from a toss of four-sided die determines the payment panel. For instance, chosen option seven and one appears during die toss earn you ₦338 if any of the balls 1, 2, 3 or 4 is drawn from the bag. Otherwise you will earn nothing. Kindly choose one option from each of the four panels. Thus, the record sheet was given to farmer to make a choice which was recorded electronically.

Instruction for Large gain one ($LG1$) *treatment*

The following four panels have ten options each. The winning prize in each panel is the amount of Naira shown under the heading “amount”. The blue balls indicate the chances of winning; ten blue balls imply hundred percent chances (sure) while one blue ball means ten percent chance. Conversely, the red balls imply loss. You earn nothing if you do not win the lottery. Kindly choose one option from each of the four panels. Your earning would be determined by tossing a die. That is, only one panel would be used for payment. Any of the number 1, 2, 3 or 4 that occurs from a toss of 4-sided die determines the payment panel. For instance, chosen option seven and one appears during die toss earn you ₦56, 265 if any of the balls 1, 2, 3 or 4 is drawn from the bag. Otherwise you will earn nothing**.** Thus, subjects were asked to make a choice from the record sheet. Their choices were recorded electronically.

Instruction for Large gain two $(LG2)$ ***treatment***

The following four panels have ten options each. The winning prize in each panel is the amount of Naira shown under the heading "amount". The blue balls indicate the chances of winning; ten blue balls imply hundred percent chance (sure) while 1 blue ball means ten percent chance. Conversely, the red balls imply loss. If you do not win the lottery you will earn nothing. Kindly choose one option from each of the four panels. Your earning was determined by tossing a die. That is only one panel was used for payment. Any of the number 1, 2, 3 or 4 that occurs from a toss of 4-sided die determines the payment panel. For instance, chosen option seven and one appears during die toss earn you ₦33, 765 if any of the balls 1, 2, 3 or 4 is drawn from the bag. Otherwise you will earn nothing**.** Lastly, farmers were asked to choice one option from each panel while their choices were recorded electronically.

Instruction for the Time Experiment

After completing the risk task, rice farmers were presented with the time experiment. Subjects can choose only plan A and never switch to plan B or switch from plan A to plan B at row one implying choosing plan B throughout or switch at any other row from plan A to B. The game ends for each series when subjects switch from plan A to B. Subjects were informed that at the end of the experiment one ball would be drawn from a bag containing 32 balls (which represent the number of rows in the time choice task) to determine the winning row and the period of payment (present, proximate or future time). Lastly, after showing the record sheet to the rice farmers, they were asked to choose between plans A and plan B for each series.

3.3 Estimation Methods

The data collected were estimated using different analytical methods in line with the objectives and hypotheses of the study. For objective one, individual farmers' willingness to risk taking was inferred from the probability associated with their choices while the correlation between willingness to risk taking (probability index) and spatial lag as well as other socio-economic variables is modelled using spatial autoregressive model (SAR) which is estimated with instrumental variable (IV) method. Instrumental variable (IV) probit is used to examine the effect of willingness to risk taking on adoption decisions (objective two). For objective three, continuous exponential function is adopted to estimate the subjective discount rate while its correlation with spatial lag and other socio-economic variables is analysed using SAR which is estimated with IV method. Lastly, the objective four, effect of time preference on adoption decisions is analysed using IV probit.

3.3.1 Examining the Determinants of Risk and Time Preferences

As noted above, the probability associated with individual farmers' choices in the risk experiment is used to judge individual farmers' willingness to risk taking. Afterward, all the observations from the four choices, from each of the four treatments in the panel lotteries were summarized using principal component and cluster analyses. Thus, farmers were categorized into less risk avoidance and high-risk avoidance. The subjective discount rate for each rice farmers is calculated from the choices made in the time experiment using a continuous exponential function of Equation 3.5.

$$F = Pe^{rt}, r = \left[log\left({}^{F}/_{P}\right)\right]/t. \qquad (3.5)$$

Where F is the future payoff, P is the present payoff, t is the time horizon corresponding to the indifference or switching points revealed by rice farmers while r is the subjective discount rate. Thereafter, the determinants of risk and time preferences (effects of spatial dependence in risky and intertemporal decision-making) were analysed through SAR estimated using IV method. The spatial weights matrix used in the SAR is defined in the next session.

3.3.2 Spatial Weights Matrix

The distance between rice farmers is estimated from the recorded GPS coordinate points (latitude and longitude) using Haversian formula. This formula uses the sin and cosine as well as the radius of the earth in kilometre. This distance is used in the weights matrix which is defined using a power function of Equation (3.6). Distance based power weights matrix has many advantages. First, unlike the binary contiguity method, neighbours may have different weights. Second, more weights are attached to shorter distance implying the closer the neighbours the more the influence. In other words, the weights are closer to one when the main distance (d) is less than the cut-off distance (s) but tend towards zero when the distance is greater than the cut-off distance. More so, assuming equal number of neighbours may be inappropriate since the number of sampled farmers is not equal across all locations or agricultural zones.

In most cited studies, the weights matrix, $\boldsymbol{W}$ is often row-stochastic or row-standardized in which the addition of each row of the matrix equals one for easy interpretation. This is often achieved by first converting the diagonal elements of the weights matrix to zero. Afterward, the matrix with zero diagonal elements is divided by the vector matrix, the sum of each row. Thus, the final matrix, $\boldsymbol{W}$ corresponds to averaging the neighbouring values (see (Case, 1992; Holloway *et al.*, 2002; Läpple & Kelley, 2015). Row standardization may increase the influence of links between observations especially those with few neighbours. This practice is however more useful for contiguity binary weights matrix. In this study, only the diagonal elements of the weights matrix are set to zero to prevent each rice farmer from being a neighbour to herself.

$$\boldsymbol{W}_{ij} = exp\left(-{d_{ij}}^2/s^2\right) \tag{3.6}$$

Where d_{ij} is the distance between farmers in locations i and j, s is the cut-off distance that tests the dependency limit between individual observations (rice farmers). The cut-off distances tested to determine the limit of spatial dependence include 10 km, 20 km, 30 km, 40 km and 60 km. The results corresponding to the spatial dependence limit are reported in this study.

3.3.3 Spatial Autoregressive Model

The spatial autoregressive model (SAR hereafter) is estimated to examine the spatial dependence effects in rice farmers' risk and time preferences or choices. The SAR of Equation 3.7 is applied because this study is interested in examining the spatial correlation and not the correlation between errors. The rearrangement of Equation 3.7 results in the data generating process (DGP) of Equation 3.8.

$$y = \rho \boldsymbol{W} y + \boldsymbol{X}\beta + \varepsilon \tag{3.7}$$

$$y = (I - \rho \boldsymbol{W})^{-1}\boldsymbol{X}\beta + (I - \rho \boldsymbol{W})^{-1}\varepsilon \tag{3.8}$$

Where: y is the $N\ X\ 1$ vector of probability index which measures willingness to risk taking (in the case of risk experiment) or subjective discount rate which measures time preferences (in the case of time experiment), ρ is a spatial dependence parameter to be estimated, which measures the correlation between a rice farmer's risk preferences and his neighbours' or rice farmer's time preference and his neighbours', $\boldsymbol{W}y$ is the $N\ X\ 1$ spatial lag vector corresponding to y. This reflects an average of willingness to risk taking index or subjective discount rate from neighbouring regions defined by the weights matrix, $\boldsymbol{W}$. $\boldsymbol{X}$ is the $N\ X\ K$ matrix of exogenous socio-economic variables that may explain risk and time preferences, β is $K\ X\ 1$ parameter associated with $\boldsymbol{X}$, I is an identity matrix with $N\ X\ N$ dimension. ε is the $N\ X\ 1$ error term which is assumed to be independently and identically distributed (*iid*).

Interpreting Spatial Lag

Expansion of $(I-\rho\boldsymbol{W})^{-1}$ from the DGP of (3.8) gives Equation 3.9.

$$(I-\rho\boldsymbol{W})^{-1} = I + \rho\boldsymbol{W} + \rho^2\boldsymbol{W}^2 + \rho^3\boldsymbol{W}^3 + \cdots \quad (3.9)$$

Substituting 3.8 into 3.7 gives 3.9. The DGP can therefore be expressed as:

$$y = \boldsymbol{X}\beta + \rho\boldsymbol{W}\boldsymbol{X}\beta + \rho^2\boldsymbol{W}^2\boldsymbol{X}\beta + \cdots + \varepsilon + \rho\boldsymbol{W}\varepsilon + \rho^2\boldsymbol{W}^2\epsilon + \rho^3\boldsymbol{W}^3\varepsilon + \cdots \quad (3.10)$$

Equation 3.10 suggests that ignoring spatial dependence in modelling the determinants of risk and time preferences may result in biased estimates. Equation 3.10 may be interpreted as follows: the expected value of each rice farmer observation (willingness to risk taking in risk experiments and subjective discount rate for time experiment) depends on the average value, $\boldsymbol{X}\beta$ plus the combination of neighbouring values scaled by the parameter measuring the spatial dependence, ρ. In other words, rice farmer's decision is a function of their socio-economic characteristics ($\boldsymbol{X}$), neighbours' characteristics, $\boldsymbol{W}\boldsymbol{X}$, neighbours' neighbours' characteristics, $\boldsymbol{W}^2\boldsymbol{X}$ and so on, with the neighbourhood influence or effect reducing with distance (Case, 1992).

The equilibrium effects suggest average total effect or total impact equals average direct effect $\left(\frac{\partial y_i}{\partial x_i}\right)$ plus average indirect effect $\left(\sum_{i=2}^{n}\frac{\partial y_i}{\partial x_i}\right)$. The average direct effect summarises the impact measure arising from the changes in the *i*th observation of observed socio-economic variables, $\boldsymbol{X}$. There are two possible interpretations (LeSage, 2008). First, it measures the average total impact on the willingness to risk taking or subjective discount rates of the farmers in *i* location? if all rice farmers in all the locations increase for example, their level of education. Second, it measures the total cumulative impact arising from a farmer in location *j* raising his level of education, for example, and the effect of this on the willingness to risk taking or subjective discount rates of all other farmers (on average). Put differently, the willingness to risk taking of a farmer in location, *i* is not only affected by the marginal change in the socio-economic variable, for instance the educational level of a farmer in that location but also by the marginal changes in the socio-economic factor in other location, *j*.

Data relating to risky and intertemporal decisions among rice farmers are random and may be correlated suggesting the possibility of spatial dependence. Therefore, on one hand, this study examines the correlation between rice farmers' willingness to risk taking and adjusted by distance willingness to risk taking. On the other hand, it examines the correlation between the subjective discount rate and adjusted by distance subjective discount rate. This prompted the application of the conventional *spatial lag* or SAR model. Considering the first-order SAR of Equation 3.7, the OLS may yield a biased estimate for two reasons. First, the presence of $(I-\rho\boldsymbol{W})^{-1}$ in the DGP of the SAR suggests that the error term is not homoscedastic or constant. Second, SAR model is not linear in parameter because of the presence of rho, ρ. The OLS parameter or marginal effect is β while the SAR parameter or marginal effect is $\beta(I-\rho\boldsymbol{W})^{-1}$ (Kim *et al.*, 2003).

The above limitations motivated the proposal of different alternative methods that could yield consistent estimates. These, among others include maximum likelihood estimation (MLE) method (Ord, 1975), instrumental variables, IV (Anselin, 1988b), IV and two stage least squares, TSLS (Kelejian & Robinson, 1993; Kelejian & Prucha, 1998), generalized method of moments, GMM (Kelejian & Prucha, 1999), Bayesian Markov Chain Monte Carlo (LeSage, 1997) and Quasi-Maximum Likelihood, QML (Lee, 2004). The modelling approaches differ by the assumptions made about the disturbance error, for example, unlike MLE which relies on the normality of the disturbance error, IV/GMM, QML assumes that the error term is *iid*, which itself is a limitation (Elhorst, 2014, pp. 17-20). However, some studies have argued and demonstrated the relevance of IV and GMM for having the potential to provide consistent estimate when SAR has at least one endogenous explanatory variable in addition to the spatial lag see (Fingleton & Le Gallo, 2007; Fingleton & Le Gallo, 2008; Drukker, Egger, & Prucha, 2013; Liu & Lee, 2013). Unlike OLS, IV/TSLS does not rely on zero conditional mean suggesting the estimates of IV/TSLS may not be biased. Given this advantage, this study applies instrumental variable estimation method presented in the next session.

3.3.4 Instrumental Variable: A Latent Variable Model

Given the potential endogeneity problem associated with the spatial lag variable in the SAR, an instrumental variable (IV) estimation method is used to examine the spatial dependence effects in willingness to risk taking and subjective discount rate. For single-Equation linear model, the use of IV is motivated when at least one explanatory variable is endogenous while others are exogenous. The potential sources of endogeneity in this study include omission of variables that may explain farmers' attitudes to risk and time as well as the potential measurement error from the risk and time variables. For example, some climatic and socio-economic factors may not be directly observed yet such variables may be correlated with the risk and time preferences of rice farmers.

As earlier noted, OLS is likely to yield inconsistent estimate when the spatial lag variable ($\boldsymbol{W}y$) is endogenous. Spatial model is required when the correlation between endogenous variable (spatial lag in this study) and error term is due to unobservable. In Equation (3.11), the endogenous explanatory variable, the spatial lag ($\boldsymbol{W}y$) may be correlated not only with respective probability index or subjective discount rates, y but also with the disturbance term, ε, suggesting an instrument, $\boldsymbol{Z}$ is needed to obtain the exogenous variation in $\boldsymbol{W}y$. This instrumental variable must have a direct relationship with the endogenous variable, the spatial lag but not with the dependent variable, y. An instrument, $\boldsymbol{Z}$ may be indirectly correlated with y through $\boldsymbol{W}y$ suggesting an instrumental variable must has a direct association with spatial lag but not with the error term. Put differently, an observable variable or an instrumental variable, $\boldsymbol{Z}$ must meet two conditions: First, an instrument, $\boldsymbol{Z}$ must be exogenous (valid); must not be correlated with the error, ε. Mathematically, $Cov(\boldsymbol{Z}, \varepsilon) = 0$. Second, an instrument, $\boldsymbol{Z}$ must be correlated with the endogenous explanatory variable (an instrument must be relevant), $\boldsymbol{W}y$**.** That is, $Cov(\boldsymbol{Z}, \boldsymbol{W}y) \neq 0$.

$$y = \rho \boldsymbol{W}y + \varepsilon \tag{3.11}$$

The first two conditions are necessary for consistent estimate of the IV model. At times, justification is required on the satisfaction of the first condition, notwithstanding, statistical tests are available to examine the satisfaction of both conditions. For multiple regression with multiple instruments, as in this study, the order condition for identification requires that the number of instruments must equal or greater than the number of explanatory variables in order to satisfy the above two conditions. The conventional estimation method is in two stages. However, there might be computational problem with two-stage estimation method. Therefore, in this study, the econometric software, R is applied to simultaneously estimate IV model. Simultaneous estimation is also noted to produce similar estimator to two-stage least squares when there is only one instrument for an endogenous explanatory variable (Wooldridge, 2002).

Instrumental variable (IV) method is adopted to address the potential endogeneity problem associated with the spatially lag dependent variable of the risk and time models. This raises the question, what should be instruments? The exogenous socio-economic variables and instruments may share the same properties in the multiple regression model of SAR. In other words, where exogenous explanatory variables are uncorrelated with the error term such variables could be used as instruments because they satisfy the two conditions for suitable instruments. In line with this, Anselin (2001) suggests that the choice of an instrument for the spatial lag model depends on the conditional expectation of Equation (3.8). Accordingly, $\boldsymbol{W}y$ is an endogenous covariate, $\boldsymbol{X}$ are set of exogenous variables and instruments while spatial lags of the exogenous variables ($\boldsymbol{WX}$) are set of instruments. The assumption is that only the spatial lag may be correlated with the error term. Let $\boldsymbol{Z}$ represents set of instruments ($\boldsymbol{X}, \boldsymbol{WX}$) which are assumed to be correlated with the spatial lags and $\boldsymbol{P}$ represents the endogenous variable ($\boldsymbol{Wy}$)) plus other exogenous variables. Identification is achieved with $\boldsymbol{Z}$ and $\boldsymbol{P}$ having the same column rank (just-identified) resulting in IV estimator of Equation 3.12. In this study, other variables in the risk and time models, apart from the spatial lags are assumed exogenous and therefore used as instruments plus the lag of education variable which assists in achieving exact identification.

$$\hat{\beta}_{IV} = (\boldsymbol{Z}'\boldsymbol{P})^{-1}\boldsymbol{Z}'y \qquad (3.12)$$

There different tests are often carried out with respect to the relevance of the instruments, endogeneity of the explanatory variable and validity of the instrument. These tests were examined in this study. The test of instrument relevance involves examining the significant of the Wald statistic (F test of restriction). This is often reported by the R software. However, this statistic can be computed manually in two-stage estimation; first, by running the endogenous variable against all exogenous variables plus the instruments, and second by running the endogenous variable against only the exogenous variables. The Wu-Hausman test, a test of restriction is adopted to test for the endogeneity of the spatial lag. This is also reported by the R software but may be manually estimated, first, by running the dependent variable (risk and time) against all variables plus the residuals from the first stage model, second, the dependent variable should be run against all exogenous variable excluding the instruments. This test is important because IV/TSLS may produce estimates with larger standard errors if an explanatory variable is not endogenous, thus OLS may yield consistent estimates. The third test (validity of instrument), called Sargan test which has Chi-square distribution is equally reported by the R. This test may be manually computed by running the residuals from the second stage against all variables in addition to the instruments. This also tests for over-identification restriction. Therefore, it is not reported for a model that is exactly identified.

3.3.5. Modelling Rice Farmers' Adoption Decisions

Due to the difficulty in obtaining the farm size allocated to HYV as well as unavailability of time series data, rice farmer's decision to adopt HYV is expressed in the framework of a discrete choice model. The decision of rice farmers to adopt HYV depends on farm and farmer specific characteristics, farmers' perceptions of technology attributes, risk and time preferences and institutional/community factors. Assuming A represents the decision to adopt HYV then A takes the value of 1 if a rice farmer grow HYV, and 0 otherwise. Therefore Equation 3.13 applies:

$$Prob\ (\mathrm{A} = 1|\boldsymbol{X}) = \Phi(\boldsymbol{X}, \beta),\ Prob\ (\mathrm{A} = 0|\boldsymbol{X}) = 1 - \Phi(\boldsymbol{X}, \beta) \qquad (3.13)$$

Where Prob $(.)$ is a probability function, $\boldsymbol{X}$ represents $N\ X\ K$ matrix of the explanatory variables that may explain rice farmers' decisions to adopt HYV. β is $K\ X$ 1 vector of parameters to be estimated. β measures the impact of changes in the explanatory variable, $\boldsymbol{X}$ on the probability of adoption while $\Phi(\boldsymbol{X}, \beta)$ is the cumulative distribution function. The specification of Equation 3.13 depends on the assumption of the distribution of the disturbance term, a normally distributed error term resulting in a probit model. The model is not linear suggesting the effect of the explanatory variables should be measured in terms of marginal effects which reflect a change in the probability of A attributable to a unit change in the explanatory variable ($\boldsymbol{X}$). The marginal effects may be estimated at mean of an explanatory variable or at average of all variables. For continuous variable, Marginal Effect (ME) at mean of all explanatory variable is given by Equation 3.14.

$$ME = \frac{\partial \mathrm{Prob}(A=1/X)}{\partial X} = \frac{\partial E(A/x_i)}{\partial x_i} = \Phi(X_i'\beta)\beta \qquad (3.14)$$

Where x_i represents specific explanatory variables in the adoption model, Φ is the standard normal density function. It is usually argued that the Average Marginal Effect

(AME) is better relative to the marginal effect computed at mean due largely to the fact that APE considers the average value of all observations or explanatory variables. For continuous variable, the AME is computed as shown in Equation 3.15.

$$AME = E_z\left[\frac{\partial E[\mathrm{A}/X]}{\partial X}\right] = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial Pr(A=1/x_1 \ldots x)}{\partial x_j} = \frac{1}{N}\sum_{i=1}^{N}\Phi(X_i'\beta)\beta \qquad (3.15)$$

There is also a contentious issue that the marginal effect for dummy variable may not be accurate if estimated at mean. Thus, for a dummy variable, marginal effect could be evaluated using Equation 3.16.

$$\Delta d = Pr\left[\mathrm{A} = 1/\bar{x}_{(d)}, d = 1\right] - Pr\left[\mathrm{A} = 1/\bar{x}_{(d)}, d = 0\right] \qquad (3.16)$$

Where $\bar{x}_{(d)}$is the means of all the other explanatory variables in the model. Green (2007), however noted that marginal effects are approximately equal when dummy variables are treated as continuous variables.

The parameter of the probit model (maximum likelihood estimator) is obtained by maximizing the log likelihood function. Thus probit model is a class of likelihood estimation method (MLE). The assumption of independent and identically distributed (*iid*) errors motivates the probit likelihood function defined in Equation 3.17.

$$L(\beta, A, X) = \sum_{i=1}^{N}[\Phi(X_i\beta)]^{A_i}[1 - \Phi(X_i\beta)]^{1-A_i} \qquad (3.17)$$

Due to the advantage of log-linearization, log-likelihood is always preferred. Thus, the log-likelihood function is specified in Equation 3.18. In most econometric software, the maximum log-likelihood is usually reported with the number of iterations taken for convergence. The two similar models with equal numbers of variables, the lower the log-likelihood the better the goodness of fit. Another measure of goodness of fit is the Pseudo R^2, $Pseudo\ R^2 = 1 - \frac{loglikelihood\ of\ model\ containing\ intercept}{loglikelihood\ of\ model\ without\ intercept}$. Like in OLS, the Pseudo R^2 credited to McFadden ranges between zero and one the higher the Pseudo R^2 the better the model.

$$\ln(\beta, A, X) = \sum_{i=1}^{N}\left[A_i ln\big(\Phi(X_i\beta)\big) + (1 - A_i) ln\big(1 - \Phi(X_i\beta)\big)\right] \qquad (3.18)$$

3.3.6 Probit Model with a Continuous Endogenous Covariate

Giving that a binary probit specified above may not yield a consistent estimate when at least one variable is endogenous, instrumental variable (IV) probit is applied in this study to solve this endogeneity problem, although the binary probit results are presented for comparison. That is, IV probit is adopted to test the endogeneity of risk and time preferences in the adoption decisions. The sources of endogeneity in this study may include measurement errors, omission of important variables that may explain adoption decisions as well as the simultaneity nature of the Equations. In other words, the risk and time variables may not be accurately measured yet some important variables such as environmental and socio-economic factors may not be accounted for in the adoption model. Ignoring such issues may lead to biased estimates and inference. Therefore, this study uses the spatial lags of the willingness to risk taking and subjective discount rate as instruments to represent the unobserved or latent variables in the adoption model. The modelling and estimation methods are adapted from the econometric text (Wooldridge, 2002).

$$y = \boldsymbol{Z}\delta_2 + \nu_2 \qquad (3.19)$$

$$A^* = \boldsymbol{X}\delta_1 + \alpha_1 y + \mu_1, \qquad (A = 1 \; if \; A^* > 0\,) \qquad (3.20)$$

Where A^* is as defined in Equation 3.13. y is the willingness to risk taking or subjective discount rate, $\mathbf{Z}$ is the spatial lags of y. $\delta_1 and\ \delta_2$ are the structural and reduced form parameters of Equations 3.19 and 3.20, respectively, α_1 is the parameter associated with the predicted value of y. The error terms $(\nu_2,\ \mu_1)$ are assumed to have a joint normality with zero mean and independent of $\boldsymbol{Z}$. Note that Equation 3.19 is the structural Equation while 3.20 is the reduced form for y. Independency between the two error terms suggests there is no endogeneity problem. In other words, correlation between the two error terms implies y is endogenous or there is an endogeneity problem. Therefore, Equation 3.20 is useful if y is correlated with μ_1 due to the omission of important variables or measurement errors which may be the case in the risk and time variables. ν_2 is assumed to be normally distributed suggesting y must be a continuous variable or at least has features of a continuous random variable (Wooldridge, 2002). This is the case in the risk and time variables which range from 0.1 to 1.0 and from 0.22 to 0.69, respectively. Since the error terms are jointly normally distributed, that is, the variance of μ_1 must equate to one. It follows that the error term of Equation 3.18 could be expressed as a linear function of the error term of Equation 3.19.

$$\mu_1 = \vartheta_1 \nu_2 + \varepsilon_1 \qquad (3.21)$$

Where $\vartheta_1 = cov(\nu_2, \mu_1)/var(\nu_2)$, ε_1 is independent of **Z**, ν_2 and y. The joint normal assumption for the errors suggests that ε_1 is normally distributed ($\varepsilon_1 \sim N(0, 1 - \rho^2)$. The rho ($\rho$) measures the correlation between the two errors ($\rho = corr\ (\nu_2, \mu_1)$).

Substituting 3.21 into 3.20 gives 3.22:

$$A^* = \boldsymbol{X}\delta_1 + \alpha_1 y + \vartheta_1 \nu_2 + \varepsilon_1 \qquad (3.22)$$

It suggests $\varepsilon_1\ /\boldsymbol{X}, y, \nu_2 \sim N(0, 1 - \rho^2)$. Since the distribution of the error determines the distribution of the model, a normally distributed error term gives rise to the standard normal distribution as in Equation 3.23:

$$P(A = 1/\ \boldsymbol{X}, y, \nu_2) = \Phi\left[(\boldsymbol{X}\delta_1 + \alpha_1 y + \vartheta_1 \nu_2)/(1 - \rho^2)^{1/2}\right] \qquad (3.23)$$

The conventional estimation method is two-stage, but it is often argued that the maximum likelihood estimation (MLE) method has some advantages over two-stage estimation method. It does not only produce efficient estimates, parameters of Equation 3.20 can be directly obtained; it also allows easy test for endogeneity of y which represents risk preference and time preference in this study by hypothesizing that $\rho = 0$ (Wooldridge, 2002). However, MLE is computationally demanding due to converging problem. Notwithstanding, given its advantages, MLE is adopted in this study. Thus, Equation 3.22 is estimated to identify the determinants of rice farmers' HYV adoption decisions. In the context of omitted variable, measurement error and simultaneity, the normalization assumption (variance of $\mu_1$equals one) gives the parameters of Equation 3.19 an average partial effect. In this study, Equations 3.19 to 3.23 are general specifications. The specific models relating to risk preference and adoption, and time preference and adoption are detailed in Section 5.2.3 of **Chapter Five** and Section 6.2.3 of **Chapter Six**, respectively.

3.3.7 Summary

This chapter highlighted the merits and demerits of the different methods previously applied in the literature. Since no method is free of limitation, justifications are provided on the adopted approaches. Specifically, rice farmers' risk and time preferences are elicited using panel lotteries and front-end delay methods, respectively. In addition, since OLS may yield inconsistent estimates for spatially lagged variable, the study employs IV method to examine the correlation between rice farmers' risk preferences and time preferences as well as his neighbours' decisions. Thus, separate models were estimated for the risk and time. Lastly, the potential endogeneity problem in the simultaneity adoption models in addition to addressing the omitted variable bias as well as the potential measurement errors in the risk and time variables prompt the applications of IV probit. The specific model is detailed under data and model in chapters five and six due to the spatial lags involved.

Chapter Four

4.0 Data Description

The experimental as well as the survey data collected in this study are summarized in this chapter. The experimental and survey procedures are presented in **Chapter Three**. This chapter begins with the description of rice farmers by neighbours, distance and locations. The description of the socio-economic and demographic characteristics of rice farmers is presented next. This is followed by the description of the farmers' risk and time preferences. Lastly, the results from the test of significant difference between some selected socio-economic variables across adoption groups are reported.

4.1 Rice Farmers' Neighbours by Distance and Agricultural Zones

The description of the rice farmers' neighbours by distance is presented in **Table 5.** The maximum distance covered during the survey is 143.83 km resulting in an average distance of 51.34 km. On average, about 35.3 percent of the sampled rice farmers have 116 neighbours and live within 20 km radius, about 63.6 percent of the sample have 209 neighbours and live within 40 km radius while 71.2 percent of the total sample have 234 neighbours and live within 60 km radius. This constitutes the limit of spatial dependence.

Table 5: Rice Farmers' Neighbours by Distance

Distance range (km)	No. of Neighbours	Percentage	Cumulative Percentage
0-20	116	35.30	-
20.1-40	93	28.30	63.60
40.1-60	25	7.60	71.20
60.1-80	7	2.10	73.30
100.1-120	45	13.70	87.00
140.1-160	43	13.10	100.00

Source: Data Analysis, 2017

Table 6 presents the relationship between the locations of rice farmers as well as the distance covered. In terms of agricultural zones, Ilaro, located in the far eastern part of Ogun State is the starting point. Therefore, an average distance of 5.91 km was covered in this location with 19 percent of the sample collected in this zone. The average distances discovered in Abeokuta, Ikenne and Ijebu-ode zones are 20.46, 40.72 and

126.30 respectively. These three zones constitute 28 percent, 26 percent and 27 percent of the total sample, respectively. When adjusted by distance in non-standardized weights matrix with a cut-off distance of 60 km (limit of spatial dependence), the mean adjusted by distance attitudes for SG1, SG2, LG1, LG2 and subjective discount rate are 144.09, 115.90, 133.66, 108.12 and 89.38 respectively.

Table 6: Rice Farmers by Distance and Agricultural Zones

ADP Zones	Mean	SD	Min	Max	Percent of Total Sample
Ilaro	5.91	4.88	0	22.05	19
Abeokuta	20.46	7.25	9.71	58.32	28
Ikenne	40.72	9.76	33.44	65.26	26
Ijebu-Ode	126.30	17.46	105.47	143.83	27
***Farmers Attitudes adjusted by distance (Cut-off distance = 60 km)**					
SG1	144.09		64.12	179.96	
SG2	115.90		48.92	146.06	
LG1	133.66		57.12	168.14	
LG2	108.12		43.41	137.13	
Discount rate	89.38		39.73	111.55	

Note: Distance is in km, SD = standard deviation, Min = minimum, Max = maximum
*= risk and time variables multiply by the weights matrix
Source: Data Analysis, 2017

4.2 Socio-demographic Characteristics of Rice Farmers

The description of rice farmers' socio-demographic variables is presented in **Table 7**. Age is one of the important human capital factors that determine individual productivity in most economic activities. Age is equally an important variable in farming or crop production. It determines the agility of farmers especially in the developing world where farming activities are drudgery in nature. The mean age of 46.96 years (median equals 46 years) indicates most of the sampled rice farmers are still in their active age. In addition, about 69 percent of the sampled farmers were less than 54 years suggesting this relatively youthful age may reflect the reality that rice production requires a lot of agility. Besides, it connotes farming enterprise is not attractive to older population. This result shares similarity with that reported for the national household data where about 52 percent and 84 percent of rural household heads are less than 45 years and 60 years, respectively (Akerele, 2013, p. 101).

High literacy rate or level of education is important in farming decision making. The statistic shows that 35.9 percent of the sampled rice farmers had no formal education. The mean schooling year among sampled farmers is 4.63 (median equals 6) implying 5 years of formal primary education or less than primary education. Indeed, majority (36 percent) of the sampled rice farmers have no formal education. This figure is very close to that reported by Akerele (2013, p. 101) for the national data that about 54 percent and 28 percent respectively for rural and urban household heads have no formal education. Indeed, urban dwellers have more access to education compared to rural dwellers. Education is a key requirement not only for information access but also for processing the acquired information. In fact, low educational level may suggest low access to information on the important farming techniques. Therefore, low educational level may affect farmers' preferences toward risk and time and subsequently adoption decisions.

Gender is a principal issue in crop production especially in the developing countries where both males and females are actively involved in farming activities or operations. Majority of the sampled farmers are male (67.5 percent), the relatively high proportion (32.5 percent) of sampled female farmers is an indication that both genders are fully involved in rice production in the study area. The gender disaggregation of the selected rice farmers is further depicted in **Figure 5**. This figure is a bit difference to the previously reported statistics where about 88 percent and 82 percent respectively of the national rural and urban households are males (Akerele, 2013). Generally, males engage in farming than females in the developing countries. The observed variation in this study may however be attributed to the fact that even though women assist their husbands in planting and post planting activities, most women cultivate separate parcels of land to rice production, although males cultivate more lands than females. The explanation may also be viewed from the profitable nature of the rice enterprise which motivates women towards cultivating their separate parcels of land.

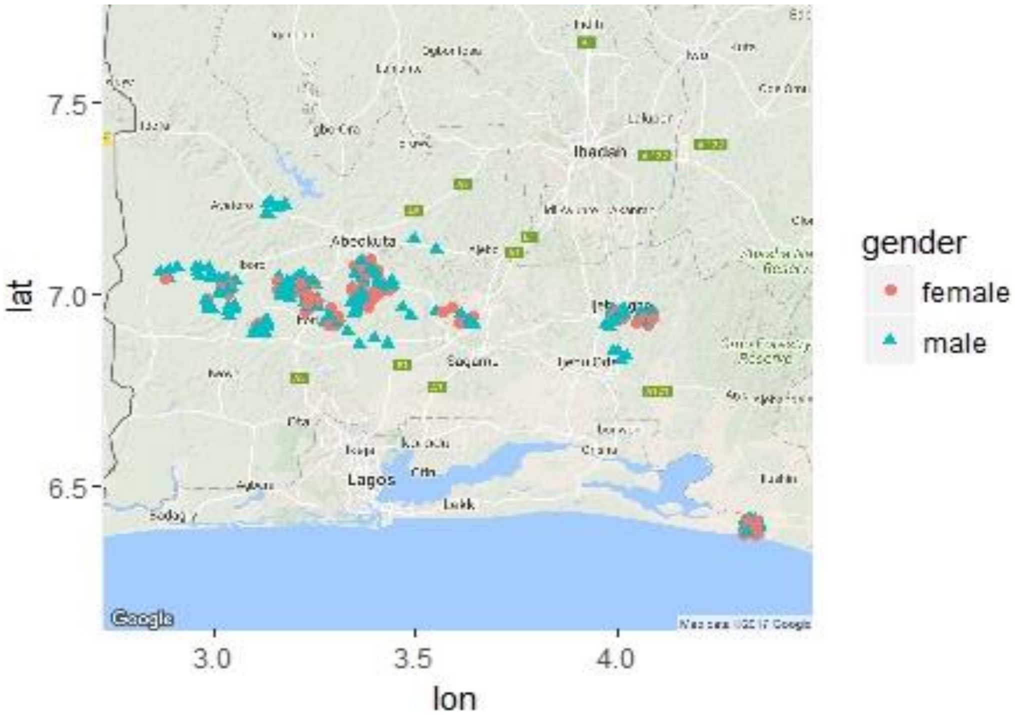

Figure 5: Distribution of Sampled Rice Farmers across Gender
Source: Data Analysis, 2017

The average family size of the sampled rice farmers is 6 persons (with a median of 6). About 65 percent of the sample have between 1 and 6 members. This agrees with Akerele (2013) who reported that about 91 percent of the nationally aggregated data have between 1 and 6 adult equivalent household members. This may imply availability of family labour for a highly labour-intensive farm enterprise like rice production. Some farmers do rely on their children especially during the holidays and weekends for bird scaring since birds constitute the major constraint to rice production and output other farmers however hire labour for rice farming while allowing their children to attend schools mostly in the neighbourhood towns.

Religion may influence farming and investment decisions. For instance, pigs are sacred in Islam thus those practicing this religion are not usually rear this animal. Since religion relates to beliefs, it may affect farmers' perception and subsequently preferences. It may also have an indirect effect on crop production or farming decisions when politically motivated. The survey shows that 55.6 percent of the sampled rice farmers practice Christian religion. This result aligns with 47 percent and 54 percent reported for household rural and urban nationally aggregated data, respectively (Akerele, 2013). The statistic of the marital status indicates that the majority (93.9 percent) of the sampled rice farmers are married suggesting additional responsibility or commitment. Also, this statistic agrees with 77 percent and 76 percent reported for rural and urban nationally aggregated data, respectively (Akerele, 2013). On one hand, being married may imply availability of family labour for rice production. On the other hand, it may suggest huge financial commitment for the family up keep and thus driving forces for increased farm size. It may also be a push factor for risky decision making.

On average, the sampled rice farmers have spent 24 years (median equals 22) farming but 20 years (with a median of 20) in rice production. This suggests that most sampled rice farmers have a cognate experience in farming. Experience is a key variable in most economic activities including farming. Farmers may learn by doing. Experience is important for decision making relating to input and output allocation and consumption. Experience may also constitute a key driver for risky decision making. More experienced farmers may produce more output per unit area relative to less experienced farmers. On the awareness or knowledge about improved rice technologies or varieties, 49 percent of the sampled rice farmers claimed they were not knowledgeable about improved rice varieties or HYV. This may be a consequence of farmers' location as majority of the sampled rice farmers live in remove locations or villages. However, this response may be arbitrary since most farmers obtained information from various sources including friends, family, neighbours, community news, cooperative associations and extension agents. Nineteen percent (19 percent) of those who claimed they were aware of improved rice varieties or 9 percent of the total sample grows HYV. The HYV grown is locally called "Agric" or "Aroso". Thus, not knowing the English name of the improved seeds corroborates the level of awareness of the sampled farmers.

In terms of farm size, an average of 1.93 hectares is cultivated to rice, out of which about 98 percent is devoted to local rice varieties. This agrees with [19]FAO which reported that an average household in Nigeria cultivate 1.8 hectares of land. The rice farm size was divided into percentile (the first percentile ranges between 0.1 and 1.6 hectares while the second percentiles ranged from 1.61 to 16 hectares). In fact, "Ofada" rice dominates (90.6 percent) the local rice grown in the study area while only 13 percent of the sampled rice farmers grow Ode-Omi rice.

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[19] This information is sourced from Nigeria at a Glance, Food and Agriculture Organisation of the United Nations. Available at: http://www.fao.org/nigeria/fao-in-nigeria/nigeria-at-a-glance/en/. Sourced on: 04/12/2017.

Table 7: Socio-demographic Characteristics of Rice Farmers

Variables	Unit	Mean/ Proportion	Median	Standard deviation	Min	Max
Age	Year	46.96	46.00	12.50	20	80
Education	Year	4.63	6.00	4.47	0	16
Male	Percent	67.5				
Household size	Number	6.00	6.00	2.99	1	21
Christians	Percent	55.6				
Married	Percent	93.9				
Farm experience (total)	Year	24.35	22.00	12.32	3	63
Farm experience (rice)	Year	20.11	20.00	12.52	1	60
Growing HYV	Percent	09				
Growing Ofada	Percent	90.6				
Growing Ode-Omi	Percent	13				
Rice farm size	Hectare	1.93	1.60	1.51	0.20	16
Other economic activities*	Yes	100				
-Trading	Yes	24				
-Other activities	Yes	21.9				
Grow others crops*	Yes	98.8				
Cropping per year*	Once	97				
Upland alone*	Yes	86.6				
Lowland alone*	Yes	11.6				
Inherited land*	Yes	55				
Rented land*	Yes	80.5				
Family labour*	Yes	98				
Hired labour*	Yes	96				
Family labour $\geq$ 18 years	Number	1.84				
Labour constraint	Yes	76.6				
Used Fertilizer	No	84.2				

*implies multiple response questions

Source: Data Analysis, 2017

As shown in **Table 7**, all the sampled rice farmers engaged in at least one off-farm income generating activities, most of whom were involved in a combination of economic activities ranging from trading, artisanship, and transportation to civil or public service. Farmers who generated income from trading alone constitute about 24 percent of the sample size. Additionally, about 22 percent of the sampled rice farmers' source livelihood from other economic activities including hunting, food (cassava) processing, pepper grinding, ministering (pastoring), livestock production, land selling, security, block making and bamboo making and suppling. In addition, majority (98.8 percent) of the rice farmers diversify their crop production with most of them growing cassava (94 percent), maize (95 percent), yam (39 percent) and vegetables (86 percent).

A substantial proportion (97 percent) of the rice farmers planted rice once in a year. The reason for this may be attributed to lack of irrigation giving the fact that majority (86.6 percent) of the rice farmers engage in upland rice production system while only 11.6 percent engaged in lowland rice production.

Land is a key factor in crop production especially in the developing countries like Nigeria where modern technologies like green house, tissue culture (currently used for banana cultivation in Israel), aquaponics (currently used for vegetables and rice production in Thailand) are lacking. The study reveals that most rice farmers accessed land from diverse sources. Considering the land tenure system in Nigeria, it is not surprising that majority (55 percent) relied on inherited land for farming or rice production. However, the sizeable proportion (80.5 percent) rented land for farming. Information from the survey also indicates that majority of rice farmers who rented land for farming are foreigners, mostly Republic of Benin and Togo descendants. Inherently, rice is a cultural crop for these farmers, majority of whom claimed they learned how to grow rice since childhood from their parents.

Labour is a very important factor in rice production especially in a developing country like Nigeria where most farmers rely on the crude method for rice production such as chasing birds using stores and cater port. This partly explains the reason why a combination of family (98 percent) and hired (96 percent) labour is used for rice production in the study area. It also suggests the use of children under 18 years for rice farming. However, majority (46.2 percent) of the respondents claimed they have no family labour below 18 years while 43.2 percent have just one family labour above this age. This is an indication of labour shortage for rice farming in the study area. Little wonder that majority (76.6 percent) claimed they are labour constrained and lack access to fertilizer (84.2 percent).

4.3 Perceptions about High Yield Rice Varieties' Attributes

Rice farmers were asked some perceptual questions relating to the improved rice technology attributes presented in **Table 8**. These attributes were explained to all the farmers in the local language to ensure farmers understand the meaning as well as the implications of each attribute before revealing their preferences. Moreover, farmers were presented with record sheets which visualise these attributes on Likert scale. All respondents or sampled rice farmers perceived the seven attributes of improved rice varieties in highly comparable way. Almost half (48.3 percent and 41.6 percent) of the sampled rice farmers respectively, ranked high yield and better taste as extremely important. Similarly, long stem, short duration, good tiller, large grain and good grain colour were ranked as very important attributes. These results suggest that rice farmers are deeply concerned about high yield and better taste. Farmers' adoption decisions may therefore reflect these important traits or attributes of improved rice varieties.

Table 8: Perceptions about Improved Rice Technology Attributes

Variable	Mean	S. D	Min	Max
High yield	4.23	0.97	1	5
Long stem	3.55	1.11	1	5
Short duration	3.78	1.14	1	5
Good tiller	3.42	1.09	1	5
Large grain	3.48	1.11	1	5
Grain colour	3.43	1.14	1	5
Better taste	4.10	0.91	1	5

Note: perception questions range from not at all important (1), somewhat important (2), important (3), very important (4) and extremely important (5)

Source: Data Analysis, 2017

4.4. Institutional and Community Factors

Institutional and community related factors may influence rice farmers' adoption decisions. The description of some of the institutional and community variables is presented in **Table 9.** The key institution factor that may has direct impact on farmers' farm decisions is access to information. Information may increase awareness about the cost and benefits associated with improved farm techniques. The results reveal that most (67.5 percent) of the sampled rice farmers source information from their friends and neighbours suggesting low source of formal information on improved rice technology in the study area. This is reflected in the access to extension service as about average (50.8 percent) of the sampled farmers claimed they never had contact with extension agents within a year. More so, about 29.8 percent of the sampled rice farmers have contact with extension agents irregularly (mostly once in a year). Indeed, the mean, minimum and maximum number of extension contact per annum are 2.36, 0 and 7.00 respectively. The statistics also show that most (78.3 percent) of the rice farmers do not belong to a cooperative society. Being a member of a cooperative society may offer saving and borrowing opportunities for farmers. This suggests that not being a member may impact negatively on their investment or adoption decisions. In contrary, about 54 percent of the farmers belong to one or more social clubs. This may have positive effect on their social lives yet it may reduce their investment capital or tendency since social clubs require huge financial contributions or commitments, most of which are used for parties. Although many studies have argued about the important of social networks in adoption decisions because membership of community association may increase information access.

Most of the sampled farmers (99.7 percent) depend on personal savings for farming while only 29.8 percent rely on friends and relatives. This implies that the majority of the sampled rice farmers do not receive financial support from formal institutions. Moreover, almost all (99.1 percent) the sampled rice farmers process local rice seeds and store for replanting while about 13.7 percent of the adopters of HYV self-processed seeds for re-planting. Rice farmers were also asked to identify the constraints to HYV seed access. While information/awareness was ranked first (78.1 percent), other factors like availability of seeds (26.1 percent), fair of yield uncertainty (17.3 percent), unwillingness to take risky decisions (40.4 percent), interest (64.7 percent) and other factors (31 percent) including the problems of birds attack, low access to market, consumer preferences and strong attachment to traditional varieties were the main identified factors.

Table 9: Institutional and Community Factors Affecting Adoption of HYV

Variable	**Most Frequent/Proportion**
Information from friends and neighbours*	67.5
No radio	66.6
Extension Contact (No contact)*	61.7
Cooperative membership (non-members)	78.3
Community association/social club	53.8
Credit source (personal)*	99.7
Local seed sources (self-processed)*	99.1
Improved seed sources (self-processed)*	13.7
Seed access/adoption constraint*	
-Information	78.1
-Availability of seed	26.1
-Fair of yield uncertainty	17.3
-Unwillingness to take risky decisions	40.4
-Personal Interest	64.7
-Other factors	31
Processing method (manual)*	99.4
Packaging method (manual)*	99.4
Live in untarred accessible road*	58.4
Live in untarred non-accessible road*	37.4

*implies multiple answer questions

Source: Data Analysis, 2017

Processing and packaging methods used may affect the market value of the processed rice. A combination of manual and machine processing and packaging methods are used by farmers in the study area. Indeed, 99.4 percent and 99.4 percent of the sampled rice farmers relied on manual processing and packaging methods, respectively. It should be noted that machines are used to complement the manual processing methods. This is because rice farmers usually parboil and dry rice grains after harvesting. Afterward, the processing process is finalised by taking the half-processed rice to the mills, which is usually located at some distance away. In other words, the survey reveals that all the sampled rice farmers rely on the crude way of rice processing, most of whom travel many miles to get to the processing centres. Again, a lot of productive time is wasted as the processing is done by queuing because limited number of milling centres are located in cities and major towns.

Accessible roads may influence farmers' adoption decisions. The survey reveals that a sizeable proportion (58.4 percent) of the sampled rice farmers lives in the untarred but accessible road areas while about 37 percent lives in bad road network areas. Good road network may aid access to information and markets. Farmers usually transport their half-processed rice to the nearest cities or towns. On one hand, bad road may hinder the transportation process causing delay and subsequently result in food waste. On the other hand, bad road networks may reduce social networking among farmers in the towns and core villages since farmers living in the remote areas may travel less frequently.

4.5 Rice Farmers' Risk Preferences: Attitudes across Stakes

One observation is dropped in the risk analysis due to incomplete information. Therefore, three hundred and twenty-eight observations (328) are reported in this session. With respect to the individual risk panel, the results show that a sizeable proportion of rice farmers are highly willing to take risk when confronted with small gain one but less willing to take risk when confronted with small loss. More so, rice farmers were motivated to taking risky decisions when faced with large stake. The reason may be attributed to the fact that most subjects tend to favour sure amount (or less risky outcomes) which is the main attribute of the SG1 and LG1 lotteries but were motivated to take risky decisions under SG2 and LG2 lotteries which have no sure outcomes. This shows sensitivity of subjects to risky outcomes as well as the size of stakes. For simplicity, and due to high correlation between the outcomes of each panel within treatment as well as the responses of farmers, average values are computed across treatments. These are reported in this chapter and used in subsequent analyses.

The distribution of rice farmers' risk preferences with respect to average treatment for SG1, SG2, LG1 and LG2 are depicted in **Figure 6**. Note that the closer the probability to 1, the lower the willingness to risk taking. The mean probability values are 0.79, 0.64, 0.73 and 0.59 respectively for SG1, SG2, LG1 and LG2 indicating rice farmers are generally less willing to take risk when confronted with gain relative to when faced with the loss lotteries. These average figures closely match the median values of 0.85, 0.65, 0.75 and 0.60, respectively for SG1, SG2, LG1 and LG2. A slightly different pattern of risk attitudes to that reported by García Gallego *et al.* (2012) is observed among rice farmers in Nigeria. This variation may be attributed to three reasons. First, this study elicited risk willingness of farmers while their study focusses on students. Thus, there is a difference in the educational level of the subjects. Second, the age groups are different, the students are younger than farmers. Lastly, the settings are different; this study is conducted among farmers in developing countries.

Comparing across stakes, willingness to risk taking is higher in large gain one compared to small gain one. Willingness to risk taking also increases for losses relative to gains. These patterns of behaviour suggest that rice farmers' risk preference moves along with lottery stake and its potentials. Indeed, the fear of losing money may motivate farmers to be more willing to take risky decisions when faced with SG2 and LG2 lotteries where zero earning is involved but less willing to take risk when faced with gain lotteries with sure outcome. In corollary, rice farmers may prefer to continue growing local rice varieties such as OFADA because these varieties offer them with "sure output or yield" suggesting unwillingness to adopt HYV which offers higher but uncertain yield. Farmers are however likely to change their perceptions and preferences if they observe their neighbours get more yield and income from growing improved rice varieties.

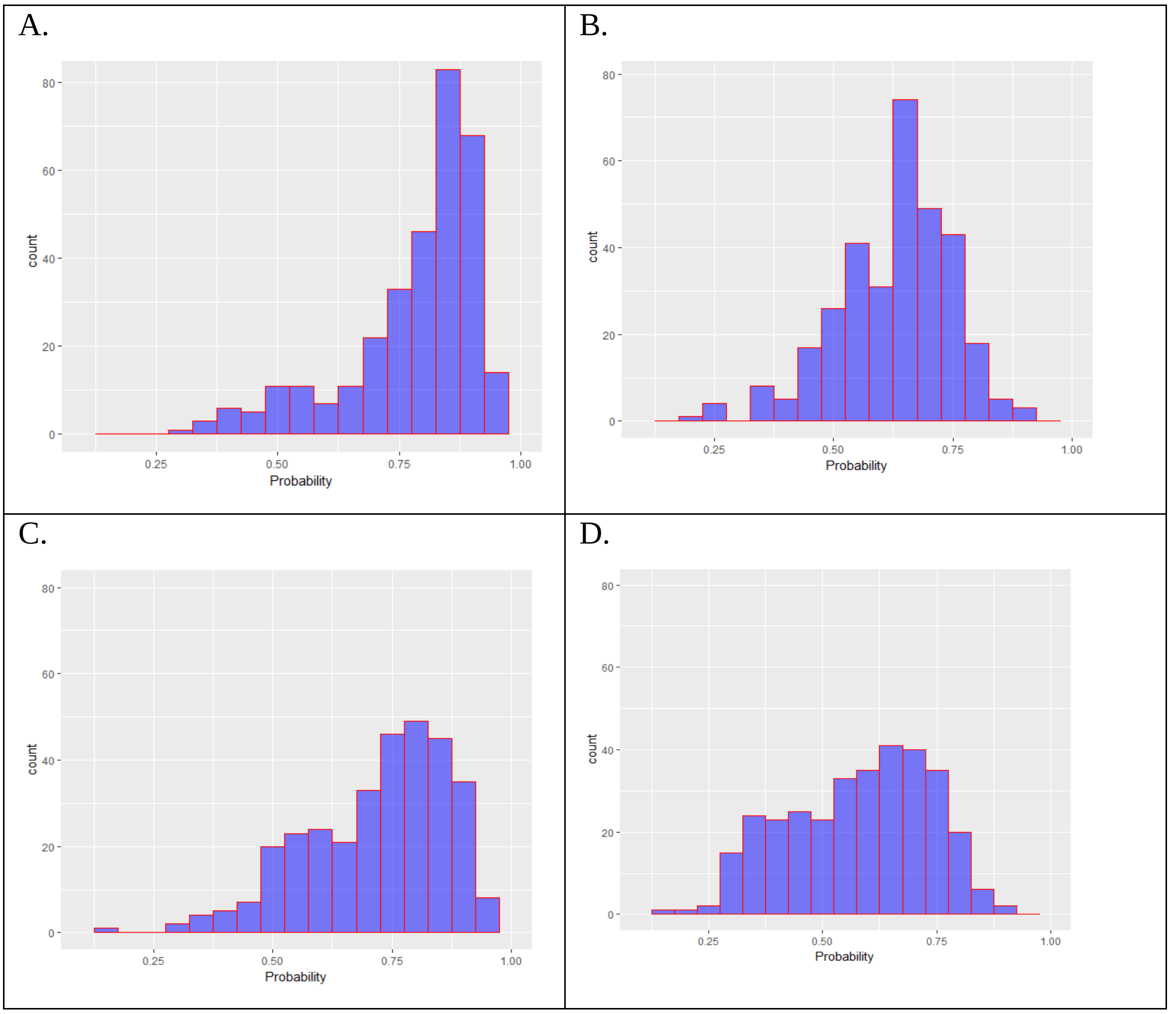

Figure 6: Distribution of Rice Farmers Showing Attitudes toward Risk Taking

A, B, C and D represents SG1, SG2, LG1 and LG2, respectively.
*The higher the probability, the less the willingness to risk taking. Willingness to risk taking is lower for SG1 than SG2. Willingness to risk taking is also lower for LG1 relative to LG2

Source: Data Analysis, 2017

4.6 Rice Farmers' Risk and Time Preferences across Gender and Education

The distribution of the risk attitudes and time preference of rice farmers across gender and education is presented in **Table 10**. Note that the higher the figure the lower the willingness to risk taking or the higher the risk avoidance. Put differently, a risk avoiding farmer has a figure that is very close to one. The results of the farmers' attitudes toward SG1 indicate that male rice farmers are more willing to take risky decisions relative to female rice farmers. By disaggregating based on the level of education, the result reveals that low educated male rice farmers (less than or equal to 3 years of schooling) are more likely to take risk. In contrary, female rice farmers having 6 and 12 years of schooling were more willing to take risky decisions. Similar pattern is obtained with respect to SG2.

The pattern of attitude in LG1 shares some similarity to that of SG1. Generally, males seem to be more willing to take risky decisions. However, female rice farmers having between 6 and 8 years of education are more willing to take risk relating to LG1. Moreover, female rice farmers having between 3 and 12 years of education show more willingness to risk relative to male rice farmers with the same level of education. With respect to LG2, female rice farmers show more willingness to risk compared to the male rice farmers. This is particularly true for female rice farmers having between 3 and 12 years of education. Similar patterns of behaviour are observed in the rice farmers' time preference with male farmers having lower subjective discount rates relative to female farmers. An important finding is that educated male rice farmers seem to have lower subjective discount rates.

Table 10: Risk and Time Preferences across Gender and Education

Gender	**Years of Schooling**							**Total**
	0.00	3.00	6.00	8.00	12.00	15.00	16.00	
SG1								
Female	0.83	0.85	0.76	0.80	0.79	-	-	0.81
Male	0.78	0.78	0.77	0.79	0.81	0.87	0.68	0.78
SG2								
Female	0.65	0.66	0.58	0.73	0.64			0.64
Male	0.65	0.63	0.64	0.66	0.62	0.59	0.42	0.63
LG1								
Female	0.76	0.76	0.69	0.74	0.84			0.74
Male	0.71	0.70	0.76	0.78	0.71	0.76	0.56	0.73
LG2								
Female	0.58	0.54	0.57	0.62	0.57			0.58
Male	0.59	0.56	0.62	0.63	0.58	0.64	0.52	0.59
Discount Rate								
Female	0.52	0.52	0.51	0.52	0.46	-	-	0.51
Male	0.49	0.48	0.47	0.48	0.48	0.45	0.46	0.48

Source: Data Analysis, 2017

4.7 Rice Farmers' Risk and Time Preferences across Gender and Age

With respect to SG1, the results indicate that male rice farmers across all ages are more willing to take risky decisions (**Table 11**). An important feature in the risk attitude of farmers across gender is the fact that young farmers between the ages of 26 and 34 years behave in an analogous manner. With respect to SG2, the summary statistics indicate there is no difference in the risk attitude of rice farmers. However, male farmers who are less than 25 years and those above 64 years show more willingness to risk relative to their female counterparts.

With respect to LG1, across all ages, male rice farmers show more willingness to risk taking relative to female rice farmers. Significant difference is however observed among farmers with less than 25 years, between 25-34 years as well as those that are above 64 years. For LG2, across all ages, female rice farmers are more willing to take risky decisions. However, younger male farmers less than 34 years show more willingness to risk taking relative to their female counterparts. Except for younger famers aged below 25 years, across the age categories, male rice farmers have lower subjected discount rates or seem to be more patient.

Table 11: Rice Farmers' Risk and Time Preferences across Gender and Age

Gender	Age Categories in years						Total
	≤25	26-34	35-44	45-54	55-64	>64	
SG1							
Female	0.88	0.76	0.83	0.79	0.80	0.85	0.81
Male	0.84	0.76	0.79	0.78	0.78	0.80	0.78
SG2							
Female	0.68	0.63	0.64	0.64	0.62	0.68	0.64
Male	0.63	0.64	0.63	0.65	0.62	0.63	0.63
LG1							
Female	0.80	0.73	0.76	0.72	0.74	0.76	0.74
Male	0.77	0.66	0.76	0.71	0.75	0.73	0.73
LG2							
Female	0.71	0.56	0.60	0.58	0.54	0.60	0.58
Male	0.61	0.51	0.62	0.59	0.60	0.62	0.59
Discount Rate							
Female	0.47	0.49	0.52	0.53	0.51	0.51	0.51
Male	0.49	0.48	0.47	0.47	0.50	0.49	0.48

Source: Data Analysis, 2017

4.8 Rice Farmers' Risk and Time Preferences across Gender and Farm size

In terms of SG1, generally across the farm size, male rice farmers are more willing to take risky decisions relative to female rice farmers (**Table 12**). More so, large scale farmers show more willingness to risk. While there is no difference in the willingness to risk of small holder farmers (<1.6ha), male farmers with relatively large farm size were more willing to take risky decision. For SG2, large scale farmers show more willingness to risk while there is no significant difference across gender. Attitude towards LG1 follow similar pattern to that of SG1 with male farmers, and large farmers more willing to take risk. This pattern is however different with respect to LG2 where small scale farmers show more willingness to risk. In terms of time preference, female farmers cultivating less than one hectare of land seem to have high discount rate relative to other categories.

Table 12: Risk and Time Preferences across Gender and Farm Size

Gender	**Farm size (percentile)**		**Total**
	>1.6 ha	< = 1.6 ha	
SG1			
Female	0.82	0.81	0.81
Male	0.77	0.80	0.78
SG2			
Female	0.63	0.64	0.64
Male	0.63	0.64	0.63
LG1			
Female	0.76	0.74	0.74
Male	0.72	0.73	0.73
LG2			
Female	0.56	0.58	0.58
Male	0.61	0.58	0.59
Discount Rate			
Female	0.49	0.52	0.51
Male	0.48	0.48	0.48

Source: Data Analysis, 2017

4.9 Rice Farmers’ Risk and Time Preferences across Gender and Distance

Rice farmers’ risk attitude is also compared across gender and distance (**Table 13**). For SG1, across gender, farmers located within the 60.1 and 80 km show more willingness to risk taking, followed by those within 140.1 and 160 km. Similarly, the pattern of attitude in SG1 is observed in SG2. For LG1, farmers within 140.1 and 160 km show more willingness to risk followed by those within 60.1 and 80 km. For LG2, farmers within 100.1 and 120 km are less willing to take risk followed by those within 140.1 km and 160 km. Similar pattern of behaviour is observed for time preference with farmers distant away having lower subjective discount rate.

Table 13: Farmers' Risk and Time Preferences across Gender and Distance

Gender	Distance in km						Total
	0-20	20.1-40	40.1-60	60.1-80	100.1-120	140.1-160	
SG1							
Female	0.83	0.83	0.80	0.73	0.84	0.73	0.81
Male	0.75	0.81	0.81	0.66	0.84	0.77	0.78
SG2							
Female	0.66	0.67	0.64	0.45	0.65	0.57	0.64
Male	0.64	0.65	0.64	0.66	0.64	0.56	0.63
LG1							
Female	0.75	0.77	0.70	0.74	0.72	0.71	0.74
Male	0.71	0.77	0.81	0.68	0.66	0.71	0.73
LG2							
Female	0.63	0.60	0.58	0.58	0.53	0.51	0.58
Male	0.63	0.58	0.65	0.58	0.49	0.58	0.59
Discount rate							
Female	0.53	0.53	0.45	0.48	0.53	0.47	0.51
Male	0.47	0.49	0.47	0.47	0.52	0.46	0.48

Source: Data Analysis, 2017

4.10 Rice Farmers' Risk and Time Preferences across Gender and Adoption Group

Table 14 presents the variation in rice farmers' risk attitude across gender and adoption group. With respect to SG1, adopters show more willingness to risk taking compared to non-adopters. Male rice farmers are generally more willing to take risky decisions relative to female rice farmers. However, female adopters show more willingness to risk than the male adopters. On the other hand, non-adopter male farmers were more willing to take risky decisions. Similar patterns of behaviour are observed with respect to SG2. Like male rice farmers, the adopters show more willingness to risk taking. Across all domain and stakes, female adopters are more willing to take risky decisions relative to male adopters. Generally, adopters of HYV have lower discount rate but male rice farmers (adopters and non-adopters have lower discount rate).

Table 14: Risk and Time Preferences across Gender and Adoption Group

Gender	Non-adopters	Adopters	Total
SG1			
Female	0.82	0.67	0.81
Male	0.80	0.68	0.78
SG2			
Female	0.65	0.52	0.64
Male	0.64	0.62	0.63
LG1			
Female	0.75	0.64	0.74
Male	0.74	0.65	0.73
LG2			
Female	0.59	0.45	0.58
Male	0.60	0.55	0.59
Discount Rate			
Female	0.52	0.41	0.51
Male	0.49	0.41	0.48

Source: Data Analysis, 2017

4.11 Agricultural Zonal Variation in Risk Attitudes

The case summary of the results of the component analysis, considering all the sixteen panels is presented in **Table 15**. The results of the component analysis revealed that five components with Eigenvalues greater than one explain 57.9 percent of the total variation. Component one explains greater proportions of SG1 panel 2 and panel 3, respectively. Component one is therefore named as risk attitude towards small gain one. Component two explains larger percentage of the LG1 panel 3 and panel 4, respectively suggesting component two reflects risk attitude towards large gain one. Component three explains higher percentage of the variation in LG2 panel 3 and panel 4, respectively implying component three is loaded around attitude towards large gain two. Furthermore, component four explains most of the variations in the SG2 panel 1 and panel 2 respectively. This suggests that component four can be referred to as attitude towards small loss. Lastly, component five explains 73.6 percent and 77.8 percent of the variation in SG2 panel 3 and panel 4, respectively. Therefore, component five is called attraction to risk returns but only in the small loss.

The principal components were summarized in line with agricultural zones. Farmers in Ikenne and Ilaro zones are less willing to take risk with respect to small gain one and large gain two while those in Abeokuta and Ijebu-Ode zones show more willingness to risk taking. The additional advantage of the modified SGG lotteries is the identification of the fifth component which captures attraction to risk. The finding shows that rice farmers are more attracted to risk taking in the small gain two. Indeed, farmers in Ikenne zone are more attracted to the risk premium. In summary, rice farmers living in rural communities or agricultural zones are more averse (avoid risk) to risk taking relative to those living in urban areas.

Table 15: Agricultural Zonal Variations in Rice Farmers' Risk Attitudes

Zones	SG1	LG1	LG2	SG2	Attraction to risk premium (SG2)
Abeokuta	-0.3786	-0.1041	-0.3813	0.07606	-0.2731
Ilaro	0.0033	**0.5490**	0.2796	**0.3864**	0.0055
Ikenne	**0.2983**	0.08805	**0.3545**	0.05066	**0.1718**
Ijebu-Ode	0.08995	-0.3736	-0.1607	-0.4045	0.1055

Note: Non-parametric Kruskal Wallis tests: The null hypotheses of same distribution across the four agricultural zones are rejected at 0.001.
The figures are the summary of principal component analysis

Source: Data Analysis, 2017

4.12 Rice Farmers' Risk Attitudes: Cluster Groups

Two clusters were observed as suggested by the principal component analysis. As shown in **Table 16,** on treatment bases, about 82.6 percent of the rice farmers highly avoid risky decisions in the small gain one domain. This high aversion to risk taking however reduces when the farmers faced the choice of small gain two (67.1 percent), large gain one (67.7 percent) and large gain two (62.2 percent). All the sixteen panels were later considered by first conducting factor analysis (identified one factor) on the treatment average and secondly classified farmers into two cluster groups. The result shows that 67.8 percent of the sampled farmers avoid taking risk while 32.2 percent show more willingness to risk taking. Therefore, most sampled rice farmers avoid taking risky decisions.

The change in the aversion level may be attributed to the fact that many farmers are afraid of losses (small and large) but attracted by the large stake monetary rewards associated with the large gain ones. This behaviour shows that even though most rice farmers are averse to risk (in gains domain), most of them are prompted to take risky decisions with increased incentives. This reflects the real life situation. For instance, rice farmers may not be willing to adopt high yielding rice technology if they perceived it offers lower yield than the already tested local rice varieties. They may however change their perceptions when observing that improved and tested rice technology would offer higher returns or income.

Table 16: Cluster Groups of Rice Farmers' Risk Attitudes

*Risk Categories	SG1	SG2	LG1	LG2	All panels
Highly Risk Avoidance	82.6	67.1	67.7	62.2	67.8
More willingness to risk taking	17.4	32.9	32.3	37.8	32.2

* Figures are in percentages

Source: Data Analysis, 2017

4.13 Test of Variation in Rice Farmers' Risk Attitudes across Adoption Group

The test of difference of mean reveals that there is a significant difference in the risk behaviour among adopters and non-adopters (**Table** 17). The results indicate that adopters of HYV are more willing to take risk relative to non-adopters. This is reflected in all the risk treatments. However, the variation is more obvious in the SG1 and LG1 than other treatments probably due to the sure outcomes associated with the stakes in these domains.

Table 17: Rice Farmers' Risk Attitude across Adoption Group

	Adopters		Non-adopters		
	Mean	**S. D**	**Mean**	**S. D**	**t-value**
SG1	0.67	0.17	0.80	0.14	4.68***
SG2	0.59	0.11	0.64	0.13	1.97**
LG1	0.65	0.15	0.74	0.15	3.13***
LG2	0.52	0.13	0.59	0.16	2.43**

***, ** imply significant at 0.01 and 0.05, respectively

Source: Data Analysis, 2017

4.14 Subjective Discount Rate and Rice Farmers' Level of Impatience

The distribution of rice farmers' time preferences and time inconsistency is presented in Table 18. Using the switching behaviour exhibited by rice farmers in each of the series in the time experiment, the study revealed that most of the rice farmers are impatient. The earlier a farmer switches, the more the level of patience. Thus, an impatient farmer switches later or never switched. In fact, most rice farmers switched in row four or never switched (**Figure 7**). On the average, rice farmers in Ogun State Nigeria switched from plan A (present or immediate future) to plan B (future) in row four (average switching point is 3.48) suggesting most rice farmers show strong preference for the present.

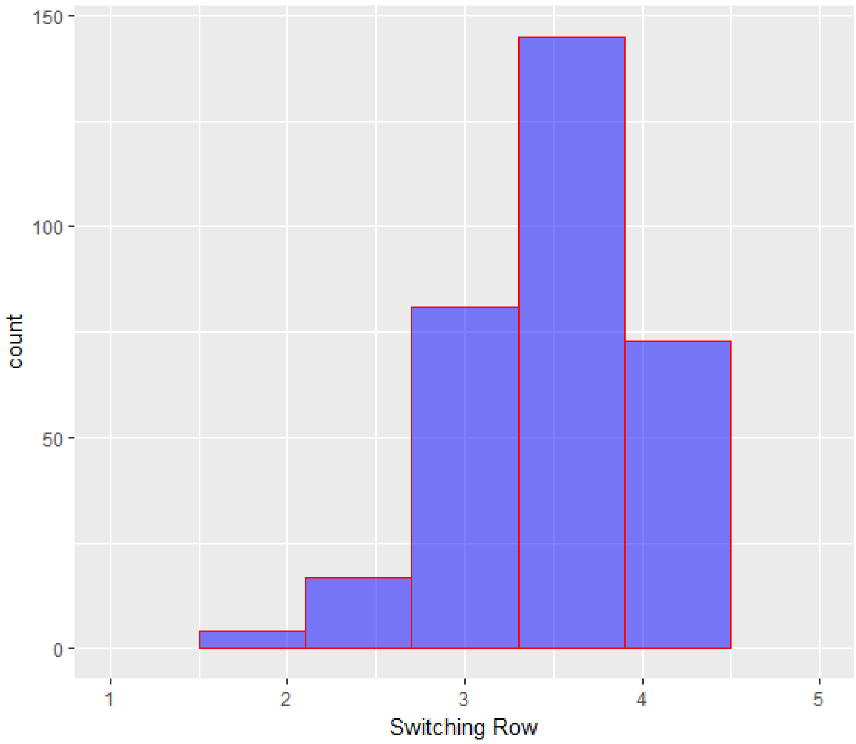

Figure 7: Rice Farmers by Average Switching Points in Time Experiment
Source: Data Analysis, 2017

As shown in **Table 18**, the average subjective discount rate of rice farmer is estimated at 0.49 (with a median of 0.49) with a standard deviation of 0.08. The minimum and maximum discount rates are 0.22 and 0.69, respectively. This result is highly comparable to an average discount rate of 47.5 percent reported among farmers in Uganda (Tanaka and Munro, 2013). High subjective discount rate implies impatience. The discount was subjected to cluster analysis. The result indicates that most (61.1 percent) of the sampled farmers have high discount rate and thus impatience while about 39.9 percent have low discount rate or patient. This result is consistent with those obtained using the average switching rows (mean of mean) revealed by farmers with respect to each series. In this case, farmers with average switching figures of over 3.48 were classified as impatient (59.6 percent) while those whose average switching figures equal to or greater than 3.48 were patient (40.4 percent).

An assessment of choice consistency was carried out using the mean and variance associated with the **switching rows** to examine the pattern of switching in the time experiment. Note that this consistency compares whether or not rice farmers switch at the same rows from each series of the time experiment. The mean of the variance is estimated at 0.97. Farmers whose variance figures exceeded 0.97 were classified as inconsistent, otherwise the farmers were consistent. About 59 percent of the sampled rice farmers were consistent (either remained patience or impatience) with their choices across the 8 series while 41 percent shows some level of inconsistency in their choices. With four impatience and choice consistency categories, about 20.7 percent of the sampled farmers were patient and consistent; 19.8 percent were patient but not consistent; 21 percent were impatient and inconsistent, while 38.6 percent were impatient but consistent. This suggests that most sampled rice farmers could be labelled as impatient due to high time inconsistency in their choices.

Table 18: Rice Farmers' Subjective Discount Rate and Choice Inconsistency

Variables	Frequency	Proportion/Mean
Discount rate		0.49
Impatience (cluster based on discount rate)		
Impatience	201	61.1
Patience	128	38.9
Impatience (cluster based on switching rows)		
Impatience	234	71.12
Patience	95	28.88
Impatience (based on switching row mean)		
Impatience	196	59.6
Patience	133	40.4
Consistency (based on switching row variance)		
Consistence	193	58.7
Inconsistence	136	41.3
Impatience and Choice Consistency (based on switching rows)		
Patience and consistence	68	20.7
Patience and inconsistence	65	19.8
Impatience and inconsistence	69	21
Impatience and consistence	127	38.6

Source: Data Analysis, 2017

4.15 Agricultural Zonal Variation in the Rice Farmers' Level of Impatience

The summary statistics of the subjective discount rate relating to the variation across agricultural zones is presented in **Table 19**. Although the non-parametric test reveals that there is no significant difference between the distribution of the subjective discount rates across the four agricultural zones, a cursory look at the average discount rates show that rice farmers in Abeokuta and Ilaro tend to have lower subjective discount rates relative to farmers living in other two agricultural zones.

Table 19: Variation in Discount Rates across Agricultural Zones

	Abeokuta	Ilaro	Ikenne	Ijebu-Ode
Mean	0.47	0.49	0.50	0.50
Median	0.47	0.49	0.51	0.49
SD	0.12	0.08	0.06	0.06
Min	0.22	0.28	0.34	0.36
Max	0.69	0.65	0.63	0.63

Note: SD = standard deviation, Min = minimum, Max = maximum

Source: Data Analysis, 2017

4.16 Subjective Discount Rate across Adoption Group and Gender

The test of difference of mean in the discount rate between adopters and non-adopters are presented in **Table 20**. The results indicate that the mean subjective discount rate of adopters is 18 percent significantly lower than that of non-adopters. In other words, the variation is statistically difference from zero at one percent level, implying non-adopters are more impatient than their adopters' counterparts.

Table 20: Subjective Discount Rates across Adoption Groups and Gender

Groups	Frequency	Mean	SD	Z-value	Degree of Freedom
Adopter	30	0.41	0.038	5.6***	327
Non-adopter	299	0.50	0.083		
Male	222	0.48	0.089	3.8***	327
Female	107	0.52	0.064		

*** implies the z-values are statistically different from zero at one percent level

Source: Data Analysis, 2017

The results of the test of difference of mean in the subjective discount rate between male and female farmers reveal that the subjective discount rates between the gender groups are significantly different from zero at one percent level of significant. In other words, the subjective discount rates of male farmers are 8 percent lower than that of their female farmers' counterparts. Giving that both gender is well represented in the sample, it can be concluded that male rice farmers are more patient than their female counterparts.

4.17 Differences in Risk Preferences across Stakes and between Risk Attitudes and Discount Rates

A test of correlation between risk preferences of rice farmers across stakes was carried out to examine the heterogeneity in farmers' attitudes. The results as presented in **Table 21** revealed that a significant correlation exists between the probability indexes (willingness to risk taking) among rice farmers across all stakes. Notwithstanding, the correlation is highest between SG1 and LG1, and between LG1 and LG2. This suggests that rice farmers have similar pattern of behaviour with respect to small and large gain one stakes. On one hand, it may be a revelation of the consistency of choices. On the other hand, it may reflect sensitivity to the size of stakes (payoffs). Relationship between risk preferences and time preferences was also examined. The results presented in Table 21 indicates rice farmers risk attitudes (willingness to risk taking) is strongly correlated with their level of impatience (subjective discount rates) but surprisingly only in the small gains (SG1 and SG2). This connotes a highly risk avoidant farmer is highly impatient. In the context of investment, and specifically adoption of improved agricultural technology, a highly risk averse and impatient farmers may not be willing to grow HYV or may show negative attitudes toward investing in modern technology or innovation. Such farmers may produce less output per land and consequently low income relative to a risk taker and patient farmer.

Table 21: Test of Differences in Risk Attitudes and across Time Preference

Risk and Time Preferences	Correlation coefficients
Risk preferences across stakes	
SG1 Vs SG2	0.393***
SG1 Vs LG1	0.434***
SG1 Vs LG2	0.272***
SG2 Vs LG1	0.242***
SG2 Vs LG2	0.285***
LG1 Vs LG2	0.483***
Risk Preferences Versus Discount Rates	
SG1 Vs DR	0.215***
SG2 Vs DR	0.235***
LG1 Vs DR	0.027
LG2 Vs DR	0.023

*** indicates coefficients are significant at 0.01 level.
DR = discount rates

Source: Data Analysis, 2017

4.18 Test of Variation in Some Selected Variables across Adoption Group

A test of difference of mean and non-parametric tests were conducted to examine the variation between some selected variables across adoption group. The results are presented in **Table 22**. The continuous variables were tested using test of difference of means while the binary variables were non-parametrically tested. The results indicate that there is no significant variation between the selected socio-economic variables across the two adoption groups in the Study Area suggesting the observed variation in rice farmers' adoption behaviour may be attributed to factors such as climatic variation and ecological condition. Interestingly, most of the selected famers (39 percent) live in bad road network areas.

Table 22: Variation in Rice Farmers' Attributes across Adoption Group

Variables	Adopters			Non-adopters			
	Mean	S. D	Proportion	Mean	S. D	[a]Proportion	[b]T-value
Age	44.47	9.91		47.21	12.72		1.15
Education	5.73	4.88		4.52	4.42		1.43
Household size	5.50	2.79		5.94	3.01		0.17
Farm size	2.25	1.49		2.00	1.51		1.21
Christian			0.53			0.56	
Male			0.73			0.67	
Married			0.90			0.94	
Abeokuta			0.17			0.29	
Ikenne			0.13			0.28	
Ijebu-Ode			0.40			0.25	
Ilaro			0.30			0.18	
Bad road			0.17			0.39	
Extension contact			0.47			0.37	
Information from friends			0.77			0.67	

Source: Data Analysis, 2017

[a]The difference in discrete variables were tested using Chi-square and results indicate there is no significant difference between the two categories of farmers.
[b]The continuous variables were tested using test of difference of mean and the results show no significant difference between the two categories of farmers.

4.19 Summary

The distance and location suggest that a vast majority (71 percent) of the sample respondents have neighbours and were located within 60 km. The overview of the data suggests that most sampled rice farmers had no formal education but had cognate experience in farming. The sampled farmers are also relatively young. In addition, both gender and agricultural are adequately representation. More importantly, majority of the rice farmers avoid risk taking and impatient with respect to time. Above all, the results of no statistical difference in the selected socio-economic factors across adoption group suggests that variation among farmers may be attributed to unobservable factors such as climatic factors.

Chapter Five

5.0 Risk Preferences, Spatial Dependence and Adoption Decisions

The role of spatial dependence in risky decision making as well as the role of risk preferences in adoption decisions is examined in this chapter. These are presented in paper format. The role of spatial dependence in risk preference is examined first followed by the effect of risk preferences on adoption decisions.

5.1 The Role of Spatial Dependence in Risky Decision Making

5.1.1 Background

The risk associated with farming decisions could be viewed from two perspectives. The first is the shocks faced by individual farmers during production (World Bank, 2008). Farmers, especially in the developing countries often face with various forms of background risks ranging from vagaries of weather and climate which cause flood, drought, pest and disease infestation to fluctuation in prices of input and output. Consequently, food security and the general wellbeing of most farmers are affected due to low farm income. Secondly, sensitivity to risk or risk preference which reflects the extent to which individuals are willing to take risky decisions (Charness *et al.*, 2013). The latter is the focus of the first part of this chapter with a specific attention to the role of spatial dependence in risky decision making. Indeed, ability to take risky decisions may be used as a management tool for background risk with positive effect on farmers' income. Many factors including access to infrastructural facilities such as accessible road as well as spatial attributes like social interaction, climatic and topographic conditions may explain the reasons for risk avoidance or willingness to taking risky decisions among farmers. Understanding such determinants of farmers' risk preference may therefore guide policy relating to risk management and investment decisions such as adoption of improved agricultural technology.

Tobler (1970) posits that closer observations or individuals may be more related relative to distant observations. In farming or crop production, data collected from farmers may be spatially related. It has also been previously argued that non-controlling for the spatial aspects of agricultural data may result in a misleading inference (Benirschka & Binkley, 1994; Bockstael, 1996; Weiss, 1996). In rice production, spatial dependency may be a consequence of variation in soil types, weather and climate, topographic and socio-economic conditions. Rice farmers may influence one another due to geographical proximity, availability or otherwise of infrastructural or institutional facilities like road, schools, markets, etc. Thus, social interaction or learning effects could be used as tool for the diffusion of agricultural innovation.

In adoption literature, for example, farmers' adoption patterns have been found to reflect the spatial variability or neighbourhood effects (Case, 1992; Holloway *et al.*, 2002; Krishnan & Patnam, 2014; Läpple & Kelley, 2015; Tessema *et al.*, 2016). Spatial dependence may reveal spatial relationship in decision making because, culturally, farmers living closely often rely on their friends and neighbours for information. However, despite the advances in spatial analysis (Anselin, 2002; LeSage & Pace, 2009), there has never been an attempt to examine the role of spatial dependence in decision relating to experimental risky decision making. This leaves a gap in the literature which this study filled by testing the hypothesis that rice farmers living closely have similar risk attitude relative to distant rice farmers.

Among many behavioural studies conducted in the developing countries, only few studies examined the zonal variation in risk attitudes (Binswanger, 1980; Binswanger, 1981; Wik *et al.*, 2004; Yesuf, 2004; Harrison *et al.*, 2005a; Yesuf & Bluffstone, 2009; Harrison *et al.*, 2010; Tanaka *et al.*, 2010; Brick *et al.*, 2012). For instance, farmers working in risky riverine areas were reportedly less risk averse in Vietnam (Nguyen & Leung, 2009; Nguyen & Leung, 2010; Nguyen, 2011). In a similar study, farmers living in the climatically least favourable regions are reportedly more averse to risk, loss and highly impatient in Uganda (Tanaka & Munro, 2014). This current study differs in terms of methods and study locations.

Social composition of farmers in Nigeria may show neighbourhood influence that extends beyond the current agricultural zonal boundaries. Insight on the existence of spatial dependence and heterogeneity in risk taking is important for policy formulation. For instance, the degree of heterogeneity in risk preference may reflect the existing economic reality of farmers within and across agricultural zones or divisions since spatial dependence captures the presence or absence of infrastructure like good road networks and functioning markets. Uncertainty may affect the livelihood of farmers, especially rural farmers who rely mainly on the traditional farming methods and lack access to information and other resources. More so, farmers tend to reflect their income status and status quo bias when making decisions. Thus, empirical evidence on the role of spatial dependence in decision making is *sine qua non* for policy analysis.

The first part of this chapter is organised as follows. While Section 5.1.1 introduces the paper, the review of empirical literature on the determinants of risk attitudes is presented in Section 5.1.2. The data and methods of analysis are presented in Section 5.1.3. Results and discussion are reported in Section 5.1.4 while Section 5.1.5 concludes the findings.

5.1.2 Empirical Evidence on Determinants of Risk Attitudes

Risk aversion has been identified as one of the important economic factors affecting financial, investment and consequently the wealth accumulation of individuals. Many attempts have been made to examine the socio-economic factors affecting the risk aversion of individuals in both the developed and developing countries. Some appealing findings reported among farmers mostly in the developing countries are summarized as follows.

Mixed results are reported between wealth/income and risk aversion. For example, a negative correlation is found in Africa (Wik *et al.*, 2004; Yesuf, 2004; Yesuf & Bluffstone, 2009; Liebenehm & Waibel, 2014) and Asia (Tanaka *et al.*, 2010; Liu, 2013). Some studies found no significant correlation in Asia (Binswanger, 1980; Binswanger, 1981). Farm size may serve as proxy for income in developing countries where most agrarian population derived their livelihood from farming. Farm size and risk aversion are found to be negatively correlated (Yesuf & Bluffstone, 2009) and positively correlated (Wik *et al.*, 2004) in Ethiopia while some studies found no significant relationship in Asia (Tanaka *et al.*, 2010; Liu, 2013). Since farm size may serve as proxy for wealth or income in rural communities, a negative correlation is hypothesized between farm size and risk avoidance in this study. In short, small holder rice farmers may be less willing to take risky decisions.

Mixed results have also been reported between education and risk aversion. For instance, educated farmers are reportedly highly averse to risk taking some developing countries (Tanaka *et al.*, 2010; Nguyen, 2011; Ihli *et al.*, 2013). However, positive relationship is reported between risk aversion and education in Southern Peru (Galarza,

2009) as well as West Africa (Liebenehm & Waibel, 2014). In line with previous findings, educated rice farmers are expected to be more willing to take risky decisions.

It is unclear whether older farmers are less risk averse than younger ones because mixed findings are documented on this variable. Some studies reported that risk aversion decreases with age; that is younger farmers are less risk averse (Harrison *et al.*, 2010; Nguyen, 2011). Negative correlation has been reported between age and risk aversion, that is older farmers are more risk averse (Tanaka *et al.*, 2010; Liebenehm & Waibel, 2014). Age is expected to be positively related with experience in farming. Thus, older farmers may show negative attitudes to risky decisions, more risk averse.

The debate on whether women are more risk averse or impatient relative to men is inclusive in the literature because while some studies provide strong statistical evidence in support of males being less averse to risk and more patient others found otherwise. Specifically, the gender variation in risk attitude is highly debateable (see (Schubert, 2006)). In finance, for instance, women have been reported to be less financially tolerant and more financially risk averse relative to men (Charness & Gneezy, 2012; Bannier & Neubert, 2016; Fisher & Yao, 2017). On the other hand, Harris, Jenkins, and Glaser (2006) attribute the gender differences in perceptions about outcomes and risky decision making to less desire for enjoyment among women. Arguably, the reverse may be the case as women tend to have higher expectations for social engagements and activities. Research also shows that social status may drive risk aversion (Stark & Zawojska, 2015). In the agricultural setting, women have been reported to be more risk averse than men in China, India and Uganda, respectively (Liu, 2013; Ward & Singh, 2014; Tanaka & Munro, 2014). On the other hand, Harrison *et al.* (2010) result indicate that females are marginally less risk averse than men while Tanaka *et al.* (2010) did not find a significant gender difference in risk attitude. In line with previous findings (García Gallego *et al.*, 2012), male rice farmers are expected to be risk takers.

Marital status is not often controlled for in empirical studies. It may however more important in decision making because it has a direct relationship with household income and expenditure. On one hand, married individual may be perceived to be risk taker to cope with the financial burden. On the other hand, married individuals may be more risk averse than the singles because of the fear of loss of income or payoffs if under intense financial pressure. That is, married individuals may be cautious of losing little money which may be used to cater for their family. Another variable that has been less examined in the literature is religion. Liu (2013) reported that religious farmers are more risk averse. Since religion relates to belief, it may affect farmers' perceptions but not necessarily affect risk preference. Therefore, there is no expectation on the direction of the religion. Like other variables, mixed results have been reported between risk aversion and family size (see for example Liebenehm and Waibel (2014) who reported positive correlation). In other words, large family size may prompt action towards taking risky decisions. Thus, rice farmers with large family size are expected to be more willing to take risky decisions.

The existing empirical studies indicate that risk preference may reflect the climatic and economic environment of individuals. For instance, studies have shown that individuals who faced income uncertainty are more likely to be highly averse to risk (Guiso & Paiella, 2008; Bezabih & Sarr, 2012). Other studies have reported the heterogeneity in risk attitudes among farmers. Bezabih and Sarr (2012) reported that the more risk averse a farmer is, the more likely he is to diversify his crops while Gollier and Pratt (1996) showed that variation in income bring about increase in risk aversion. Farmers living in rural areas were also found to show higher risk aversion in India (Binswanger, 1978). Furthermore, the study conducted by Tanaka and Munro (2014) revealed that farmers located in low rainfall areas showed higher aversion to risk in Uganda. Notwithstanding, this is the first study to examine the spatial heterogeneity in risk preference. In line with past studies, rice farmers living in the rural areas or remote villages which lack access to good road networks are expected to show less willingness to risk taking or risk averse.

5.1.3 Data and Spatial Autoregressive Model

Rice farmers' willingness to risk taking or risk avoidance level[20] was elicited using bi-dimensional panel lotteries first proposed by Sabater-Grande and Georgantzis (2002). The panel lotteries have four treatments with four panels each: small gain one (SG1), large gain one (LG1), small gain two (SG2) and large gain two (LG2). Details about the risk elicitation methods are presented in Chapter three. All the variables used for the

[20] Following Binswanger (1980) and Binswanger (1981), a number of studies have experimentally examined farmers' risk attitudes using different methods. Most risk preference elicitation methods in the literature are categorized into laboratory or field (Harrison & Rutstrom, 2008; Charness *et al.*, 2013). The risk experiment in this study belongs to the class of artefactual or lab experiment on the field. The term risk avoidance is introduced in this study in place of risk aversion to refer to an individual farmer who is strongly less willing to take risky decision, and because the parameter of the curvature of the utility function is not estimated.

analysis in this Section have been previously described in **Chapter Three**. The definitions of the variables are presented in **Table 23**.

Table 23: Definitions of Variables used in the Risk Model

Variables	Definition
Dependent Variables (Risk Preferences)	
SG1	Small gain one probability index
SG2	Small gain two probability index
LG1	Large gain one probability index
LG2	Large gain two probability index
Explanatory Variables	
Spatial lags	Spatial weights lags of the probability indexes
Age	Actual age in years
Education	Years of formal schooling
Male	1 if male, 0 if female
Christians	1 if Christian, 0 otherwise
Married	1 if married, 0 otherwise
Household size	Number of household
Farm size	Rice farm area in hectare
Bad road	1 if farmers live in untarred poor-accessible road area

Source: Author's Compilation, 2017

Theoretical motivation is central to the application of spatial models (Anselin, 2002; LeSage & Pace, 2009). In this study, spatial dependence is assumed to be a proxy to some latent variables such as climatic, geographic, ecological and socio-economic conditions. In other words, the observed variation in rice farmers' willingness to risk taking may be associated with infrastructure, cultural values, climatic conditions, etc. These unobservable variables are accounted for through the neighbouring values of the rice farmers' willingness to risk taking index, assuming the utility a rice farmer derived from the panel risk lotteries in location *i* share some relationship with the utility derived by his neighbours in location *j*. This justifies the application of SAR model which captures the dependency between observational units (Anselin, 1988a). It is also assumed that rice farmers maximize the payoff or expected payoff in the panel risk lotteries. Given this assumption, Equation (5.1) applies.

$$Max\ P(y_i, y_j; \boldsymbol{X}) \tag{5.1}$$

Where P is a utility function, y_i represents rice farmer in location *i*; y_j represents rice farmer in location *j*; and $\boldsymbol{X}$ is the vector of farmers' exogenous (and endogenous) socio-economic variables. Equation (5.1) implies that utility derived by rice farmer in location *i* may be related with the utility derived by his neighbours in location *j*, given farmers' socio-economic factors ($\boldsymbol{X}$). The maximization objective produces a spatial reaction function, $y_i = F(y_{ij}, \boldsymbol{X})$ which forms SAR of (5.2). The resulting data generating process (DGP) of Equation (5.3) reveals a global spill over because $(I - \rho\boldsymbol{W})^{-1}$ links y_i to all $\boldsymbol{X}$ through a multiplier, the spatial weights matrix, ($\boldsymbol{W}$).

$$\boldsymbol{y_r} = \rho\boldsymbol{W}\boldsymbol{y_r} + \boldsymbol{X}\beta + \varepsilon \tag{5.2}$$

$$\boldsymbol{y_r} = (I - \rho\boldsymbol{W})^{-1}\boldsymbol{X}\beta + (I - \rho\boldsymbol{W})^{-1}\varepsilon \tag{5.3}$$

In Equations (5.2) and (5.3), $\boldsymbol{y_r}$ is a column vector of willingness to risk taking. This is a probability index corresponding to farmers' choices in the panel lotteries, which ranges between 0.1 and 1 with an index of 1 indicating highly unwilling to risk taking[21]. Different models were estimated for SG1, SG2, LG1 and LG2 to compare rice farmers' risk attitudes across treatments or stakes. The ρ measures the strength of spatial dependence or spatial correlation between risk willingness of rice farmers and the adjusted-by-distance mean risk willingness of his neighbours. $\boldsymbol{W}$ is the $N \times N$ weights matrix defined in Equation **3.6** under Section **3.3.2**. Different distance cut-off points including 10 km, 20 km, 30 km, 40 km, 50 km and 60 km were tested to examine the limit of spatial dependence. $\boldsymbol{X}$ is $N \times K$ vector of exogenous explanatory variables. β is a $K \times 1$ vectors of parameters to be estimated. $\boldsymbol{W}\boldsymbol{y_r}$ is a spatial lag which is the weighted average of risk willingness in the neighbourhood locations. Lastly, $\rho\boldsymbol{W}\boldsymbol{y_r}$ relates the utility derived by individual rice farmers from the risk experiment with that derived by his neighbours. In other words, the spatial lag is included to explain the variation in the willingness to risk taking across the study area. The disturbance term is assumed to be independently and identically distributed, $\varepsilon \sim N(0, \boldsymbol{I}\sigma^2)$.

Expanding $(I - \rho\boldsymbol{W})^{-1}$ as an infinite series results in Equation 5.4. Substituting Equation 5.4 into Equation 5.2 results in Equation 5.5.

$$(I - \rho\boldsymbol{W})^{-1} = I + \rho\boldsymbol{W} + \rho^2\boldsymbol{W}^2 + \rho^3\boldsymbol{W}^3 + \cdots \tag{5.4}$$

$$\boldsymbol{y_r} = \boldsymbol{X}\beta + \rho\boldsymbol{W}\boldsymbol{X}\beta + \rho^2\boldsymbol{W}^2\boldsymbol{X}\beta + \cdots + \varepsilon + \rho\boldsymbol{W}\varepsilon + \rho^2\boldsymbol{W}^2\epsilon + \rho^3\boldsymbol{W}^3\varepsilon + \cdots \tag{5.5}$$

Rho (ρ) is not restricted between -1 and 1 (LeSage, 2008). This suggests it cannot be linearly interpreted as a conventional correlation between rice farmers' willingness to

[21] Risk preference has been defined as the extent to which individual is willing to take risky decisions (Charness *et al.*, 2013). Therefore, willingness to risk taking is used interchangeably with risk avoidance and risk aversion in this study since the parameter of the curvature of the utility function is not estimated.

risk ($\boldsymbol{y_r}$) and the adjusted by distance willingness to risk ($\boldsymbol{Wy_r}$). Since the DGP reflects the simultaneity of the spatial autoregressive process, it follows that from Equation 5.5, the expected value of individual farmer willingness to risk taking, $\boldsymbol{y_r}$ depends on $\boldsymbol{X}\beta$ plus the neighbouring values of rice farmers scaled by the dependence parameter, ρ. In other words, in line with Case (1992), rice farmers' willingness to risk taking is a function of their socio-economic characteristics, $\boldsymbol{X}$, neighbours' characteristics, $\boldsymbol{WX}$, neighbours', neighbours' characteristics, $\boldsymbol{W}^2\boldsymbol{X}$ as so on, with the neighbourhood influence reducing with distance.

Given the possibility of the correlation between the spatial lag ($\boldsymbol{Wy_r}$) and the disturbance error**,** ε instrumental variable (IV) estimation method is applied to address the potential endogeneity of the spatially lag risk variables. In other words, the potential correlation between the spatial lag ($\boldsymbol{Wy_r}$) and the error term (ε) is examined using IV. IV is also noted to yield comparable results to two-stage least squares estimation method. The main change in the application of IV is the choice of an instrument which must satisfy some conditions noted in Section 3.3.4 Instrumental Variable: A Latent Variable Model**)** of **C**. According to Anselin (2001), the choice of an instrument for the spatial lag model depends on the conditional expectation of (5.2). Thus, $\boldsymbol{X}$ could be used as exogenous variables and instruments and their spatial lags, $\boldsymbol{WX}$ are useful set of instruments. If $\boldsymbol{Z}$ represents instruments ($\boldsymbol{X}, \boldsymbol{WX}$**)** and $\boldsymbol{P}$ represents the endogenous variable (spatial lag or $\boldsymbol{Wy_r}$) plus other exogenous variables ($\boldsymbol{X}$)**.** It follows that $\boldsymbol{Z}$ does not correlate with the disturbance term, ε but correlated with the spatial lag. The order condition for identification is $\boldsymbol{Z} \geq \boldsymbol{P}$. Therefore, in this study, $\boldsymbol{P}$ has the same column rank as $\boldsymbol{Z}$ resulting in the IV estimator: $IV_{\hat{Z}} = (\boldsymbol{Z'P})^{-1}\boldsymbol{Z'y_r}$. In other words, it is assumed that all other variables in the model, apart from the spatial lag are exogenous and were therefore used as instruments plus the lag of education variable.

There different tests are carried out with respect to the relevance of the instruments, endogeneity of the explanatory variable and validity of the instrument. The test of instrument relevance involves examining the significant of the Wald statistic reported by the R software. The Wu-Hausman test, a test of restriction, which has F-distribution is adopted to test for the endogeneity of the spatial lag. This is also reported by the R software. This test is important because IV may produce estimates with larger standard errors relative to OLS if the spatial lag variable is not endogenous. Thus, it is called test of consistency of OLS. The third test for the validity of instrument, often called Sargan test which follows Chi-square distribution is also reported by R. It may also test for over-identification restriction, thus it is not often reported for exactly identified model.

5.1.4 Results and Discussion

The results of the instrumental variable (IV) models of the SAR respectively for SG1, SG2, LG1 and LG2 are presented in **Table 24**. The null hypotheses of weak instruments (relevance of instruments) are rejected indicating the instrumental variables used are strong enough to obtain consistent estimates. In addition, the null hypotheses for the Wu-Hausman test of the consistency of OLS are rejected for all the risk treatment models suggesting OLS may not yield consistent estimates. Indeed, the coefficient of the spatial lag or spatial dependence parameter is smaller under OLS relative to IV estimate (see **Table 31** under **Appendix A: Additional Tables**). The Wald statistic which is significantly different from zero for all the treatment models attest to the overall goodness of fit of the models. Note that 60 km is the limit of spatial dependence in this study, therefore, the corresponding results are reported, respectively for SG1, SG2, LG1 and LG2. This is in agreement with Roe *et al.* (2002) and Kim *et al.* (2003) who reported a limit for spatial dependence in their studies.

Similar results are obtained for all the treatments indicating rice farmers' attitudes across stakes are comparable. Factors that significantly explain rice farmers risk attitudes toward small gain one (SG1) include age, religion, farm size, gender, marital status, bad road and spatial dependence while age, religion, gender, marital status, bad road and spatial dependence significantly determined attitudes towards small gain two (SG2). Similarly, age, farm size, gender, marital status, bad road and spatial dependence are the determining factors for attitudes toward large gain one (LG1) while attitudes toward large gain two (LG2) are significantly explained by age, gender, marital status, bad road and spatial dependence. Note that positive coefficients imply less willingness to risk taking (or risk avoidance) while negative coefficients show more willingness to risk taking. This section is devoted to explanation of the significant variables, with the main finding presented last (with less specific attention to the risk treatments since similar results are obtained for all treatments).

The results (all risk treatments) revealed that older rice farmers avoid risky decisions or are more risk averse relative to the younger farmers. This is in line with the expectation and strongly supports the views previously expressed by most empirical studies which reported a negative correlation between age and risk aversion (Tanaka *et al.*, 2010;

Liebenehm & Waibel, 2014) but is contrary to other findings that risk aversion decreases with age (Harrison *et al.*, 2010; Nguyen, 2011). Older farmers may be less interested in taking up risky and productive investment due to the perceived less years to be spent on earth. They may have strong desire and expectation for enjoyment, more willing to enjoy life goodies because death is inevitable. On the other hand, the desire to invest in youthful age for higher future outcomes and economic benefits may constitute a push factor to younger farmers who show more willingness to risky decisions.

For SG1 and SG2, the results presented in **Table 24** show that farmers practising Christianity are less willing to take risky decisions or avoid taking risky decisions compared to their counterparts practising other religions especially Islam. Past studies reported that religious farmers are risk averse (Liu, 2013; Liebenehm & Waibel, 2014). In this study, it may be difficult to infer how religious an individual is, yet the results indicate that Christian farmers statistically and significantly behave differently to other farmers. Religion may drive farmers' belief as well as influencing their level of gambling but not necessarily their farm or investment decisions. For example, there is no clear distinction between Muslim and Christian farm households in most parts of Western Nigeria where the study is conducted. Notwithstanding, the political element of religion may contribute to the preferences revealed by the subjects.

The findings also indicate that, with respect to SG1 and LG1, farmers with small land holdings are less willing to take risky decisions relative to large-scale farmers. This suggests additional hectare of rice farm increases the likelihood of risk taking among rice farmers. This result is plausible and consistent with the expectation and previously reported findings including Yesuf and Bluffstone (2009) and Binswanger (1978). There are two possible reasons for this finding. On one hand, small-scale farmers may require significant income to expand their scope of operation which may make them reticent to taking risky decisions. On the other hand, large farms may imply additional financial requirements or commitments thus taking risky decisions might be adoptable strategies to increase farm income. If farm size is a proxy for wealth or income (which is often the case in the developing world), it may be safe to conclude that the result agrees with previous findings, which reported that wealthier farmers are less risk averse especially in the developing countries (Wik *et al.*, 2004; Yesuf, 2004; Yesuf & Bluffstone, 2009; Tanaka *et al.*, 2010; Liu, 2013; Liebenehm & Waibel, 2014). Indeed, small farm size is a reflection of low income and possibly the prevalence of poverty.

The coefficient of education is not significantly different from zero, the results show that an additional year of schooling may increase rice farmers' level of willingness to taking risky decisions. This implies educated farmers are more likely to take risky decisions relative to non-educated farmers. Educated farmers are likely to possess more information which may drive their willingness to risk taking. More so, knowledge and awareness may be transferred more easily among educated farmers. This may subsequently affect farmers' risky decisions. In short, literate farmers may process the information on the risk game more especially the consequences of gains and losses.

The results as shown in **Table 24** also revealed that in all the four risk treatments, male rice farmers are less likely to take risky decisions relative to their female counterparts. This is contrary to expectations and previously reported findings in the literature that males are general risk takers (see similar study by (García Gallego *et al.*, 2012)). It is also opposed to the findings reported among farmers in the developing countries that females are averse to risk than their male counterparts (Liu, 2013; Ward & Singh, 2014; Tanaka & Munro, 2014). It is however in agreement with Harrison *et al.* (2010) who find a marginal difference between the risk aversion of male and female. This finding also disagree with previously reported findings on the financial risk behaviour between male and female, that women are less financially tolerant and more financially risk averse relative to men (Charness & Gneezy, 2012; Bannier & Neubert, 2016; Fisher & Yao, 2017). It also disagrees with Harris *et al.* (2006) who attributed the gender differences in perceptions about outcomes and risky decision making to less enjoyment tendency among women.

One possible reason for this finding is that male rice farmers may attach less importance to the lottery stakes or perceived them as liquidity capital relative to female farmers who may attach more value to the monetary rewards offered by the lotteries. This proposition is based on the fact that on average, male rice farmers cultivate more land for rice production compared to female farmers indicating males get more income from farming and possibly other economic activities. In addition, women tend to have higher expectations for social engagements and activities which may push their desire and willingness towards taking risk. This attitude may also be viewed from the fact that male rice farmers may have strong attachment to status quo or endowment effect. In other words, as stressed in the literature review section, male rice farmers who constitute the larger proportion of the sample may not be willing to lose the 'certain' yield from the traditional rice varieties or be less willing to pay a price for the 'uncertain' yet higher yield from the improved rice varieties.

Furthermore, in all the risk treatments, married rice farmers show less willingness to risk taking (avoid risky decisions) relative to single farmers. Although there is no *a priori* expectation on the direction of marital status, the finding seems plausible. As earlier noted, single farmers or individuals tend to care less about the possibility of loss relative to the married individuals who may perceive loss as a threat to their livelihood due to family responsibility and financial commitments. In other words, married farmers may be highly averse to taking risky decisions especially when confronted with certain outcomes. This result also agrees with the popular saying that a bird at hand is better than two in the bush because married individuals have more financial pressing and would probably do everything within their capacity to avoid risky outcomes or avoid losing money. Arguably, married farmers may show more desire to risk taking as an option for gaining more money to cater for their family financial needs.

In both the developed and developing countries, rural areas generally lack access to infrastructural facilities compared to urban areas. For example, bad road networks may limit movement and access to information and market thereby limiting the production and income potential of farmers. It can therefore influence farmers' behaviour. The results (for all treatments) show that farmers living in the untarred bad road network areas are less willing to take risky decisions compared to those living in more accessible road areas. This suggests that lack of infrastructural facilities may have a negative impact on the risk taking ability of individual farmers. These results are consistent with the expectation. Note that this study is possibly the first of its kind to include the road variable in risk models examining the determinants of risk attitudes. Rural areas are often associated with poverty attributable to lack of access to social amenities and infrastructural facilities. Indeed, poor farmers have been found to be more risk averse especially in the developing countries (Lawrance, 1991; Wik *et al.*, 2004; Yesuf & Bluffstone, 2009). Since roads are important development infrastructure, it may be safe to conclude that this finding agrees with Binswanger (1978) who reported that farmers living in rural areas are more averse to risk in India as well as Tanaka and Munro (2014) whose finding shows that farmers living in the climatically least favourable and low rain areas show higher aversion to risk. Access to good road may be an indication of economic opportunities. Thus, this finding aligns with those reported on the potential of higher risk aversion in income variability (Guiso & Paiella, 2008; Bezabih & Sarr, 2012). Urban dwellers may naturally have higher tendency for risk taking due to familiarity with the uncertainty associated with the city lives. Put differently, low tendency for risk taking in the rural areas may be attributed to less risky rural environment relative to urban environment. Supportably, the descriptive statistics show that farmers living in the rural agricultural zones are less willing to take risk relative to those living in the urban zone. Therefore, access to road network significantly explains farmers' risk aversion behaviour in the study area.

The main finding: There is evidence of spatial dependency in risk preferences

Hypothesis one: there is a spatial dependence or correlation in risk preferences of rice farmers

More importantly, willingness to risk taking or risk avoidance is spatially determined as indicated by the significant coefficients of all the spatial lags in all the risk treatments' results presented in **Table 24.** This is predicated on the positive and statistical significance of the spatial variable which measures the correlation between the risk preferences of a farmer and adjusted by distance risk preference of his neighbours. Past studies have reported a limit for spatial dependence with spatial parameter, rho increases up to a particular distance and later decreases (Bell & Bockstael, 2000; Areal *et al.*, 2012). A similar pattern is observed in this study with 60 km constituting the limit of spatial dependency in risky decision taking. Since this is the first study to examine the effect of spatial dependence or correlation in risk taking or risk preference, comparison would only be based on related studies. In fact, the results obtained from this study agree with many related previous studies including Ward and Pede (2015) who found evidence of positive neighbourhood influence in hybrid rice adoption in Bangladesh. It also agrees with previously presented findings on the positive and significant effects of spatial dependence in adoption decisions (Case, 1992; Holloway *et al.*, 2002; Holloway *et al.*, 2007; Krishnan & Patnam, 2014; Wollni & Andersson, 2014; Ward & Pede, 2015; Tessema *et al.*, 2016). In line with *a priori* expectations, farmers living closely with one another may behave similarly, have similar patterns of adoption or may be in the same income categories. As stressed by Läpple and Kelley (2015), similar patterns of adoption suggests targeting farmers in cluster locations may aid diffusion of agricultural innovation.

Recall that the expectation of willingness to risk taking (Equation 5.5) among rice farmers is a function of their socio-economic characteristics, neighbours' characteristics, neighbours', neighbours' characteristics, as so on, with the neighbourhood influence reducing with distance (Case, 1992). It follows that in addition to the observed socio-economic variables, rice farmers' risky behaviour is influenced by spatial dependence or attributes of their neighbours as well as the socio-economic environment (unobserved factors) where individual farmers reside. Specifically, with respect to SG1, willingness to risk taking (risk avoidance) among rice farmers is expected to decrease by 23 percent ((average $\boldsymbol{W}y_r * coefficient$) (144.09)*0.0016)) as the distance increases from the centre of radius to 60 km. For SG2, LG1 and LG2 the percentage decreases in willingness to risk taking (risk avoidance) associated with increasing distance are 22 percent (115.90*0.0019), 26 percent (133.66*0.0019) and 21 percent (137.13*0.0019), respectively. In other words, the further the distance among the farmers the less likely they would behave in similar manner. This is a plausible finding that could reflect the geographical relationship among individuals irrespective of the locations. For instance, farmers in Nigeria as a geographical entity may have similar behaviour which may differ from their counterparts in Ghana due largely to the distance.

Informal communication and interaction are common phenomenon in both urban and rural areas of most developing countries due largely to clustering and informal setting. The revelation in this finding shows that rice farmers are related climatically, geographically, socially, culturally and ecologically. In line with the first law of geography attributed to Tobler (1970), rice farmers living closely may behave similarly relative to distant rice farmers. In other words, rice farmers located very close to one another, up to 60 km exhibit similar risk attitudes. This may reflect in their decisions to adopt improved agricultural technology. In summary, the results indicate that risky behaviour of a rice farmer is positively and significantly related to her neighbours' suggesting there is a significant positive impact of neighbourhood influence in risky decision among rice farmers in the study area.

Table 24: The Effect of Spatial Dependence on Rice Farmers' Risk Preferences

Variables	SG1	SG2	LG1	LL
Spatial Dependence				
Spatial lag	0.0016***	0.0019***	0.0019***	0.0019***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Farmer Specific Factors				
Age	0.0032***	0.0021***	0.0022**	0.0019**
	(0.0009)	(0.0008)	(0.0010)	(0.0008)
Education	0.0043	0.0002	0.0035	0.0037
	(0.0025)	(0.0025)	(0.0026)	(0.0024)
Christian	0.0498**	0.0498***	-0.0263	0.0217
	(0.0217)	(0.0185)	(0.0207)	(0.0191)
Household size	0.0021	0.0027	0.0016	0.0004
	(0.0031)	(0.0034)	(0.0034)	(0.0037)
Farm size	-0.0163**	-0.0047	-0.0155*	-0.0074
	(0.0075)	(0.0056)	(0.0081)	(0.0069)
Male	0.0559**	0.0498***	0.0616***	0.0580***
	(0.0234)	(0.0196)	(0.0217)	(0.0210)
Married	0.3103***	0.2214***	0.3089***	0.2137***
	(0.0611)	(0.0556)	(0.0587)	(0.0509)
Location				
Bad road	0.1097***	0.0549***	0.1123***	0.0595***
	(0.0206)	(0.0186)	(0.0208)	(0.0195)

Source: Data Analysis, 2017

N = 328

Diagnosis Statistics:
Weak instruments: SG1 = 30562.80 (p < 2E-16), SG2 =23621.55 (p<2E-16), LG1 = 25382.5 (p<2E-16), LL= 18951.71(p<2E-16)
OLS consistency: SG1 = 29.15 (p=1.31E-07), SG2= 57.88 (p=3.16E-13), LG1= 71.4 (p=1.05E-15), LL= 36.59 (p=4.08E-09)
Wald Tests: SG1 = 787.9 (p<2.2E-16), SG2= 753.4 (p<2.2E-16), LG1 =738 (< 2.2E-16), LG2 =492.9 (<2.2E-16)

5.1.5 Concluding Remarks

This study provides insights into the role of spatial dependence in risky decision-making among rice farmers in developing country with specific attention on Nigeria. The results indicate that farm and farmers' specific factors such as age, marital status, and gender; bad road networks and spatial dependence significantly determine rice farmers' willingness to risk taking or risk avoidance attitude. Specifically, rice farmers' risk attitude is spatially dependent while farmers' locations were found to contribute significantly to risk taking with farmers living in bad road network or remote areas avoid risky decisions relative to others who live in more accessible road condition areas.

Emanating from the findings of this study, the following policy options are recommended. First, heterogeneity in risky decisions should be giving special consideration in the design and formulation of policies and programmes that would improve the living conditions of rice farmers living in rural areas. For example, rural farmers may show higher aversion to risk than urban farmers or farmers living in the more developed agricultural zone and subsequently less willing to take risky investment decisions such as adopting improved farm technologies. Adequate information about the risk attitude of rural farmers is important to persuade such farmers in changing their attitudes to undertaking risky investment decisions which may have significant income effects. Second, improvement in the road networks of rural areas is recommended. Good and accessible roads will not only increase rice farmers' level of awareness or information on improved agricultural technology but also increase the chances of transporting and marketing farm produce. Above all, the evidence of spatial dependency in risky decisions is a pointer to the existence of social interactions among farmers. It also shows the likelihood of similar behaviour among farmers living closely. Such spatial dependency is a revelation that geographical, ecological, climatic and socio-economic conditions reflect in rice farmers' risky decisions. It follows that policy makers, government and development partners should not only consider individual socio-demographic variables as the only determining factors in risky decision making while formulating policy relating to risk management but should include the spatial aspects of decision making.

5.2 Risk Preferences, Spatial Dependence and Improved Rice Technology Adoption Decisions

5.2.1 Background

Poor growth in agricultural productivity is a significant bane to the economic development of most developing countries where agriculture remains a primary source of livelihood and key contributor to gross domestic product (GDP). Low agricultural productivity in this region may be attributed to many factors ranging from weak public institutions (extension services, finance and insurance markets), ineffective policies, inadequate irrigation to low use of improved farm practices or technologies (Development and Cooperation, 2012). Subsequently, most farmers produce less per unit of land.

Specifically, high yield rice varieties (HYV) may enhance farmers' yield and income yet adoption of technological innovation is still doubtful. Decisions to adopt improved agricultural technology are affected by many factors including risk and uncertainty associated with the potential benefits of such technology (Feder, 1980). Most past policy actions in the developing countries involved huge investment in extension services to facilitate adoption of agricultural innovation. Notwithstanding, farmers learn improved farm practices from one another through interpersonal communication and social interaction. Social learning effects, along with other unobserved spatial aspects such as local climatic and topographic conditions may manifest in farmers' risky decision making. Therefore, if accounted for, spatial dependence and risk attitudes could be influential devices for the diffusion of agricultural technological innovation.

Despite the advances in the adoption literature, there is no study directly examining the endogeneity of farmers' risk preference in adoption decisions. Therefore, this study contributes to the existing adoption literature in two ways. First, the endogeneity of risk preference in adoption decisions is examined. Risk attitudes of individual farmers are often measured in diverse ways suggesting the possibility of estimation bias or measurement error. Their omission in adoption model may result in omitted variable problem. Second, many variables are latent and therefore often omitted in adoption model. For instance, adoption decisions may exhibit spatial heterogeneity. Inclusion of spatial lag of the risk preference as an instrumental variable in the adoption model captures some of these unobservable factors. Therefore, both the exogenous and endogenous variables are considered in this study by directly controlling for willingness to risk taking and indirectly incorporating spatial dependence into adoption model. The existing social norms and cultural values among rice farmers in Nigeria may constitute neighbourhood influence and reflect in their adoption decisions. Therefore, knowing the risk-taking ability of individual farmers and the spatial relationship associated with it may aid the diffusion of improved agricultural technology since a highly risk taking farmer could serve as a contact farmer for his neighbours.

Literature on agricultural technology adoption demonstrates that adoption decisions may be explained by many factors. These could be categorized into farm and farmer specific characteristics, technology attributes, institutional factors, social learning and attitudes toward risk and uncertainty (Feder *et al.*, 1985; Foster & Rosenzweig, 2010). Among other factors, risk aversion has been reported to constitute a hindrance to the acceptance of improved agricultural technology (Marra *et al.*, 2003; Liu, 2013; Ward & Singh, 2014; Barham *et al.*, 2014; Barham *et al.*, 2015; Ward & Singh, 2015). Spatial dependence effect is also important in adoption decisions especially among small holder farmers. Nevertheless, the role of spatial dependence and risk aversion in adoption of improved technology has been independently examined (see (Liu, 2013; Läpple & Kelley, 2015)). Ignoring either of these aspects in the analysis may produce biased results and misleading inference. For example, attitudes formed by a farmer towards improved technology after being aware of its advantages may affect his neighbours' decisions. Put differently, a farmer may be risk averse because his neighbour is risk averse.

Though adoption patterns may reflect spatial variability, very few studies have sought to examine spatial relationships in adoption decisions. These studies found evidence of spatial dependence effects in adoption (Case, 1992; Holloway *et al.*, 2002; Krishnan & Patnam, 2014; Läpple & Kelley, 2015; Tessema *et al.*, 2016). However, farmers' willingness to risk taking is not considered by most empirical studies. Information about the benefits of available HYV is important for its acceptance. Giving this fact and the likely impact of the unobserved factors suggest that spatial dependence may play a key role in risky decision-making. Shortly put, spatial dependence may reveal spatial relationships in decision making especially when farmers living closely rely on their friends and neighbours for information.

In line with Tobler (1970), it is assumed that closer farmers may behave in a similar way than distant farmers. The connotation of this is that individuals living closely may behave similarly relative to distant individuals. Since the data collected from individual farmers in points may have a spatial relationship, it follows that farmers living closely may exhibit similar adoption patterns. Past spatial studies admitted this fact by submitting that omission of spatial dependence in agricultural data may produce a biased result and misleading inference (Benirschka & Binkley, 1994; Bockstael, 1996; Weiss, 1996). This study applies spatial data (risk and adoption) from rice farmers in Nigeria. Farmers may emulate one another due to proximity or influence of one or more of the spatial characteristics (local climate socio-economic conditions). This may consequently manifest in their risky investment decisions and constitute a policy tool for the acceptance of technological innovation.

The remainder of this chapter is structured as follows. The review of the literature on factors affecting agricultural technology adoption decisions is reported in Section 5.2.2. Section 5.2.3 describes the data and estimation methods. Results and discussion are presented in Section 5.2.4 while Section 5.2.5 concludes the findings with policy suggestions.

5.2.2 Determinants of Improved Agricultural Technology Adoption Decisions

Many factors may influence decisions to embrace and apply improved agricultural technologies, especially in the developing countries where the technological gap is well acknowledged. In line with related previous studies on improved farm and conservation technologies, these variables are categorised in this study into farm and farmer specific characteristics, institution and community factors, and perception of improved technology attributes, risk preferences and spatial dependence. Most studies on adoption focus on specific factors, including farm size (Feder, 1980; Feder & O'Mara, 1981; Feder, 1982; Just & Zilberman, 1983), farm size, credit constraint and risk aversion (Feder, 1982), risk and learning (Hiebert, 1974). The variables considered in the adoption decision model are briefly examined below.

Farm and Farmer Specific Factors

The role of land in farm production decisions cannot be over-emphasized since no meaningful production can take place without land. Land could also serve as a proxy for other factors like credit access and income in the rural areas. For example, wealthy farmers may easily access large expanses of land due to access to credit and strong economic and political power relative to poor farmers. Therefore, in line with empirical studies (see for examples, (Nkonya *et al.*, 1997; Alene *et al.*, 2000; Dadi *et al.*, 2001; Anley *et al.*, 2007; Davey & Furtan, 2008), it is hypothesized that farm size will have positive effect on the propensity to adopt improved rice technology.

Variables like education, age and gender are important human capital that have been found to determine adoption decisions. For instance, empirical studies reported that education increases the propensity of adoption of improved agricultural technology (for examples (Nkonya *et al.*, 1997; Hossain, Bose, & Mustafi, 2006; Mendola, 2007; Läpple *et al.*, 2015; Anik & Salam, 2015)). In line with past studies, education is hypothesized to have a positive effect on HYV adoption decisions. Age may serve as a proxy for farm experience in the rural areas where most farmers usually start farming at a younger age. In line with previous studies (for examples (Hassan, Njoroge, Mugo, Otsyula, & Laboso, 1998a; Baidu-Forson, 1999; Anley *et al.*, 2007; Läpple *et al.*, 2015)), it is hypothesized that age will have a negative effect on the adoption of HYV. Males and females may have different responsibilities at home and farm as well as differing in allocation and investment decisions. However, there is no *a prior* expectation on the effect of gender on the adoption of HYV.

Household size and marital status are components of human capital often included in adoption models. In developing countries, many farmers depend on family labour for crop production suggesting more family members may translate into more family labour. Large family size may constitute a push factor for taking risky investment decisions. However, mixed results have been reported in the literature. Notwithstanding, farmers with large household size are expected to show positive attitude towards the adoption of HYV in line with Ahmed (2015) and Alene *et al.* (2000). Married farmers may have more family members compared to single farmers. It is therefore hypothesized that married rice farmers should be more likely to adopt HYV. In terms of religion, the practitioners of the two dominant religions, Christianity and Islam in the study area may be equally likely in making decisions. The type of rice production system engaged in by farmers is also hypothesized to have a significant effect on farmers' adoption decisions. Therefore, farmers growing upland rice are expected to be more likely to adopt HYV.

Institutional and Community Factors

Another component of the variables often considered in the adoption model is institutional and community factors. For example, Kebede *et al.* (1990) emphasized the role of information in the acceptance of improved agricultural technology in Ethiopia. Extension contact has been reported to have a positive influence on the adoption of improved agricultural technology (Nkonya *et al.*, 1997; Hassan, Njoroge, Njore, Otsyula, & Laboso, 1998b; Anley *et al.*, 2007). Farmers may rely on the information provided by extension agents to make decisions relating to farm production. Where such contact exists, it is expected to have a significant positive effect on farmers' decisions. However, some farmers may not have access to extension services or have only one contact with the extension agents within a year. In such instances, extension contact may not have a significant effect on farmers' decisions.

Low extension services in developing countries often encourage farmers to rely on social networks as source of information. For example, social networks and learning have been reported to have positive impact on the diffusion of improved farm practices (Foster & Rosenzweig, 1995; Bandiera & Rasul, 2006). Access to information positively impacted improved legume technology adoption in Tanzania and Ethiopia (Asfaw, Shiferaw, Simtowe, & Lipper, 2012). Social learning effects are also reportedly swaying farmers' adoption processes (Foster & Rosenzweig, 1995; Bandiera & Rasul, 2006; Conley & Udry, 2010; Krishnan & Patnam, 2014). In assessing attitude towards the adoption of improved sunflower in Northern Mozambique, Bandiera and Rasul (2006) show that farmers rely on information from family and friends. In India, Foster and Rosenzweig (1995) reported that propensity to adopt HYV increases when farmers learn from their neighbours. Similarly, Conley and Udry (2010) revealed that pineapple farmers learn from their neighbours in Ghana. Farmers residing in villages may have late information about HYV due to low access to formal education and poor road networks. This information gap may be bridged by farmers' neighbours.

Rice farmers with greater social networks are more likely to have access to information. Therefore, farmers who relied on information from friends and neighbours may show positive or negative attitudes towards the adoption of HYV depending on the neighbour influence and personal perception. Accessible road networks may also aid access to information and market. It is therefore hypothesized that less accessible road networks may negatively affected the probability of adopting HYV. Three dummies representing agricultural zones are included in the adoption model to control for the effect of locations. It is hypothesized that farmers living in low rainfall or dried agricultural zones may be more likely to adopt HYV.

Perceptions about Improved Technology Attributes

Perceptions of farmers on the attributes of HYV may significantly influence adoption decisions. The attributes included in the adoption model included high yield, short duration, long stem and good tiller. These are hypothesized to have positive effects on the propensity to adopt improved rice varieties in line with previous studies (Adesina & Zinnah, 1993; Adesina & Baidu-Forson, 1995).

Risk Preference

Above all, this study examines the effect of risk avoidance on adoption decisions. Advances in the literature suggest that farmers in developing countries are risk averse (Harrison *et al.*, 2010; Tanaka *et al.*, 2010). Low HYV adoption rates in developing countries have also been attributed to higher risk aversion among farmers. For example, Knight *et al.* (2003) reported a negative relationship between risk aversion and adoption in Ethiopia while Engle-Warnick *et al.* (2007) affirmed ambiguity aversion reduces the propensity of adoption in Peru. Liu (2013) revealed that more risk averse and loss averse farmers were late BT cotton adopters while those who overweighed small probabilities constituted early adopters in China. Moreover, Liu and Huang (2013) concluded that risk aversion reduces the adoption of pesticides among Chinese farmers while Ward and Singh (2015) showed that risk and loss aversion decrease willingness to adopt new rice technology in India. Notwithstanding, past studies in Nigeria ignore the role of risk aversion in adoption decisions (Saka & Lawal, 2009; Tiamiyu *et al.*, 2009; Adedeji *et al.*, 2013; Dontsop Nguezet *et al.*, 2013; Awotide, Alene, Abdoulaye, & Manyong, 2015). Therefore, in line with past studies, it is hypothesized that risk averse farmers should be less likely to adopt HYV.

Spatial Dependence

Although there are existing studies incorporating neighbourhood effects in adoption model, spatial dependency in experimental risky decision making or spatial aspects of risk preference have never been exploited in the literature. Spatial factors and attributes like farmers' locations, community norms, and ecological, geographical and climatic conditions may affect farmers' adoption learning processes and subsequently adoption decisions. Inclusion of spatial dependence or spatial lag of willingness to risk taking captures these unobservable variables. Empirical evidence of neighbourhood effects in adoption patterns include sickle adoption in Indonesia (Case, 1992), HYV adoption decisions among Bangladesh rice farmers (Holloway *et al.*, 2002), maize seed and fertilizer adoption in Ethiopia (Krishnan & Patnam, 2014), organic farming adoption among Irish farmers (Läpple & Kelley, 2015) and conservation tillage adoption in Ethiopia (Tessema *et al.*, 2016). These studies conclude that neighbours tend to behave similarly. Previous studies found a negative effect of distance to information on the timing of adoption (Lindner *et al.*, 1979; Lindner *et al.*, 1982). In brief, the literature points to the importance of both spatial relationship and risk aversion in adoption decisions. However, while some studies linked risk aversion with adoption (Liu, 2013; Liu & Huang, 2013; Barham *et al.*, 2014; Barham *et al.*, 2015) others examined the relationship between spatial dependence and adoption decisions (Läpple & Kelley, 2015; Tessema *et al.*, 2016). Both aspects are considered in this study using spatial lag as a proxy for unobserved factors that may influence rice farmers' adoption decisions.

5.2.3 Data and Model

The type and method of data collection as well as the description of the variables used in the model considered in this section have been previously discussed in Chapters three and four, respectively. Notwithstanding, the definitions of the variables used in the adoption model are presented in **Table 25**. There is vast literature on the adoption of agricultural technological innovation with different studies applying different modelling approaches. For examples, adoption decisions may be modelled using binary outcome models (Rahm & Huffman, 1984; Shakya & Flinn, 1985; Kebede *et al.*, 1990); two stage models such as Tobit (Nkonya *et al.*, 1997; Alene *et al.*, 2000; Fufa & Hassan, 2006), Heckman (Dadi *et al.*, 2001), double hurdle (Hassan *et al.*, 1998b; Tambo & Abdoulaye, 2012; Anik & Salam, 2015); survival or duration models (Fuglie & Kascak, 2001; Liu, 2013), multivariate probit (Ahmed, 2015), bivariate probit (Neill & Lee, 2001) or three stages (Saha *et al.*, 1994). In summary, binary model is the appropriate approach when a decision making unit faces a situation of two technology options. However, a two-stage procedure may yield consistent estimate relative to a binary model when at least one variable is endogenous in the adoption decisions model.

As earlier noted, some variables may be omitted in the adoption model due to difficulty in measurement. These variables are captured by the spatial lag of the willingness to risk taking which is instrumental to climatic condition, topographic condition and other unobserved variables. Moreover, preferences for risk are assumed to be endogenous in the adoption decisions. Therefore, this potential endogeneity problem in the binary outcome variable is addressed using instrumental variable (IV) probit or probit model with a continuous endogenous covariate. The structural model as well as its reduced form are specified as follows.

$$\boldsymbol{Y_1} = \boldsymbol{X}\alpha + \rho \boldsymbol{W}\boldsymbol{Y}_1 + \nu \quad (5.6)$$

$$y_2^* = \boldsymbol{Y}_1\beta + \boldsymbol{X}\gamma + \varepsilon \quad (5.7)$$

Where $\boldsymbol{Y_1} = N\ X\ 1$ vector of endogenous variable. This is an index of willingness to risk taking, the average probability values corresponding to farmers' choices in each treatment of the panel lotteries. This ranges between 0.1 and 1 with an index of 1 indicating highly unwilling to take risk. $\boldsymbol{X} = N\ X\ K$ vector of exogenous variables that affect adoption decisions. $\boldsymbol{WY_1} = N\ X\ 1$, vector of the instrumental variable (spatial lag). Kindly note in addition to the spatial lag as instrumental variable, all other variables in the adoption model are assumed to be exogenous and thus used as instruments. $\boldsymbol{WY_1} = \boldsymbol{Z}$, the instrumental variable (spatial lag). This is the weighted average of risk willingness in the neighbourhood locations. The ρ is a scalar parameter that determines the correlation between willingness to risk taking by a rice farmer and the adjusted-by-distance mean risk willingness of his neighbours. $\boldsymbol{W}$ is the $N \times N$ weights matrix defined in Equation 3.6. The weights matrix corresponding to 60 km is used in this model. Lastly, $\rho\boldsymbol{WY}$ implies the utility derived by rice farmer from the risk experiments (all treatments) is related to that derived by his neighbours'. This spatial dependency tendency may be attributed to social interaction, geographical proximity and climatic condition associated with farmers' locations.

y_2^* represents HYV adoption decisions. Note that y_2^* is not observed. Therefore, Equation 5.8 applies:

$$y_2 = \begin{cases} 0, & y_2^* < 0 \\ 1, & y_2^* \geq 0 \end{cases} \quad (5.8)$$

The above univariate model is estimated to identify the determinants of rice farmers' HYV adoption decisions. A significant correlation between the disturbance errors of the two models suggests that these models are related. Otherwise, a binary probit may be estimated in a single equation. Statistical tests are available in the Stata software used in the analysis of the data in this study.

The error terms are jointly normally distributed, $(\varepsilon, \nu) \sim N(0, \boldsymbol{\delta_i})$ with the first element of the error matrix normalized to one to identify the model. $\beta = N\ X\ 1$ vector of parameter corresponding to the predicted value of the first stage Equation, γ is the vector of structural parameters in the second stage adoption model while α is the vector of the parameters of the first stage equation.

The order condition for the identification of the structural parameters is that the number of variables in the first stage model (risk model) is greater than or equal to that of the second stage equation (reduced form or adoption decision model). Note that Stata 14 treats all other variables in the risk model as exogenous. Therefore, in addition to the spatial lag of the risk variable, other exogenous variables are used as instruments to exactly identify or just-identify the model.

As defined in **Table 25**, the farm and farmer specific factors considered in the adoption model include age, education, religion, household size, farm size, gender, marital status and production system. The institutional and community factors hypothesized to have effect on rice farmers' adoption decisions include extension contact, information from friends, locations (agricultural zones) and road network. High yield, long stem, short duration and good tiller capacity are the perceived improved technology attributes hypothesized to affect adoption decisions. Finally, risk preference is considered to examine the effect of rice farmers' willingness to risk taking on HYV adoption decisions.

Table 25: Definitions of the Variables used in the Adoption Decisions Model

Variables	Definition
Dependent Variable	
Adoption	1 if rice farmers adopt, 0 otherwise
Explanatory Variables	
Farm and Farmer Specific Variables	
Age	Years
Education	Years of formal schooling
Religion	1 Christian, 0 otherwise
Household size	Current household members
Farm size	Size of land cultivated to rice production in the last season
Male	1 if male, 0 otherwise
Married	1 if married, 0 otherwise
Upland	1 if upland production system, 0 otherwise
Perceptions of HYV Attributes	
High Yield	Perceived high yield importance
Long stem	Perceived long stem importance
Short duration	Perceived short duration importance
Good Tiller	Perceived tiller supremacy importance
Institutional and Community Factors	
Friends	1 if rely on information from friends, 0 otherwise
Extension contact	No of contact with extension agents
Bad road	1 for less accessible road, 0 otherwise
Locations	3 dummies for agricultural zones (1 if Ikenne, Ijebu-Ode and Ilaro, 0 otherwise)
Risk Preference	
Risk avoidance	Less willingness to risk taking or tendency to avoid risky decision

Note: perception questions are measured on 5 scales ranging from not at all important (1), somewhat important (2), important (3), very important (4) and extremely important (5)

Source: Author's Compilation, 2017

5.2.4 Results and Discussion

The results of the predictors of adoption decisions, with the emphasis on the role of risk preference are presented in **Table 26**. Different models were estimated for the four risk treatments of the panel lotteries (SG1, SG2, LG1, LG2) for comparison using Stata 14. A different model is considered since a spatial lag used as instrument is calculated for each probability index which represents willingness to risk taking for each treatment of the panel lotteries. The Wald statistics of 219.59 ($p<0.000$), 258.41 ($p<0.000$), 375.74 ($p<0.000$) and 386.02 ($p<0.000$) are respectively significantly different from zero for all the four treatments attesting to the overall significance of the two-stage adoption models. The null hypotheses of no endogeneity were also rejected for the four treatments suggesting risk preferences are endogenous determinants of rice farmers' adoption decisions. The correlation (with correlation coefficients of 0.96, 0.99, 0.99 and 0.99) between the standard errors of the risk (structural Equation) and adoption (reduced form) models is significantly different from zero for all the four treatments suggesting the models are better estimated in two stages (simultaneously estimated using IV probit) rather than using binary probit. In other words, all the results confirm the dependency of the risk and adoption models implying binary probit would yield inconsistent estimates. In summary, the model treating risk preferences as endogenous variables yields consistent estimates compared to that where risk preferences are assumed to be exogenous (see **Table 32** under **Appendix A: Additional Tables** for details and comparison). It is worth noting that the coefficients of the risk preferences obtained for all the four models are larger relative to that obtained when risk preferences are treated as exogenous variables. The standard errors are also lower, respectively for the models treating risk as endogenous variable. The results indicate gender, location, extension contact; perceptions about improved rice technology attributes and risk avoidance are the factors that significantly determine the decisions of rice farmers to adopt HYV in the study area. The significant variables are explained next with the key finding presented first.

Main Finding: Risk Avoidance significantly explain adoption decisions

Hypothesis two: Risk preference is endogenous and significantly explain adoption decisions

The results of this study indicates that adoption of HYV is not only explained by farmers' socio-economic characteristics, location and perceptions of technology attributes but also by risk avoidance or willingness to risk taking. Therefore, the above stated hypothesis (hypothesis two) is accepted. In fact, the results presented in **Table 26** reveal that risk avoidance decreases the propensity to adopt improved rice technology. A rice farmer who is strongly unwilling to take risky decisions (highly risk avoidant farmer) is less likely to adopt HYV relative to a farmer having strong willingness to risk taking. The literature suggests that adoption of improved agricultural technology is often determined by the degree of risk, ambiguity and uncertainty associated with it. A highly risky technology may offer more yield and income to farmer yet farmers' level of aversion to risk may reduce their adoption tendency. In general terms, risk loving farmers are likely to be early adopters or allocate a larger proportion of their farm size to improved farm technologies while farmers who avoid risk are likely to lag behind. Thus, the results evidently support the correlation or relationship between real-life decisions (HYV adoption and experimental risk lotteries).

On one hand, this finding agrees with the previous studies which reported that neighbourhood farmers influence one another in the process of adopting improved agricultural technologies (Case, 1992; Holloway *et al.*, 2002; Holloway *et al.*, 2007; Läpple & Kelley, 2015). On the other hand, it confirms the negative effects of risk avoidance or risk aversion in the adoption of improved agricultural technology in line with previous studies (Marra *et al.*, 2003; Liu, 2013; Ward & Singh, 2014; Barham *et al.*, 2014; Barham *et al.*, 2015; Ward & Singh, 2015). Farmers may adopt improved innovation if it offers them more yield and income relative to local or traditional varieties. The decisions to accept such innovation are not a direct process as they may be complicated with many factors. Risk aversion has been identified as one of such important factors that plays a significant role in the adoption processes or acceptance of innovation. Risk averse farmers may lag behind, waiting to see the significant effects of innovation on other farmers' yield and income. This suggests that risk attitudes may have some spatial element associated with them. This spatial factor is controlled for in this study using spatial lag of the risk variable as instrument. With respect to risk, it can be concluded that the results of this study shows a negative relationship between risk attitude (risk avoidance) and probability of adopting HYV. In addition, farmers living closely or in the same agricultural zone may influence one another while making risky investment decisions such as the adoption of improved farm practices.

More importantly, given that a spatial lag is used as instrument in the first stage model, it suggests rice farmer's adoption decisions are not only influenced by risk avoidance but also by her neighbour's decisions. This is a confirmation that rice farmers living very closely interact with one another while such interaction effects may manifest in adoption decisions and patterns. Social interaction and learning effects, in addition to other spatial factors such as variation in weather and climate, topographic, ecological conditions and soil types may be proxy for (or captured by) spatial dependence. These external factors are important in the diffusion of agricultural innovation. It therefore suggests that farmers living closely may exhibit similar patterns of adoption which have important implications for the diffusion of technological innovation.

Farm and Farmers' Specific Factors

Two socio-economic variables: education and farmer size are often tested by most cited studies. Given the importance of these two variables, a cursory explanation is presented on them despite that their coefficients are not statistically different from zero. The result shows that an additional year of education increases the probability of adopting HYV. Education is an impetus to accessing information. It may also be viewed as a gateway to market access because a well-informed farmer is more likely to have access to market information including awareness about input and output prices. Consequently, education may aid risk taking among farmers.

The result presented in **Table 26** indicates that Christian rice farmers are less likely to adopt HYV relative to farmers practising other religions such as Islam and traditional worshipers. This agrees with the results obtained under the risk attitudes where Christian farmers show less willingness to risk taking. There is no *prior* expectation on the effect of religion on adoption decisions but it agrees with previous finding that religious farmers are risk averse (Liu, 2013). Although religion affiliation relates to belief, it may not necessarily affect individual farmers' perceptions as well as input and output allocation or production and investment decisions. However, it provides information on the risk taking ability across religious values in additional to individual assessment which most studies are limited to. In brief, religion is inherent in individual and it may influence individual choices in some ways.

Gender is an important economic tool that could be used to disaggregate economic agents. In fact, the analysis of the economic policy of all nations may not be complete if gender issues are given less attention because it cuts across various aspects of life. The finding shows that male rice farmers are less likely to adopt improved rice varieties implying the probability of adopting HYV decreases for males relative to females. Although contrary to expectation, and previously reported findings that males are risk takers, this result agrees with Davey and Furtan (2008). One plausible reason while this finding is robust is the fact that female farmers are well represented in the data which reduces the biasness of non-representation. One the other hands, the findings may be linked to the peculiarity of the rice production enterprise which is labour intensive and involves a lot of drudgery work. Female headed households may be under more financial pressure and thus more innovative and willing to undertake new investment relative to their male counterparts. Furthermore, male rice farmers may be strongly bias towards status quo relative to their female counterparts. In addition, male may have strong feeling towards losing the 'sure' output or yield from the traditional varieties than their female counterparts. It could also be view from income perspective as male farmers, on average cultivate more land and earn more income from rice production than female farmers. Males equally have higher tendency to diversify their livelihood and income generating activities. In line with past studies, wealthy individuals are less averse to risk taking (Wik *et al.*, 2004; Yesuf, 2004; Yesuf & Bluffstone, 2009; Tanaka *et al.*, 2010; Liu, 2013; Liebenehm & Waibel, 2014). Therefore, the desire to increase farm income by female farmers may constitute push factor for the adoption of HYV.

The coefficient of farm size is not statistically different from zero but it may worth making some statements on this variable. The size of holding is an important production input for an economic agent. In the farming context, no meaningful production could take place without access to such indispensable production input. In fact, land is the most important production resource in the developing countries where this enterprise is largely agrarian. A positive relationship has been reported between adoption rates and farm size (Alene *et al.*, 2000; Dadi *et al.*, 2001; Adedeji *et al.*, 2013). Although the coefficient of farm size is not statistically different from zero, consistency with the expectation, the result may suggest large scale farmers have higher propensity to adopt HYV relative to smallholder farmers. As noted earlier, large scale farmers may have access to credit and other production inputs relative to small holder farmers. This input access advantage may be a driving force behind their desire to adopt improved agricultural technology relative to small-holder farmers.

Institutional, Community and Location Factors

Community and institutional variables are hypothesized to explain farmers' adoption decisions. The results indicate that rice farmers located in Ikenne and Ijebu-Ode agricultural zones are less likely to adopt HYV relative to farmers residing in Abeokuta agricultural zone. On the other hands, farmers living in Ilaro agricultural zone are more likely to adopt HYV relative to farmers living in Abeokuta. Variability in climatic environment is one possibility for this pattern of behaviour. Farmers living in the drier zone, Ilaro, have higher propensity to adopt HYV due largely to the fact that improved rice varieties are stress-tolerance and drought resistant. This is possibly (as shown in the significant of the coefficients) followed by Abeokuta zone, Ikenne zone and Ijebu-Ode zone, respectively. The finding could be a revelation that farmers residing in the low rainfall zone prefer improved rice technologies which are drought-resistant and suitable for their climate. The trend is probable for other zones where those in low land areas, Ijebu-Ode zone are least likely to adopt improved rice varieties because these category of farmers may have high preferences for improved rice varieties that could be developed or bred to suite their climatic environment. In other words, geographical proximity may explain the pattern of adoption among rice farmers in line with the spatial analysis which reveals that rice farmers located within 60 km show similar risky behaviour. Over all, motivation for growing improved rice varieties may come from the desire to increase yield and farm income and ensure food security.

Access to information and infrastructure is another reason farmers may behave heterogeneously across locations. As stressed by past studies, access to information may reduce the tendency of adopting HYV. For instance, Kebede *et al.* (1990) submit that low access to information reduces probability of adoption in Ethiopia. Indeed, farmers living in the rural agricultural zones or remote areas may have less access to information compared to urban dwellers. Access to information may therefore influence the decisions to adopt or otherwise. Since rural areas lack access to infrastructural facilities such as accessible roads and schools, rural rice farmers' access to information may be limited. This result agrees with previous findings that farmers living in rural areas are resource poor and often less willing to take risky decisions (Lawrance, 1991; Wik *et al.*, 2004; Yesuf & Bluffstone, 2009). In summary, the finding confirms that rural farmers show less desire towards adopting improved agricultural technologies and farm practices.

Both formal and informal information is important in the dissemination of improved agricultural technological innovation. As shown in Table 26, access to extension services has positive and significant effect on the adoption of HYV. This finding is consistent with previous findings which reported a positive and significant effect of extension contact on the adoption of improved agricultural technology (Polson & Spencer, 1991; Alene *et al.*, 2000; Moser & Barrett, 2006; Oladele, 2006). Farmers usually rely on the information provided by extension agents to make informed farm production and investment decisions. However, one major challenge confronting farmers in most developing countries like Nigeria is low extension services since one extension agent service over one thousand farmers. This limits access to information and subsequently investment in improved agricultural innovation by farmers. Therefore, most farmers rely on their social networks for information on improved practices.

Perceptions about Improved Rice Technology Attributes

Characteristics of improved seeds or rice varieties such as high yield, long stem, short duration, cooking qualities such as ease of cooking and taste have been previously reported as one of the key factors influencing farmers' adoption decisions. With the exception of high yield, the results indicate that rice farmers who highly ranked HYV attributes such as long stem, shorter growing cycle and good tiller important in making adoption decisions are less likely to adopt HYV. This is contrary to previous findings who reported a positive relationship between farmers' perceptions of HYV attributes' superiority and adoption decisions (Adesina & Zinnah, 1993; Adesina & Baidu-Forson, 1995; Kallas *et al.*, 2010). It however, agrees with Mehar, Yamano, and Panda (2015) who found male farmers showing strong preference for high yield and marketable traits in India. One plausible reason may be attributed to the fact that even though these attributes are perceived important, a sizeable proportion of rice farmers in the study area were not growing HYV; having strong preference for a local delicacy OFADA rice. However, rice farmers perceived high yield is an important attribute in adopting HYV. This is shown in the coefficient of this variable which is positive and significantly different from zero. One argument that could be put forward is that, among various attributes, yield is perceived as most important. This is not surprising since higher yield implies more income. Again, most improved agricultural technologies are developed central to producing more output per hectare of land to appeal to farmers' judgment and acceptance. It can therefore be submitted that farmers attached more importance to high yield relative to other attributes due largely to the desire to obtaining higher yield and subsequently higher income.

Table 26: Effect of Risk Preference on Adoption Decisions

Variables	SG1	SG2	LG1	LG2
Risk Preference				
Risk avoidance	-7.6850***	-8.3689***	-7.9113***	-9.0092***
	(0.6742)	(0.6266)	(0.5321)	(0.6605)
Farm and Farmers Specific Factors				
Age	-0.0015	-0.0059	-0.0076	-0.0001
	(0.0096)	(0.0065)	(0.0072)	(0.0072)
Education	0.0617	0.0167	0.0204	0.0389
	(0.0432)	(0.0328)	(0.0292)	(0.0277)
Christian	-0.0746	0.0159	-0.4742***	0.0152
	(0.1685)	(0.1477)	(0.1468)	(0.1568)
Household size	-0.0215	0.0013	-0.0098	-0.0253
	(0.0378)	(0.0303)	(0.0308)	(0.0396)
Farm size	0.0154	0.0537	-0.0317	0.0527
	(0.0854)	(0.0649)	(0.0560)	(0.0702)
Male	-0.7156*	-0.4016	-0.4286*	-0.4332
	(0.3951)	(0.2916)	(0.2588)	(0.2734)
Married	0.1114	-0.0237	0.3880	0.1929
	(0.4254)	(0.3691)	(0.4050)	(0.3540)
Upland rice	0.0700	0.2017	-0.1145	0.0170
	(0.2838)	(0.2531)	(0.3192)	(0.3305)
Agricultural Zones/Locations				
Ikenne	-0.6433	-0.5309	-0.3852	-0.6016
	(0.8489)	(0.7992)	(0.6478)	(0.6505)
Ijebu-Ode	-0.0702	-0.3789	-0.2292	-0.6240**
	(0.5618)	(0.4570)	(0.3383)	(0.2923)
Ilaro	0.9992***	0.6164***	1.0188***	1.7128***
	(0.2994)	(0.2256)	(0.2461)	(0.2237)
Community and Institutional Factors				
Extension contact	0.0360	-0.0098	0.0593***	0.0265
	(0.0277)	(0.0244)	(0.0221)	(0.0249)
Friends	-0.2479	-0.2209	0.1403	0.2188
	(0.2298)	(0.1869)	(0.1752)	(0.1805)
Perceptions about Technology attributes				
High yield	0.3092***	0.1341	0.2633**	0.0714
	(0.1119)	(0.0973)	(0.1095)	(0.1056)
Long stem	-0.1595	-0.1697	-0.1347	0.0572
	(0.1562)	(0.1213)	(0.1230)	(0.1211)
Short duration	-0.4060	-0.2981	-0.2999*	-0.5558***
	(0.2685)	(0.2051)	(0.1571)	(0.1564)
Good tiller	-0.3940*	-0.2468	-0.2823*	-0.3040**
	(0.2315)	(0.1832)	(0.1510)	(0.1497)
Constant	6.7752***	6.5916***	6.5119***	6.0872***
	(1.8807)	(1.6713)	(1.4339)	(1.5361)
Tests of Correlation of Errors				
Corr. (SE2 and SE1)	0.9626***	0.9877**	0.9878***	0.9922***
Sigma (SE1)	0.1275***	0.1219***	0.1313***	0.1281***

SG1: Wald test of exogeneity (correlation = 0): Chi squares (1) = 10.60, Prob > chi2 = 0.0011
Wald Chi2 (18) =219.59, Prob > chi2 = 0.000

SG2: Wald test of exogeneity (correlation = 0): Chi squares (1) = 12.00 Prob > chi2 = 0.0003
Wald Chi2 (18) = 258.41, Prob > chi2 = 0.0000

LG1: Wald test of exogeneity (correlation = 0): Chi squares (1) = 18.60, Prob > chi2 = 0.0000
Wald Chi2 (18) = 375.74, Prob > chi2 = 0.0000

LG2: Wald test of exogeneity (correlation = 0): Chi squares (1) = 21.42, Prob > chi2 = 0.0000
Wald Chi2 (18) = 386.02, Prob > Chi2 = 0.0000

Note: SE2 = standard error of the adoption model, SE1 = standard error of the risk model, Sigma = standard error of risk model, SE = Standard Error, Corr. = correlation, Figures in the parentheses are the SE. *, **, *** implies coefficients are significant at 10%, 5%, and 1%, respectively. Figures in parentheses are standard errors. Number of Observation (N=329)

Source: Data Analysis, 2017

5.2.5 Conclusion and Policy Suggestions

This study provides some insight into the correlation between real life decisions, willingness to risk taking (risk avoidance) and adoption decisions among rice farmers in Nigeria. In addition to socio-demographic factors, risk avoidance significantly explains rice farmers' adoption decisions. It is evident that most rice farmers in this study area were less willing to take risky decisions. It was also empirically shown that rice farmers' risk willingness is spatially correlated. In other words, significant correlation exists between the risk preference of a rice farmer and his neighbours. This type of behaviour is predicated on the fact that informal interaction usually exists among farmers living closely. Rice farmers geographically behave in a comparable manner by showing similar patterns of adoption. Moreover, farmers living in the less rainfall agricultural zones are more willing to take risky decisions relative to those living in the more climatically favourable zone. More importantly, risk avoidance driven by spatial dependence reduces the probability of adopting HYV.

In addition, it was demonstrated that misleading inference is possible if we fail to control for the spatial dependence or endogeneity of risk preferences in the adoption decisions' model. Spatial heterogeneity occurs due to the socio-economic, geographical, ecological and climatic characteristics of any region. These attributes may extend beyond the boundaries of the existing agricultural zones. It therefore follows that wrong policy may be applied if the existence of spatial dependence across agricultural zones or the fact that risk preference may be an endogenous variable in adoption model is ignored. Evidence of spatial dependency in risk taking suggests some unobservable factors may be correlated within farmers' locations. Put differently, the correlation between the risk preference variable and the error term in the adoption model suggests the use of instrumental variable probit to produce consistent estimates. It follows that the use of instruments implies some important variables may be omitted in the adoption model. These factors may constitute a driving force for risky decisions among rice farmers. Identifying these factors will aid policy at ensuring the acceptance of agricultural technological innovation. This study therefore suggests the following policy options.

First, heterogeneity in adoption decisions suggests that rural areas deserve special attention. The adoption model consistently indicates that farmers located in the low rainfall zone are more willing to take risky decisions or adopt HYV relative to others who reside in urban areas or agricultural zone. Thus, provision of infrastructural facilities such as irrigation and accessible roads will not only aid farming practices in the rural areas but also encourage the diffusion of technological innovation. Second, the statistical significance between the spatial dependence (spatial lag) and risk preference is a pointer to social influence and social learning effects. It also connotes some factors which drive farmers' decisions are unobservable. Farmers do not live in isolation suggesting policy intervention relating to HYV adoption and diffusion could be targeted at farmers' neighbours in addition to paying specific attention some of the unobservable factors that drive decisions. Interpersonal communication and social interaction can serve as effective tool for the diffusion of agricultural innovation especially in the rural areas which often lack educational facilities. Third, risk aversion is an important driver of farmers' decisions with respect to technology adoption. It is therefore imperative to use farmers' ability to taking decisions as an effective tool for risk management. In conclusion, in developing agricultural technological innovation for farmers' acceptance, adequate attention should not only be given to farmers' personal factors but also perceptions about improved technology attributes, spatial attributes and willingness to taking risky decisions. Further research should focus on the identification of the unobservable factors that influence farmers' decision making.

Chapter Six

6.0 Time Preference, Spatial Dependence and Adoption Decisions

This chapter examines the role of time preference and spatial dependence in improved rice technology adoption decisions. First, it examines the role of spatial dependence in temporal decisions followed by the effects of time preference on the decisions to adopt improved rice technology.

6.1 Spatial Dependence in Intertemporal Decisions

The first Section of this chapter focuses on the role of spatial dependence in decisions relating to time. Brief background information is presented next.

6.1.1 Background

In Economics, intertemporal decisions describe a situation where the current choice made by a decision maker (DM hereafter) or individual may be related or affected by the available future choices. In other words, intertemporal decisions relate to a choice between present or future outcomes or between immediate and distant or delayed future outcomes. It is often argued that intertemporal decisions have several applications and implications in everyday lives. It may affect the utility function and subsequently the wealth accumulation as well as the general welfare of individuals (Andersen *et al.*, 2008). This is because a DM which gives more preference to a present payoff or outcome is generally described as impatient. The impatience may be associated with a loss, such as waiting for three months or investing today to reap the benefit in three months may yield more reward than present consumption. While countless researches have been conducted to examine the socio-economic factors affecting the level of impatience or subjective discount rates among individuals, the spatial dependence or correlation among DM has never been a focus of any study. Therefore, this current study bridges this gap and contribute to the existing literature by examining the spatial correlation in time preference using instrumental variable method. The implications of this spatial dependence are drawn in this Section and extended to adoption, investment decisions under uncertainty in the second part of this chapter.

Several attempts have been made to examine the impact of individual impatience on their investment options or tendency to invest in productive activities. For instance, in assessing the determinants of participation in development programmes, Ashraf, Karlan, and Yin (2006), it was reported that women with lower discount rates are more likely to open savings account in the Philippines while the Bauer, Chytilová, and Morduch (2012) study reveals that among Indian villagers, women having strong preference for the present are less likely to borrow micro credit. In another related study, Dupas and Robinsona (2013) conclude that present-biased women are more likely to utilize the group saving method by saving in the safe lock. Nevertheless, all the above cited studies focus on credit as an investment facilitator. Studies by Le Cotty *et al.* (2017) and Le Cotty, Maître D'Hôtel, Soubeyran, and Subervie (2015a) show a negative relationship between impatience and fertilizer adoption among farmers in Burkina Faso. In a similar study, Le Cotty, Maître D'hôtel, Soubeyran, and Subervie (2015b) point out that impatience and risk aversion reduce the propensity to use grain storage. Some attempts have also been made to simultaneously examine risk and time preferences among farmers in both the developed and developing countries, investment decisions are not addressed by these studies (Andersen *et al.*, 2008; Tanaka *et al.*, 2010; Tanaka & Munro, 2014; Liebenehm & Waibel, 2014). Notwithstanding, spatial dependency in decision making is beyond the scope of most cited studies.

Spatial dependence or social network effects may be a catalyst for spreading information in rural areas and serve as alternative to extension services in disseminating agricultural technological innovation to farmers because neighbours do interact and communicate informally. For instance, learning from extension agents and other farmers was reported to increase adoption and its intensity in Madagascar (Moser & Barrett, 2006). More so, using distance to road as a proxy to market access, Neill and Lee (2001) show that probability of adopting cover crop technique reduces with distance from road in Honduras. A review study reveals that contact with farmers who possess knowledge about improved agricultural technology may increase the propensity of adopting such improved technology (Guerin & Guerin, 1994). Nevertheless, the above cited studies measured spatial relationships among farmers in diverse ways ranging from contact with other farmers, contact with extension agents to distance from the road. This current study examines the spatial dependency in intertemporal decisions among rice farmers using a power distance weights matrix.

Examining individual farmers' level of impatience differs from spatial correlation in their intertemporal decisions. Like most DM, farmers do relate with one another due to geographical proximity. Indeed, if well-coordinated, the level of interpersonal communication and interaction that exists among farmers may be more influential in the diffusion of technological innovation than extension agents. Thus, informal interaction and communication is a valuable information dissemination tool especially in a social setting of most developing countries where extension services are not certain. Similar patterns of preferences may connote similar adoption behaviour. In such instances, progressive farmers may be identified and put forward as role models for others to facilitate the acceptance of improved farm practices.

The first part of the second result chapter is divided into five Sections. While Section 6.1.1 introduces the paper, Section 6.1.2 presents the review of literature on the determinants of individual impatience. The data used as well as the empirical model estimated are presented in Section 6.1.3. The results and discussion are the focus of Section 6.1.4 while Section 6.1.5 concludes the findings and highlights some policy options emanating from the study.

6.1.2 Predictors of Rice Farmers' Time Preference or Impatience

There have been some behavioural studies examining individual level of impatience in both the developed and developing countries. Time preference of an individual may depend on many factors including cultural, health and environmental ones. For instance, time preference of an individual has been largely attributed to trust, present and future needs as well as present and expected income (Fisher, 1930). Research conducted on 53 countries indicates that many subjects did not only discount immediate future more than the distant future, individual time preference is culturally dependent (Wang, Rieger, & Hens, 2016). Recent studies equally demonstrated the impact of health factors like obesity on the time preferences of individuals (Brown & Biosca, 2016). Recent advances in the literature also suggest that subjective discount rates and level of impatient depend largely on the nature and type of goods, with individual more impatience for food items relative to money and other material goods (Ubfal, 2016). Nevertheless, many variables such as location and climatic factors that could explain individual time preference may not be easily and directly observed. These are accounted for by the spatial dependence.

The study relies on the empirical studies in the selection of time preference covariates. Some of the identified socio-economic variables reportedly correlated with individual time preference especially in the developing countries include income, farm size, education and age. Poor individuals have been found to be more impatient and having higher subjective discount rates in Indonesia, Ethiopia and Zambia (Holden, Shiferaw, & Wik, 1998), India (Pender, 1996), six developing countries (Poulos & Whittington, 2000), Ethiopia (Yesuf, 2004), Russia and Vietnam (Anderson & Gugerty, 2009), Vietnam (Tanaka *et al.*, 2010; Nguyen, 2011). Discount rates are also reported to reduce with income, implying the rich are more patient in Bolivia (Kirby, Godoy, Reyes-García, Byron, Apaza, Leonard, Perez, Vadez, & Wilkie, 2002). Farm size may be a proxy for wealth or income especially in rural communities where livelihood is largely dependent on the size or parcel of land a household has access to. Indeed, a strong positive correlation is observed between farmers' income from rice farming and farm size allocated to rice production in this study. Given the above assumption, smallholder farmers may not only be impatient or biased to the present but also show negative attitudes toward the adoption of HYV. Therefore, a negative correlation is hypothesized between farm size and subjective discount rates or impatience.

Education is an important human capital that drives individual life decisions especially investment choices. Among many studies, Tanaka and Munro (2014) reported a negative relationship between education and subjective discount rates in Uganda. In their study Kirby *et al.* (2002) find education to decrease with discount rate suggesting educated individuals are more patient. Indeed, educated farmers may have foresight, more patience and willingness to adopt HYV relative to less educated or illiterate farmers. It is therefore hypothesized that less educated rice farmers may be more impatient.

Age has been identified as one of the important determinants of time preference as well as wealth accumulation of an individual. Age may determine income acquisition and consequently saving and consumption (Modigliani, 1954; Sablik, 2016) In fact, older individuals may be patient because of higher income and access to durable assets acquired in their prime age. Notwithstanding, mixed results have also been reported between age and impatience as well as age and risk aversion in developing countries. For instance, research finding by Kirby *et al.* (2002) show that subjective discount rates among the Bolivian villagers increase with age while Chesson and Viscusi (2000) find older business managers in the USA exhibiting higher discount rates. In addition, Nguyen (2011) reports a positive correlation between age and subjective discount rate in Vietnam while other studies report a negative relationship between these two variables (Tanaka *et al.*, 2010; Liebenehm & Waibel, 2014). As age may be positively related to farming experience; older rice farmers are expected to be more impatient and show negative attitudes toward the adoption of improved agricultural innovation.

Women are generally conceived as being more risk averse and altruistic than men. For example, studies by Ward and Singh (2014) and Ward and Singh (2015) reveal that women are more risk averse than men in India. In their online study, Dittrich and Leipold (2014) find more men with high tendency for being impatient than women. The role of gender in everyday life decisions as well as economic activities is well documented (see (Niederle, 2014). Although studies like Wang *et al.* (2016) did not find a significant correlation between gender and impatience, nonetheless, men may be more likely take risky and future yielding income decisions.

Very few studies have attempted to examine the correlation between individuals and their religious affiliation among which is Liu (2013) who found religious farmers to be more averse to risk. Although religion relates to belief, it may or may not affect farmers' perceptions and time preferences and subsequently adoption decisions. It is however, difficult to predict the relationship between religion and subjective discount rates. Like most other variables, mixed results have been reported between family size and impatience. For example, Liebenehm and Waibel (2014) found positive correlation between family size and subjective discount rates. Large family size and indeed family pressure may constitute a push factor for impatience. Conversely, it may encourage rice farmers to take risky investment decisions. Since family size may indicate additional responsibility, married rice farmers with probably large family size may be more impatience but more willing to adopt HYV.

Lastly, the direction of location in the study area is difficult to infer. Nonetheless, location is strongly linked to ethnicity and could be used as proxy for availability of infrastructure like roads. Rice farmers in rural agricultural zones or untarred road network areas may be less willing to take risky decisions, have high subjective discount rates and subsequently be less willing to adopt improved rice varieties.

6.1.3 Data and Empirical Model

The variables used in this Section have been described in **Chapter Four** while **Table 27** presents the definitions. Theoretical motivation mainly drives the application of spatial models (Anselin, 2002; LeSage & Pace, 2009). Observed variation in rice farmers' subjective discount rates may be caused by latent factors relating to infrastructure, cultural values, climatic conditions, etc. These unobservable variables may be accounted for through the neighbouring observations of the rice farmers' subjective discount rate assuming the utility derived by a rice farmer from the intertemporal decision in location *i* is correlated with that derived by his neighbours in location *j*. Giving this utility maximization objective, Equation 6.1 applies:

$$Max\ U\left(y_{ti}, y_{tj}; \boldsymbol{X}\right) \qquad (6.1)$$

Where U is the utility function, y_{ti} represents rice farmer time preference in location *i*; y_{tj} represents rice farmer time preference in location *j*; and $\boldsymbol{X}$ is the vector of exogenous socio-economic variables that may explain rice farmers' intertemporal decisions. It suggests that utility derived by rice farmer in location *i* may directly related with the utility derived by his neighbours in location *j*, given farmers' socio-economic variables ($\boldsymbol{X}$). Accordingly, Anselin (2002) posits that the maximization objective produces a spatial reaction function, $y_{ti} = F\left(y_{tij}, \boldsymbol{X}\right)$ which forms (6.2). The resulting data generating process (DGP) of Equation (6.3) reveals a global spill over because $(I - \rho\boldsymbol{W})^{-1}$ links y_i to all $\boldsymbol{X}$ through a multiplier, the spatial weights ($\boldsymbol{W}$).

$$\boldsymbol{y_t} = \rho\boldsymbol{W}\boldsymbol{y_t} + \boldsymbol{X}\Upsilon + \varepsilon \qquad (6.2)$$

$$\boldsymbol{y_t} = (I - \rho\boldsymbol{W})^{-1}\boldsymbol{X}\Upsilon + (I - \rho\boldsymbol{W})^{-1}\varepsilon \qquad (6.3)$$

In Equations 6.2 and 6.3, $\boldsymbol{y_t}$ is a $N\ X\ 1$ column vector of the subjective discount rates of rice farmers. The ρ is a scalar parameter that determines the correlation between the subjective discount rate of a rice farmers and the adjusted-by-distance mean discount rates of his neighbours. $\boldsymbol{W}$ is the $N \times N$ weights matrix defined from the distance between rice farmers (3.6) while $\boldsymbol{X}$ is $N \times K$ vector of exogenous explanatory variables **(Table 27)**. Υ is a $K \times 1$ vectors of associated exogenous variable parameters to be estimated. $\boldsymbol{W}\boldsymbol{y_t}$ is a $N\ X\ 1$ spatial lag representing the weighted average of subjective discount rates in the neighbourhood locations as defined by the weights matrix. Lastly, $\rho\boldsymbol{W}\boldsymbol{y_t}$ assumes that the utility derived by a rice farmer from the intertemporal choice is related to that derived by his neighbour and attributable to many factors including social interaction, communication, climatic and topographic conditions. In other words, the spatial lag is included to explain the variation or heterogeneity in the subjective discount rate across the Study Area. This variation may not be captured by the binary variables for agricultural zones. The disturbance term is assumed to be individually and identically distributed, $\varepsilon \sim N(0, \boldsymbol{I}\sigma^2)$.

Table 27: Definition of the Variables Used in Time Preference Model

Variables	Definition of Variables
Dependent Variable	
Time Preference	Subjective discount rates
Explanatory Variables	
Age	Individual farmers' age in years
Education	Years of formal schooling
Christian	1 if rice farmer is a Christian, 0 otherwise
Family size	Number of household members
Farm size	Size of farm holdings in hectare
Marital status	1 if married, 0 otherwise
Male	1 if male, 0 otherwise
Bad road	1 if farmers reside in bad road network areas, 0 otherwise
Weighted discount rate/ spatial dependence	Spatially lagged subjective discount rates

Source: Author's Compilation, 2017

Three different tests were carried out with respect to the relevance of the instruments, endogeneity of the explanatory variable and validity of the instrument. The test of instrument relevance involves examining the significant of the Wald statistic. The Wu-Hausman test, F test of restriction is adopted to examine the endogeneity of the spatial lag in the time model. This test is important because IV/2SLS may produce estimates with larger standard errors if an explanatory variable is not endogenous, thus OLS may yield consistent estimates. The third test (validity of instrument), called Sargan test has Chi-square distribution. It may also be used for over-identification restriction. Therefore, it is not reported in the case of just-identified model.

6.1.4 Results and Discussion

The results of the instrumental variables estimation method relating to the spatial dependence effects in intertemporal decision are presented in **Table 28**. It is evident that a strong instrument is used as indicated by the rejection of the null hypothesis of the weak instrument (relevance of instruments). The null hypothesis of the endogeneity of spatial lag (consistency of OLS) proposed by Wu-Hausman is equally rejected suggesting OLS may not yield consistent estimates (OLS coefficients and standard errors are presented in the last two columns of **Table 28**, respectively for comparison). More importantly, the Wald statistics attests to the overall goodness of fit of the model. The results indicate that age, Christian, married, locations (bad road) and spatial dependence or spill-over effect significantly determine rice farmers' level of impatience. The significant variables are explained next with the main finding presented first.

Main finding: there is evidence of spatial dependence in intertemporal decisions.

Hypothesis There: there is a spatial dependence in rice farmers' time preference

There is evidence of spatial dependence effects in intertemporal decisions among rice farmers. In other words, there is a significant correlation between the subjective discount rates of a farmer and his neighbours. It suggests a positive correlation exists between the subjective discount rates of a rice farmer and the adjusted by distance discount rates of his neighbours. The reasons for this result may be in many folds. First, it suggests that interaction exists among rice farmers living closely. Second, rice farmers' time preference may be correlated due to geographical proximity. Third, this correlation may be linked to the presence or absence of infrastructural facilities in farmers' location. Lastly, the significant relationship between farmers' time preferences may be due to the fact that farmers share knowledge about life experiences coupled with the potential level of education. In other words, the subjective discount rates among rice farmers is expected to increase by 13 percent ((average $Wy_t * coefficient$) (89.38)*0.0015)) as the distance increases from the farmer at the centre of the radius to 60 km suggesting the farther apart farmers are the more likely they behave differently.

Proximity offers an opportunity for social interaction and interpersonal communication. Such informal communication may reflect in the way individuals behave. This may reflect in farmers' attitudes to decision making. The closer the individuals the more likely they will behave in a homogenous manner. The level of heterogeneity, if modelled using dummy a variable may produce biased results. Spatial dependency captures this heterogeneity. For example, factors like geographical land scape, ecological and climatic as well as socio-economic conditions of most areas are often difficult to measure. Spatial dependence points to the realization that behaviour may not be homogenous across agricultural zones or political land division.

The first statistically significant farm and farmer specific variable that explains the level of impatience among farmers is age. The results indicate that older rice farmers are more impatient relative to the younger ones. This agrees with Kirby *et al.* (2002) who reported that subjective discount rates increase with age among Bolivian villagers. It is also in agreement with Chesson and Viscusi (2000) who reported that older business managers in USA exhibit high discount rates. It is however in disagreement with other studies which reported a negative relationship between impatient and age (Tanaka *et al.*, 2010; Liebenehm & Waibel, 2014). The reasons could be viewed from two perspectives. First, it may be a consequence of the marital responsibility of farmers as most of the sampled rice farmers are married. Marital status is an indication of financial burden and possibly a source of pressure on married individuals. This corroborates Tanaka and Munro (2014) who found household heads to be more impatience than other (single) individuals in Uganda. Put differently, being a head of a household is an indication of marital responsibility in addition to farming and other commitments. It also suggests a potential unexpected financial responsibility that could push individuals especially older ones towards having strong preferences for immediate consumption. Second, older farmers may have an ardent desire for enjoying their remaining 'short life' and thus present income within their lifetime. As stressed by Fisher (1930), older farmers may evaluate their life cycle and see the reason to enjoy the probably short remaining years of their life. It is also well acknowledged in the life cycle income hypothesis that older individuals save less and consume more relative to prime-age individuals (Modigliani, 1954). Therefore, for low income individuals such as farmers in the developing world, temptation for immediate consumption may drive strong desire impatience at older age.

The coefficients of education, farm size and gender are not statistically different from zero, it may be worth adding some notes on these key economic variables. The result indicates that educated rice farmers are more impatient. Higher education may be related to gainful employment and subsequently higher income. In the farming context, specifically in adoption decision, educated farmers may have more desire for growing HYV relative to less educated farmers. In this respect, adopters may be regarded as highly patient individuals. The sign of the coefficient of farm size agrees with expectations. Assuming farm size as a proxy for income or wealth which is often the case in rural areas of most developing countries, the result indicates that small holder rice farmers are more impatient. Small holder farmers have been adjudged as poor individuals attributable to their size of land holding and over-reliance on rain-fed agriculture. Similarly, the coefficient of gender is not statistically different from zero, the result reveals that male rice farmers are more impatient relative to their female counterparts which is contrary to expectation. Males may have more economic responsibility than females, more willingness to take risky investment decisions relative to females and have a higher tendency to be less biased to the future or ignore the temptation associated with the present.

Another variable that statistically significantly explains rice farmers' intertemporal decisions is rice farmers' religious affiliation. The results in **Table 28** show that Christian farmers are less patient when compared to farmers who affiliated with other religion like Islam as well as the free thinkers and traditional worshipers. It is worth reminding the readers that very few studies have attempted to control for the effect of religion in decision making model. These studies conclude that religious farmers are more risk averse (Liu, 2013; Liebenehm & Waibel, 2014), although it is difficult to define the type of religion among farmers. This result also agrees with that reported under the risk model in chapter five indicating that rice farmers' attitudes toward risky and intertemporal decisions are highly comparable in term of religion. This similar pattern of behaviour may not be coincident but rather reflect the existing reality with respect to farm decisions. In other words, a risk seeker and patient farmers may show more desire for improved agricultural practices relative to a risk avoidant or impatient farmers. Religion may not directly affect individual farmers' farm decisions yet it could have an indirect effect on production, consumption as well as financial decisions.

Married rice farmers are statistically more impatient relative to single farmers. This result agrees with that reported under the risk in Chapter Five. Arguably, married individuals have more financial obligations than single individuals. This may constitute a push factor to impatience in spending as well as strong desire for immediate consumption. Impatience may prevent farmers from investing in the future with respect to children's education as well as income generating activities. In the farming context, impatient farmers may be biased towards status quo and show less preference to growing improved rice varieties despite the yield and income potential.

Farmers living in rural agricultural zones or bad inaccessible road network areas are more impatient relative to those living in urban agricultural zone or accessible road network areas. This is in line with the *a priori* expectation. High incidence of poverty is often associated with the rural areas and that poor individuals are generally more impatient (Tanaka & Munro, 2014). Indeed, rural communities lack access to infrastructural facilities such as accessible roads, hospital, schools, pipe borne water, to mention a few. The poverty trap may not only be a temptation to individual farmers but also constitute a push factor for impatience. Poverty may push rural dwellers to wanting to favour present income relative to future income. Another reason may be linked to weather and climate. There is a slight variation in the rainfall distribution pattern across the four agricultural zones in Ogun State (Apantaku *et al.*, 2004). The level of farmers' impatience may vary across climatic zone corroborating Tanaka and Munro (2014) who observed higher discount rate among farmers living in the uni-modal rainfall zone of Uganda.

Table 28: Determinants of Rice Farmers' Impatience

Variables	Estimates	S. E	t-value	p-value	OLS Estimates	OLS S .E
Spatial Dependence						
Time spatial lag	0.0015***	0.0002	6.86	3.6E-11	0.0014***	0.0002
Farmers' Factors						
Age	0.0029***	0.0006	4.85	1.92E-6	0.0030***	0.0005
Education	0.0021	0.0016	1.36	0.1762	0.0021	0.0014
Christian	0.0569***	0.0118	4.80	2.41E-6	0.0578***	0.0119
Family size	-0.0010	0.0021	-0.46	0.6440	-0.0011	0.0023
Farm size	-0.0057	0.0044	-1.30	0.1949	-0.0055	0.0044
Male	0.0091	0.0127	0.72	0.4749	0.0110	0.0137
Married	0.1775***	0.0413	4.30	2.29E-5	0.1812***	0.0267
Location						
Bad road	0.0285**	0.0122	2.33	0.0202	0.0281**	0.0123

Diagnostic Statistics (IV): Weak instruments/relevance: 30490.11 (DF: 1, 320) p < 2E-16
Wu-Hausman test of endogeniety: 52.93 (DF: 1, 319), p < 2.69E-12
Wald test: 1077 (DF: 9, 320), p < 2.2E-16
Diagnostic Statistics (OLS): Residual standard error: 0.1077 (DF: 320)
R-squared: 0.9545,
Adjusted R-squared: 0.9533
F-statistic: 746.5 (DF: 9, 320), p-value: < 2.2E-16
Number of Observation (N=329), S.E = standard error
Source: Data Analysis, 2017

6.1.5 Concluding Notes

The result in this sub-Section shows that spatial dependency exists in intertemporal decisions among rice farmers in Ogun State Nigeria. The spatial dependence effect in intertemporal decisions points to the fact that some factors are correlated in farmers' location. In other words, there is spatial heterogeneity in rice farmers' decisions. This attests to the fact that neighbourhood influence or social interaction exist or constitute day-to-day activity among farmers. Examining such spatial dependency has many policy implications. First, ignoring spatial dependence in time preference model may result in overestimation or underestimation of such model. Second, the finding points to the importance of social networks in decision making. Social interaction may serve as a tool for exchanging information between farmers. Lastly, spatial heterogeneity or spatial dependence may aid the understanding of adoption as well as the diffusion pattern of agricultural technological innovation.

6.2 Explaining Rice Technology Adoption Decisions: The Roles of Time Preference and Spatial Dependence

6.2.1 Background

Food insecurity has entered into academic debate many decades ago but gain more popularity among academia following the Word Food Summit in the early 1970's. Doubtless, improving agricultural productivity may enhance food security (food availability and food access) at the household level. Nonetheless, many factors impede productivity and such variables deserve adequate attention. Improved agricultural technology can play a pivotal role in enhancing food security especially in developing countries. However, farmers do not usually adopt such technology, which is attributable to many factors including uncertainty in decisions and social interaction effects (Feder *et al.*, 1985; Foster & Rosenzweig, 2010). Other factors that may explain the reasons for adoption or non-adoption of improved agricultural technology include farm and farmer specific characteristics, technology attributes, institutional and community factors, social learning and attitudes toward risk and time.

While observable socio-economic factors have been extensively examined, intrinsic factors such as attitudes toward risk, ambiguity, uncertainty and time have received less attention in the literature. Although the role of risk aversion in adoption decisions has been relatively addressed, that of time preference has received less attention in the literature yet the spatial dependency in such decisions is often ignored. Addressing both extrinsic and intrinsic factors is pertinent for policy evaluation in developing countries. Thus, this chapter pays special attention to the relationship between rice farmers' impatience, spatial dependence and adoption decisions.

Attitudes toward risk and time, as well as spatial dependency are some of the factors often omitted in adoption decision model attributable to the difficulty in measurement. Like risk, time preference requires experimental measurement before it can be considered universal in adoption decisions. Moreover, spatial factors like social and cultural norms, social networks, soil type, climatic and topographic conditions of a location could be endogenous or exogenous in adoption decisions. Farmers' subjective discount rates may be spatially dependent, yet adoption patterns may reflect this spatial dependency. Individual farmers' heterogeneity in time preferences may affect utility function and subsequently investment decisions including adoption of improved agricultural technology.

Time preference relates to intertemporal decisions. It is a preference for present outcome relative to delayed outcome (Frederick *et al.*, 2002). It can also be viewed as a trade-off between gains and pains. Thus, how individuals make decisions between two or more payoffs at different points in time may measure their patience or impatience levels. These decisions have implications on various aspects of life including savings, investment and health. For example, adoption is an investment decision under uncertainty. A farmer may decide to grow HYV today based on the perceived future utility. In developing countries like Nigeria, farmers often lack access to basic amenities and incentives for farming. Poor access to farm input like credit may cause temptation for immediate consumption or result in high subjective discount rates (Pender, 1996; Holden *et al.*, 1998; Shively, 2001). This temptation for immediate consumption usually has negative effects on investment decisions (Marglin, 1963; Feldstein, 1964). Therefore, impatience resulting from the temptation for immediate consumption may reflect not only in decisions to grow improved agricultural technology but also the income status of individual farmers.

Farmers are reportedly risk averse and impatient in the developing countries (Yesuf, 2004; Yesuf & Bluffstone, 2009; Tanaka *et al.*, 2010; Nguyen, 2011; Liebenehm & Waibel, 2014). Poor farmers are also found to exhibit higher risk aversion and high discount rates (Lawrance, 1991; Wik *et al.*, 2004; Yesuf & Bluffstone, 2009). Higher level of impatience may affect poor farmers' resource allocation behaviour and investment decisions. Put differently, both higher aversion for risk and impatience may have negative consequences on consumption and utility. Time preference could also be viewed as trade-offs between continuous growing traditional varieties and adopting high yield rice varieties (HYV) to obtain higher future income. A farmer whose objective is to maximize expected utility should not only care about present income but also how to increase future income. An important question is how do farmers weight future events that have economic values? Shortly put, a decision not to grow HYV today may have negative impact on future consumption and wealth.

While future consumption optimizers may be willing to take risky adoption decisions, the *laissez faire* and impatient farmers may be reluctant. Moreover, since farming involves making a commitment today with the expectation of future outcome, farmers who undertake risky production decisions today, in the face of uncertainty are more likely to experience yield gain and earn more income. In other words, strong preferences for traditional seed varieties (status quo bias) may imply low interest in HYV and future wealth. This study therefore tests the hypothesis of endogeneity of time preference in adoption decisions. This was based on the premise that spatial dependence is instrumental for unobserved variables like social interaction, climatic conditions and topographic conditions.

The remainder of this chapter is sectioned as follows. Existing literature on factors affecting improved agricultural technology adoption decisions is presented in the next section. This is followed by the data and empirical models in Section 6.2.3. While Section 6.2.4 is devoted to results and discussion, Section 6.2.5 concludes the findings.

6.2.2 Determinants of Improved Agricultural Technology Adoption Decisions

Studies examining the determinants of improved agricultural technology adoption decisions are diverse and may be difficult to compress. While some studies focus on conservative technology others pay attention to improved divisible agricultural technology such as seeds, herbicide and fertilizer. The common feature, however is that most previous studies focus on specific variables. These among others include farm size (Feder, 1980; Feder & O'Mara, 1981), land tenure (Feder, 1980); education and information (Foster & Rosenzweig, 2010); credit constraints (Feder, 1982); social learning and networks (Foster & Rosenzweig, 1995; Conley & Udry, 2010) and perceptions about technology attributes (Adesina & Zinnah, 1993; Adesina & Baidu-Forson, 1995). Other studies have reported the effects of risk aversion (Feder, 1980; Feder, 1982; Liu, 2013; Ward & Singh, 2015); risk and ambiguity aversion (Barham *et al.*, 2014; Ward & Singh, 2015) and time preference (Le Cotty *et al.*, 2015a) on the adoption of agricultural technological innovation. A recent study examines the role of aspiration in the adoption of agricultural innovation and reported positive correlation in Ethiopia suggesting aspired farmers are innovators (Mekonnen & Gerber, 2016).

In their review of the determinants of adoption of agricultural innovation, Feder and Umali (1993) emphasized that agricultural climatic environment plays significant role in the adoption of improved technology. Hiebert (1974) examined the role of risk and learning on adoption of fertilizer in the Philippines and argued that access to information and ability to decode information have significant positive impact on farmers' adoption decisions. However, while many attempts have been made to examine the role of risk aversion on adoption, time preference has received less attention. Therefore, this chapter focuses on this intrinsic factor, time preference instrumental by spatial dependence. As indicated above, many factors have been hypothesized to influence adoption decisions of farmers especially in the developing countries. These variables are categorised in this study into farm and farmers' specific characteristics, institution and community factors, perception about improved technology attributes, risk preference, time preference and spatial dependence.

Despite the advances in the adoption literature, very few studies have attempted to examine the relationship between subjective discount rate and adoption decisions. In assessing the determinants of participation in development programmes, Ashraf *et al.* (2006) reported that women having lower discount rates are more likely to open commitment savings account in Philippines. Moreover, among 573 random samples in rural India, Bauer *et al.* (2012) found present biased women to be more likely to borrow micro credit. However, the above cited studies focus on credit access as investment option. In their adoption study, Le Cotty *et al.* (2017) and Le Cotty *et al.* (2015a) reported a negative relationship between impatience (not risk aversion) and fertilizer adoption among farmers in Burkina Faso. This study ignores many variables that may explain adoption decisions. In a related study, impatience and risk aversion were found to reduce the propensity to use grain storage in the Burkina Faso (Le Cotty *et al.*, 2015b). Recent finding by Di Falco and Kohlin (upcoming) suggests a negative impact of rate of time preference on the adoption of conservative tillage in Ethiopia. Notwithstanding, the above cited studies differ from the current study in terms of methods. This study directly observe the effect of time preference in adoption decisions and indirectly examines the role of spatial dependence in adoption decisions.

Spatial relationships with respect to intertemporal decisions or subjective discount rates have never been a subject of discussion in the literature. Spatial factors such as farmers' locations, community norms, geographical and climatic conditions may affect farmers' adoption learning processes and subsequently investment decisions. There is evidence of neighbourhood effects in adoption patterns, for example, sickle adoption among rice farmers in Indonesia (Case, 1992), improved variety adoption decisions among Bangladesh rice farmers (Holloway *et al.*, 2002), maize seed and fertilizer adoption in Ethiopia (Krishnan & Patnam, 2014), organic farming adoption among Irish farmers (Läpple & Kelley, 2015), social networks and spatial diffusion of hybrid maize among

Bangladeshi farmers (Ward & Pede, 2015), conservation tillage adoption in Ethiopia (Tessema *et al.*, 2016). These studies conclude that farmers living closely exhibit similar behaviour. Nevertheless, spatial correlation in intertemporal decisions is beyond the scope of the above cited studies. Therefore, this gap is filled by examining the spatial dependency in decisions relating to adoption and attitude towards time.

This study also considers some farm and farmers' specific factors such as farm size, education, age and gender in the adoption decision model. The effect of farm size may depend on other factors. For example, the land tenure system and the non-functionality of the credit market in most developing countries may deter access to land and subsequently affect investment decisions. Wealthy farmers may have access to large expanses of land and higher amounts of credit than poor farmers. Among other studies, Dill, Emvalomatis, Saatkamp, Rossi, Pereira, and Jardim Barcellos (2015) found large and diversified farms to be less likely to adopt improved management practices in beef production in Brazil, notwithstanding, in line with empirical studies relating to improved seed and conservative technology (see for examples (Nkonya *et al.*, 1997; Alene *et al.*, 2000)), a positive relationship is expected between farm size and propensity to adopt improved rice varieties.

Socio-demographic variables like education, age and gender are common human capital that have been reported to significantly explain adoption decisions in different contexts. For instance, studies have shown that education increases the propensity to adopt improved agricultural technology (see for examples (Mendola, 2007; Läpple *et al.*, 2015; Anik & Salam, 2015). In line with past studies, it is hypothesized that education would have a positive effect on rice farmers' HYV adoption decisions. Age of a farmer is another dimension of human capital that is correlated with farming experience especially in the rural areas where most farmers usually start farming at an early age. In line with previous study like (Baidu-Forson, 1999; Fufa & Hassan, 2006; Anley *et al.*, 2007), it is hypothesized that age will have negative effect on the adoption of HYV. In other words, older farmers are expected to be less willing to adopt HYV.

Many farm activities in the developing countries like Nigeria are gender-specific. Gender plays a significant role in both house and farm decisions. For instance, males and females may have different responsibilities at home and in farms with males carrying out farm operations such as clearing and planting while females devote their time to harvesting and marketing farm produce. Therefore, males and females may differ in allocation and investment decisions. However, the role of gender on adoption decisions, although it may be diverse, it has not been adequately explored in the literature. Some authors have argued that the choice of adoption of improved farm technologies may differ between males and females and largely depend on the technology traits. For instance, in India, Mehar *et al.* (2015) reported that female farmers based their decisions on cooking quality and stress-tolerance rather than the high yielding and marketable traits considered by their male counterparts. Therefore, while gender may drive decisions to adopt HYV, there is no prior expectation on the direction of this indispensable variable.

This study also controls for family size being a component of human capital. Family labour is an important production factor. In many developing countries, farmers do rely on family labour to carry out production activities including clearing, planting, weeding, harvesting and marketing. In rural communities, for example, more family members may translate to availability of family labour for farming operations. Although mixed results have been reported in the literature, notwithstanding, farmers with large family size are expected to show positive attitude to adoption of HYV in line with Ahmed (2015) and Alene *et al.* (2000). Married farmers may have more family members compared to single farmers. Large family size may be a push factor for risky investment decisions. It is therefore hypothesized that married rice farmers may have more household members which may put them under pressure to accept improved technological innovation.

Some institutional and community factors are equally important in the adoption decisions. Specifically, extension contact has been reported as having a positive and significant influence in explaining the adoption of improved agricultural technologies (Polson & Spencer, 1991; Moser & Barrett, 2006; Oladele, 2006). Farmers often rely on the information provided by extension agents to make decisions relating to farm production and investment. Where such contact exists, it is expected to have a significant positive impact on farmers' decisions and subsequently improve their welfare. However, where access to extension services is limited as in the case where farmers have only one contact or no contact with the extension agents within a year in the Study Area, extension contact may not have a positive and significant effect on farmers' decisions.

Inadequacy of extension services in most developing countries often encourage farmers to rely on social networks as an alternative source of information. For example, Maertens and Barrett (2013) applied probit model and reported the significant effects of social learning networks on agricultural technology adoption in India. In Madagascar, Moser and Barrett (2006) revealed that farmers who learn from extension agents and other farmers have higher propensity to adopt system of rice intensification. Similarly, Conley and Udry (2010) found positive effects of learning from other farmers in a social networks in the adoption of fertilizer for pineapple production in Ghana. However, Baerenklau (2005) reported that neighbourhood influence is less relevant relative to risk preference among dairy farmers in adopting the intensive farming technique in the USA.

Villagers or rural dwellers may have late information about improved seeds due to low access to formal education as well as poor road networks yet such information gap may be bridged by their neighbours. Social networks may not only increase information access but also constitute an influential device on decision making relating to production and consumption. Rice farmers with greater and influential social networks are more likely to be acquainted with information about market prices, as well as availability or otherwise of improved seeds. It is expected in this study that farmers who rely on friends and neighbours may be more willing to adopt improved rice varieties. Accessible road networks may also not only aid access to information and markets but also encourage farmers to produce their preferred crops. It is therefore hypothesized that less accessible roads typical of rural areas may have a negative effect on the probability of adopting HYV. In line with the above hypotheses, three dummies representing agricultural zones are included in the model to control for the effect of locations. Thus, farmers living in low rainfall areas or agricultural zones may be more likely to adopt HYV.

Lastly, the perceptions of farmers about the attributes of improved agricultural technologies may significantly influence adoption decisions. Using probit and ordered probit in estimating the recursive effect of perception on adoption in Ethiopia, Negatu and Parikh (1999) reveals that perception affects adoption and adoption affects perception. Many attributes may be considered but this study considers high yield, short duration, long stem and good tiller capacity which were ranked on a Likert scale of one to five with five being extremely important. In line with previous studies, these attributes are hypothesized to have positive effects on the probability of adopting improved rice varieties (Adesina & Zinnah, 1993; Adesina & Baidu-Forson, 1995).

6.2.3 Data and Models

The data used in this second part of the chapter has been previously described in **Chapter Four**. Notwithstanding, the variables are defined in **Table 29**. Giving the advantages of the front-end delay, rice farmers were presented with two monetary plans, A and B. While plan A presents both present and future rewards, plan B presents only future rewards. Rice farmers' subjective discount rate was estimated using a continuous exponential function (Equation 3.5), $F = Pe^{rt}$, $r = \left[log\left({}^{F}/_{P}\right)\right]/t$. Where r is the subjective discount rate, F is the future amount, P is the payoff offers at present while t is the time horizon. Some variables that may explain adoption decisions are not often observed. These may be captured in spatial dependence or spatial lag of the subjective discount rates. Time preference is also hypothesized to be endogenous in the adoption decisions due to the potential measurement error and omitted variables. Put differently, some variables are often omitted in the adoption model attributable to the difficulty in measurement. Therefore, the endogeneity problem in the binary outcome variable was addressed using instrumental variable (IV) probit. In this model, the spatial dependence or spatial lag of subjective discount rates is instrumented for social network, climatic condition, and topographical condition in addition to other unobserved socio-economic variables. The two-stage estimation models are as specified below.

$$\mathbf{S}_1 = \boldsymbol{X}\alpha + \theta\boldsymbol{W}\boldsymbol{S}_1 + \mu \qquad (5.6)$$

$$p_2^* = \boldsymbol{S}_1\omega + \boldsymbol{X}\gamma + \varepsilon \qquad (5.7)$$

Where $\boldsymbol{S}_1$ is the N by 1 vector of endogenous variable, the subjective discount rates estimated from the intertemporal decisions revealed by rice farmers in the time task. $\boldsymbol{X}$ is the N by K vector of exogenous variables that may explain adoption decisions as defined in **Table 29**, $\boldsymbol{WS_1}$ is the N by 1 vector of instrument (spatial lag of subjective discount rate). This is the weighted average of subjective discount rates in the neighbourhood locations. θ is a scalar parameter that determines the spatial correlation or dependency between the subjective discount rate of a rice farmer and the adjusted-by-distance mean discount rates of his neighbours. $\boldsymbol{W}$ is the N by N weights matrix defined in Equation (3.6). Lastly, $\theta\boldsymbol{W}\boldsymbol{S}_1$ is based on the assumption that the utility derived by a farmer in the intertemporal decisions may be related to that derived by his neighbours'. This spatial dependency tendency may result from social interaction, geographical proximity and climatic condition. Note that Equation 5.6 is structural with the dependent variable having a feature of a continuous variable while Equation 5.7 is a reduced form, having a binary dependent variable. Therefore, p_2^* represents unobserved HYV adoption decisions. The observed form is defined in Equation 5.8.

$$p_2 = \begin{cases} 0, & p_2^* < 0 \\ 1, & p_2^* \geq 0 \end{cases} \qquad (5.8)$$

The error terms $(\varepsilon, \mu) \sim N(0, \boldsymbol{\delta_i})$ with the first element of the error matrix normalized to one to identify the model. A significant correlation between the disturbance errors of the two models suggests that a strong relationship exists between the two (Equations 5.6 and 5.7). Otherwise, a binary probit may be estimated in a single Equation. ω is $N\ X\ 1$ vector of parameter corresponding to the predicted value of the first stage Equation, γ is the vector of structural parameters in the second stage adoption model while α is the vector of the parameters of the first stage Equation.

The order condition for identification of the model is that the number of variables in the first stage model (time model) is equal to or greater than that of second stage Equation (adoption decision model). Note that the Stata software (Stata 14) treats other variables in the adoption decision model as exogenous. Thus, other variables in the model are used as instruments in addition to the spatial lag of the time preference as an instrumental variable to just-identify (exactly identified) the model.

The farm and farmer specific factors considered in the model include age, education, religion, household size, farm size, gender, marital status and type of production system. The institutional and community factors hypothesized to have significant effects on rice farmers' adoption decisions include extension contact and information from friends and neighbours. The location variables include three dummies for agricultural zones. High yield, long stem, short duration and good tiller capacity are the perceived improved rice technology attributes hypothesized to impact farmers' adoption decisions. Above all, subjective discount rate is an indispensable variable considered to affect rice farmers' HYV adoption decisions.

Table 29: Variables used in the Adoption Decisions Model

Variables	Definition
Dependent Variable	
Adoption	1 if rice farmer grows HYV, 0 otherwise
Explanatory Variables	
Time Preference	
Impatience	Subjective discount rates; the higher the rate the more the impatience
Farm and Farmers' Specific Variables	
Age	Years
Education	Years of formal schooling
Religion	1 Christian, 0 otherwise
Household size	Numbers of household
Farm size	Land cultivated to rice in hectare
Male	1 if male, 0 otherwise
Married	1 if married, 0 otherwise
Upland	0 if upland production, 0 otherwise
Perceptions about HYVs Attributes	
High Yield	Perceived high yield importance
Long stem	Perceived long stem importance
Short duration	Perceived short duration importance
Good Tiller	Perceived tiller supremacy importance
Community and Institutional Factors	
Friends	1 if rely on information from friends, 0 otherwise
Extension contact	No of contact with extension agents
Locations/Agricultural Zones	
Ikenne	1 if farmers are located in Ikenne zone, 0 otherwise
Ijebu-Ode	1 if farmers are located in Ijebu-Ode zone, 0 otherwise
Ilaro	1 if farmers are located in Ilaro zone, 0 otherwise
Abeokuta	Reference zone

Note: perception questions range from not at all important (1), somewhat important (2), important (3), very important (4) and extremely important (5).

Source: Author's Compilation, 2017

6.2.4 Results and Discussion

The result of the determinants of HYV adoption decisions among rice farmers is presented in **Table 30**. The Wald statistics with a Chi-square value of 9.28 ($p<0.023$) informs the decision to reject the null hypothesis of no endogeneity. This confirms that time preference is an endogenous determinant of rice farmers' adoption decisions. The results also show that the standard errors of the first and second models are significantly related with a correlation coefficient of 0.99 ($p < 0.016$) suggesting a binary probit might produce an inconsistent estimate. However, the results of the binary probit treating time as an exogenous variable are presented in **Table 33** (**Appendix A: Additional Tables)** for comparison. An important distinction between the two models is that the coefficient of the impatient or subjective discount rate is larger under the instrumental variable model in addition to the binary probit model having a larger standard error for this variable. The significant variables are explained below with the main finding presented first.

Main finding: impatience significantly explains adoption decisions.

Hypothesis four: time preference (impatience) is endogenous and significantly explains rice farmers' adoption decisions.

Even though most literature emphasizes the role of risk aversion in decision relating to improved agricultural technology, the degree of impatience among individual farmers is equally important since uncertainty relates to time. The result statistically shows that impatience or high subjective discount rate decreases the propensity to adopt HYV. This finding agrees with Le Cotty *et al.* (2017) and Le Cotty *et al.* (2015a) who reported that impatient farmers are less likely to adopt fertilizer in Burkina Faso. It is also in line with the conclusion reached by Di Falco and Kohlin (upcoming) and Yesuf (2004) that the rate of time preference decreases the likelihood of adoption of conservative tillage and other land management technology, respectively in Ethiopia. Attitudes to time is important in investment decisions (Liebenehm & Waibel, 2014). On one hand, this result of this study is consistent with previous studies that reported the importance of time preference in savings and investments (Ashraf *et al.*, 2006; Bauer *et al.*, 2012; Dupas & Robinsona, 2013).

Adoption decisions are usually associated with uncertainty which is partly explains by time preferences. Uncertainty about the future and bias for the present may encourage present consumption among small-holder farmers especially in the developing countries where incidence of poverty is very high. Higher yield is an important attribute of improved technologies like improved rice varieties yet decisions to adopt or otherwise are often deterred by some degree of risk and uncertainty. Moreover, as rain-fed agriculture is determined by nature, enjoying higher future yield and income requires farmers to make, not only risky but also timely investment decisions. One important implication of this finding is that patient farmers may be early adopters. Put differently, patient rice farmers, as shown in the descriptive chapter, are adopters with higher potential to cultivating more land or less land but get higher yield than impatient farmers. These categories of farmers may serve as a contact group for other farmers who may emulate them and make decisions based on proven records.

Since spatial dependence (spatial lag) is assumed to be an exogenous (instrumental variable) in this study, it correlation with the time preference suggests that it plays a significant role in rice farmers' adoption decisions. In other words, a significant correlation between individual farmers' subjective discount rates and the subjective discount rates adjusted by distance is a pointer to the existence of neighbourhood or spatial dependence effects as well as the tendency in influencing farmers' adoption decisions. It suggests farmers living closely may influence the decisions of one another. It is therefore in agreement with many studies which reported significant spatial and neighbourhood influence in the adoption of improved agricultural technology (Case, 1992; Holloway *et al.*, 2002; Holloway *et al.*, 2007; Wimalagunasekara *et al.*, 2012; Krishnan & Patnam, 2014; Wollni & Andersson, 2014; Ward & Pede, 2015; Tessema *et al.*, 2016). Specifically, Ward and Pede (2015) observe neighbourhood influence in hybrid rice adoption decision among farmers in Bangladesh. In summary, rice farmers' time preference is spatially correlated with impatience driven by spatial dependence partly explaining some of the observed variation in farmers' adoption processes.

Other variables that significantly explain rice farmers' HYV adoption decisions include household size, gender, location and reliance on neighbours for information. It is however important to explain two key variables in adoption process, education and farm size. Against expectation, the coefficient of education, though it has a positive sign, is not significantly different from zero, the direction of the sign indicates that educated patient rice farmers have higher propensity to grow HYV. In terms of farm size, the results presented in **Table 30** indicate that farmers with large farm size have higher propensity to adopt improved rice technology. In developing countries, most small holder farmers are reported to be impatient and risk averse. Specifically, risk aversion and impatience have been empirically demonstrated to reduce farmers' income in Africa (Yesuf, 2004; Yesuf & Bluffstone, 2009; Tanaka *et al.*, 2010; Nguyen, 2011; Liebenehm & Waibel, 2014). Since most farmers in this part of the world operate at subsistence level, it suggests a relationship exists between impatient, farm size and adoption decisions. Put differently, the finding shows that small-holder farmers are not only impatient but also show less tendency to investing in improved agricultural technology.

This study controls for family size. However, the result suggests that rice farmers with fewer household members are more likely to adopt HYV. This is contrary to expectation and previously reported findings by Ahmed (2015) and Alene *et al.* (2000). Although in developing countries, farmers often rely on family labour as a cheap source of production input especially in the rural communities. One possible reason for this result is the fact that the average household size reported in this study is 6 persons which is very low relative to what have been reported by many studies in the developing countries. Secondly, most farmers now enrolled their children in schools due to more awareness about the importance of Western education and the likely impact on the income and livelihood of individuals as well as the family. This suggests rice production may be carried out only by adult family members as well as the engagement of rotatory labour.

The finding indicates male rice farmers are less likely to adopt HYV compared to their female counterparts. There is not an *a priori* expectation on the direction of gender but the finding agrees with the earlier findings under risk and adoption wherein male rice farmers show less willingness to taking risky decisions. This result also agrees with the previously reported finding by Mehar *et al.* (2015) in India that female farmers based their decisions on cooking quality and stress-tolerance while males favoured high yielding and marketable traits. It is a revelation that adoption decision making may be gender specific. Like many economic agents, farmers' attitudes depend largely on the circumstances as well as their gender orientation. Gender determines the choice of occupation, educational attainment, business and many more. Therefore, it is not too surprising to observe different behavioural attitudes across gender.

Among the community and institutional factors, the results reveal that farmers who rely on information from friends and neighbours in social networks are less likely to adopt HYV. The main reason that could be deduced from this is most farmers are not currently growing improved rice varieties because their neighbours are not growing them. This is evident by the reported low adoption rates in the study. It is plausible since farmers live in a geographical space. Therefore, this result is contrary to expectation and mostly reported findings about the positive effects of social networks on adoption decisions (Moser & Barrett, 2006; Conley & Udry, 2010; Maertens & Barrett, 2013). Nevertheless, it supports Baerenklau (2005) who found neighbourhood influence less relevant among dairy farmers in USA. The roles of social networking cannot be over-emphasized in the process of accepting or rejecting agricultural technological innovation. Indeed, the significant roles played by friends and neighbours in the adoption of innovation are well acknowledged (Foster & Rosenzweig, 1995; Foster & Rosenzweig, 2010). Notwithstanding, these roles may be positive or negative depending on technology type, setting, time as well as other factors. For example, it is not uncommon to find farmers negatively influencing themselves on the acceptance or the rejection of innovation when one or some group of other farmers have experimented such technology. A typical example is the experimental trial approach or the use of contact farmers to experiment the yield advantage of some improved seeds. If the outcome proves to be better, others farmers may emulate and adopt such technology. If otherwise, such technology would be out rightly rejected.

Farmers located in Ilaro agricultural zone are significantly more likely to adopt HYV relative to farmers living in Abeokuta zone. The positive coefficient of the Ijebu-Ode variable also suggests that farmers in this zone have higher propensity to adopt HYV relative to those in Abeokuta probably due to the low land nature of the Ijebu-Ode zone. There are two possibilities for this behaviour. First, the result may confirm the variation in the attitude to time and adoption among farmers residing in the rural and urban agricultural zones. Rural areas generally lack access to infrastructural facilities such as schools, accessible roads, hospitals which limits the economic potential of the rural dwellers since remoteness may affect access to information and awareness. Furthermore, agricultural zones may not only reflect access to information but also access to city markets. For instance, using distance to road as a proxy to market access Neill and Lee (2001) reported that probability of adopting cover crop technique reduces with distance from road in Honduras. Second, the result may reflect the climatic condition or pattern of the existing agricultural zones. For example, Ilaro is the driest zone attributed to lower rainfall, followed by Abeokuta, Ikenne and Ijebu-Ode, respectively. The result therefore suggests that willingness to adopt HYV is higher among farmers living in the climatically least favourable zone of Ilaro.

Lastly, with the exception of high yield, the results show that farmers' perceptions about improved agricultural technology attributes decrease the likelihood of adoption. This is contrary to expectations and previously reported findings (Adesina & Zinnah, 1993; Adesina & Baidu-Forson, 1995). As previously revealed, farmers may base their adoption decisions on different factors including technology traits such as potential for market, yield advantage, resistance to drought and stress, taste, cooking quality in line with Mehar *et al.* (2015). One plausible explanation is the fact that most farmers perceived these attributes important in the adoption of improved rice varieties yet most sampled farmers are not currently growing HYV. Earlier reported result under risk and adoption suggests that most rice farmers attached more weights to high yield than other attributes. This positive relationship between high yield and adoption is observed in the current result.

Table 30: Effects of Impatience on HYV Adoption Decisions

Variables	Coefficients	SE	Z-value	P-value
Time preference				
Impatience	-15.0322***	1.2664	-11.87	0.000
Farm and Farmers' specific factors				
Age	0.0081	0.0067	1.21	0.225
Education	0.0270	0.0309	0.87	0.382
Christian	0.1004	0.1489	0.67	0.5
Household size	-0.0581*	0.0340	-1.71	0.088
Farm size	0.0023	0.0760	0.03	0.976
Male	-0.6009**	0.3014	-1.99	0.046
Married	0.2571	0.3709	0.69	0.488
Upland rice	0.1553	0.2120	0.73	0.464
Locations/Agricultural zones				
Ikenne	-0.2302	0.5964	-0.39	0.700
Ijebu-Ode	0.1711	0.3347	0.51	0.609
Ilaro	0.4138*	0.2433	1.7	0.089
Institutional and Community Factors				
Extension contact	-0.0168	0.0223	-0.75	0.450
Friends and Neighbours	-0.5654***	0.2062	-2.74	0.006
Perceptions about HYV attributes				
High yield	0.0087	0.0840	0.1	0.918
Long stem	-0.1244	0.1223	-1.02	0.309
Short duration	-0.0511	0.1965	-0.26	0.795
Good tiller	-0.0032	0.1926	-0.02	0.987
Constant	7.1817	1.8378	3.91	0.000

Correlation between SE. of time and adoption model = 0.99 (sig=0.016), SE of time model = 0.072 (sig. = 0.004)
Wald Chi 2 (13) =306 (p< 0.38). Wald test of exogeneity (correlation = 0): Chi 2 (1) = 9.28 (p< 0.023)

Note: SE = standard error, ***, **, * implies coefficients are significantly different from zero at 1 percent, 5 percent and 10 percent , respectively. Number of Observation (N = 329)

Source: Data Analysis, 2017

6.2.5 Summary and Conclusion

Improved agricultural technologies often offer higher yield and income benefits to farmers. However, adoption rates are usually at lower pace as farmers take time to decide whether to accept such technology or otherwise. This is attributable, among other factors to the uncertainty associated with improved agricultural technology.

Preference for time is one of the key factors in adoption decisions. This is often omitted by many studies due to the difficulty in measurement. This study therefore tests the endogeneity of farmers' subjective discount rates in the adoption of HYV among rice farmers in Ogun State Nigeria.

This finding reveals that in addition to socio-demographic variables, intrinsic factors are important in explaining reasons for making decisions to adopt HYV. It was not only shown in this study that most rice farmers in the study area have high subjective discount rates, but also empirically proven that a relationship exists between the impatience level of a rice farmer and his neighbours. Farmers living in the agricultural zones with less rainfall show more willingness to adopt HYV relative to those living in the more climatically favourable zone. Above all, impatience driven by spatial dependence reduces the propensity to adopt improved rice varieties. This suggests that misleading inference is a possibility if spatial dependence is not controlled for in the adoption model. Spatial heterogeneity may be attributed to many factors including socio-economic, geographical, ecological and climatic conditions of any region. These attributes may extend beyond agricultural zones' borders suggesting the application of inappropriate policy if spatial dependence effect and time preference are ignored in the adoption model.

The following policy options are suggested. First, farmers located in the least favourable climatic or drier areas are more likely to adopt HYV. Such farmers should be targeted and encouraged to adopt innovations in order to increase their output and productivity. Provision of infrastructural facilities would not only aid farming practices in the rural areas but also encourage the diffusion of technological agricultural innovation. Second, since farmers do not live in isolation as shown in the spatial dependence effects, policy intervention with respect to encouraging the adoption and diffusion of HYV could be targeted at farmers and their neighbours. In other words, in the absence of functioning schools and low extension services, interpersonal communication and social networks can serve as effective tools for the diffusion of agricultural innovation. Third, in developing agricultural technological innovation for farmers' acceptance, adequate attention should not only be given to farmers' personal factors but also perceptions about improved technology attributes, spatial characteristics and intertemporal decisions. Furthermore, a patient farmer has higher propensity to adopt HYV relative to impatient farmers. This suggests identifying the more patient farmers and encouraging such farmers to accept improved agricultural technology may partly solve the problems of low income as well as food insecurity which characterizes most developing countries like Nigeria. In conclusion, the evidence of spatial dependency in time preference suggests that certain unobservable factors drive farmers' intertemporal decisions. Such drivers of decisions if identified, may aid policy in ensuring the acceptance of agricultural technological innovation. Are these factors climatic, social or economic or combinations of many variables? Further research should focus on the identification and incorporation of these unobservable factors that influence farmers' adoption decisions into adoption models.

Chapter Seven

7.0 Conclusions and Policy Implications

This Section begins with a summary of the key problems addressed in this study followed by the key findings of the study. The policy implications are presented next. In addition, it discusses the contributions to knowledge, the limitations of the study and concludes with suggestions for further research.

7.1 Summary of the Study and Key Findings

Modern agricultural innovation, such as improved seeds, is often released to farmers especially in the developing countries with the primary objective of increasing their yield, income, food security and welfare. However, farmers do not always adopt, which is attributable to many reasons. Specifically, low technological advancement is one of the bottlenecks to the agricultural growth in Nigeria as most farmers in this country rely on crude methods of farming, rainfall and hardly use improved agricultural innovation. Therefore, the main question addressed in this study is why do some farmers adopt and others do not adopt improved rice varieties? Identifying the key factors responsible for rice farmers' attitudes toward the adoption of improved agricultural innovation is important for policy intervention.

Adoption of improved agricultural technology is associated with many factors including farm and farmers' specific characteristics, technology attributes, environmental conditions, institutional factors, social networks and learning as well as attitudes toward risk and time. Well-informed, educated, large or wealthier farmers may show positive preference for the adoption of improved technology relative to small or poor farmers due to access to formal education, information and credit. Smallholder farmers may also be averse to risk and time for many reasons. However, where supply constraints are limited and some neighbours adopt such improved technology, research is required to provide insight into the intrinsic reasons for adoption and non-adoption behaviour.

Notwithstanding, many factors affecting agricultural technology adoption are unobservable or latent explaining the reason for their omission in the analysis by most studies. These factors, including topographic and climatic conditions, absence and infrastructure may explain the degree of heterogeneity in farmers' decisions. These variables may also show some degree of correlation with socio-economic factors often included in adoption models. This motivates this study to examine the roles of spatial dependence in rice farmers' decision-making with the implications for HYV adoption decisions in Nigeria.

In addressing this broad objective, this study provides answers to four specific objectives, specified in **Chapter One**. These specific objectives which emanating from the research questions were achieved using experimental and survey data collected from rice farmers in Ogun State Nigeria. The descriptive statistics of the rice farmers socio-demographic factors and farmers' attitudes toward risk and time are presented in **Chapter Four**. The study examines the role of spatial dependence in risk preference as well as the effect of risk preference on rice farmers' adoption decisions. This was achieved first, using an instrumental variable for the determinants of risk avoidance and to test the hypothesis of spatial dependence in risk preference; second instrumental variable probit model to identify the determinants of adoption decisions as well as the hypothesis of that risk preference is not only a significant factor affecting adoption decisions but an endogenous variable in the adoption model. The empirical results for these two objectives were presented in **Chapter Five**. Similar methodological approaches used in **Chapter Five** were adopted in the results presented in **Chapter Six** to identify the determinants of rice farmers' impatience (and test the hypothesis of spatial dependence in time preference) as well as the determinants or predictors of rice farmers' adoption decisions (testing the hypothesis that time preference is an endogenous determinant of adoption decisions). The next section summarises the results in line with the research questions and hypotheses tested.

7.1.1 Linking Research Questions with Empirical Findings

The statistical tests conducted in the descriptive chapter reveal that rice farmers in Ogun State Nigeria are mostly risk avoiding and impatient. However, the adopters are more willing to take risky decisions relative to non-adopters. In addition, the adopters evidently have lower subjective discount rates. The empirical findings are presented next.

Research Question One: What factors determine rice farmers' willingness to risk taking or risk avoidance? Are rice farmers' risk preferences spatially determined? Hypothesis one: there is a spatial dependence or correlation in rice farmers' time preference.

The results of the instrumental variable reveal that, with respect to small gain one, risk avoidance is positively influenced by farm size but negatively influenced by old age, gender, marital status and bad road networks. This suggests large scale farmers are more willing to take risky decisions relative to small scale farmers. On the other hand, farmers living in the rural areas or bad road network areas are less willing to take risky decisions attributable to their environmental and living conditions. In terms of small gain two, while education has a positive and significant influence on willingness to risk taking or risk avoidance, age, marital status, gender, and bad road networks have significant negative impacts. This suggests educated rice farmers are more likely to take risky decisions while farmers living in the rural areas avoid taking risky decisions. In line with the large gain one, the results show that large-scale farmers are more willing to take risky decisions while older, male, married farmers as well as those living in the rural areas or poor road condition areas show less willingness to taking risky decisions. For large gain two, willingness to risk taking is negatively influenced by age, male, marital status and bad road networks. Above all, rice farmers risk preference is spatially determined (spatially correlated) up to 60 km suggesting several spatially related variables (not usually accounted for), influence farmers' decisions.

Research Question Two: Does risk avoidance or risk preference have a significant effect on rice farmers' adoption decisions? Hypothesis two: risk preference is an endogenous determinant of adoption decisions

Results of the instrumental variable probit reveal that farmers' socio-economic, community, institutional, locations, perceptions about the attributes of improved technology as well as willingness to take risks (risk avoidance) significantly explain rice farmers' adoption behaviour. The results indicate that male rice farmers are less likely to take risky decisions while farmers located in Ilaro agricultural zone are more likely to adopt HYV relative to farmers in other agricultural zones. This suggests the tendency of the farmers living in the climatically least favourable location to have ardent desire for yield-enhancing and drought-tolerance varieties. The results also show that Christians are less likely to adopt HYV. Although most farmers in the study area have less access to extension services, the finding shows that contacts with extension agent increases the probability of adoption. In addition, perceptions about the importance of high yield have significant positive influences on HYV adoption decisions while the perceptions about the importance of short duration and good tiller negatively influence rice farmers' adoption decisions. This suggests farmers attached more importance to yield than other attributes of improved technology in the study area. Above all, risk preference has a significant negative effect on decisions to grow HYV and a highly risk avoidant farmer is less likely to adopt HYV relative to a highly risk loving farmer. Lastly, risk preference is an endogenous determinant of rice farmers' adoption decisions.

Research Question Three: What factors determine rice farmers' time preference? Are rice farmers' subjective discount rates spatially determined? Hypothesis three: time preference is spatially related or correlated.

The results of the instrumental variable reveal that age, religion, marital status, bad road and spatial dependence have a significant impact on rice farmers' level of impatience. Older rice farmers have a high subjective discount rate (impatience) while Christian and married rice farmers have a lower discount rate relative to Muslim and single rice farmers. In addition, farmers living with bad road conditions are more impatient, which is attributable to their production environment. Above all, farmers' subjective discount rate is spatially determined (correlated) up to 60 km suggesting there is spatial correlation among rice farmers' time preference, which is attributable to factors like socio-economic conditions, climatic, ecological and topographic conditions which may drive intertemporal decisions.

Research Question Four: Does impatience significantly explain rice farmers' adoption decisions? Hypothesis four: time preference is an endogenous determinant of adoption decisions.

The instrumental variable probit results reveal that rice farmers' adoption decisions are significantly explained by household size, gender, locations and impatience. Indeed, male rice farmers and those with larger family size have lower propensity to adopt HYV. Farmers located in Ilaro are also less likely to grow HYV relative to farmers located in Abeokuta. In addition, farmers who rely on information from friends and neighbours are less likely to adopt HYV. Above all, farmers having high subjective discount rate or impatient farmers have lower propensity to grow improved rice varieties. Lastly, time preference is an endogenous variable that significantly explain farmers' adoption decisions.

7.2 Policy Implications

The Nigerian rice sector faces both macro and micro economic issues which constitute constraints to actualizing its potentials. The review of the challenges presented in Section 2.1 of **C** suggests that increasing the use of improved rice technology or adoption rates of the existing improved varieties may not only increase rice output but also reduce rice importation significantly. Therefore, the central question is what factors drive the attitudes of rice farmers toward adopting improved rice technology? The appealing findings from this study provide answers to the above questions. The policy options from the findings are as follows:

First, the results of the determinants of risk avoidance and impatience reveal that decision-making does not only depend on farm and farmers' specific factors which many past studies limit their model to, but also on farmers' neighbourhood influence. In other words, a significant spatial correlation between rice farmers' willingness to take risks; and impatience suggests spatial influence and social learning effects are prevalent among rice farmers. In fact, spatial clustering exists among rice farmers. Rice farmers do not live in isolation; farmers are spatially and geographically related. It follows that policies aimed at encouraging the adoption and diffusion of improved farm (rice) technology should particularly consider the roles of spatial dependence in decision making. The appropriate policy must pay specific attention to the social and geographical connectivity among farmers. Proper coordination of social networks may aid the dissemination of information relating to improved farming practices. Put differently, progressive farmers should be identified among clustering groups, thus policy intervention relating to HYV adoption and diffusion could be targeted at farmers' neighbours or progressive farmers who will aid the spread of innovation.

Second, heterogeneity in decision-making suggests that climatically least favourable agricultural zones and rural areas deserve special attention. All the model results consistently indicate that farmers located in the rural agricultural zones are less willing to take risky decisions. These categories of farmers may produce less output and yield due to a negative attitude towards accepting technological innovation. Another important revelation of this study is that spatial dependence may extend beyond the existing borders of agricultural zones. Therefore, provision of infrastructural facilities like accessible roads to the rural areas will not only aid improved farming practices but also encourage the diffusion of technological innovation across the existing agricultural zones. Attention should also be given to the interpersonal communication and social interaction that exist in the climatically least favourable areas or rural agricultural zones which lack good road networks and other infrastructural facilities.

Third, non-adoption of improved rice varieties is largely attributed to the riskiness of such technology as well as the strong desire for present consumption relative to future consumption. Therefore, in developing technological innovation for farmers' acceptance, specific attention should be given to the riskiness of technology and the potential benefits associated with such technology. For example, the yield advantage of improved rice varieties should be attractive enough to farmers so that a farmer who decided to adopt today and wait for three months may be better off for exercising some level of patience. Farmers may be more willing to accept risk reducing agricultural technology relative to accepting risk increasing technology. Therefore, breeders should take cognisance of this and commensurate the benefits offered by agricultural technology with the level of riskiness.

Fourth, among the socio-economic variables, extension contacts significantly determine rice farmers' decision-making. Awareness is key in the acceptance of technological innovation. Education is an important social capital that facilitates access to information, credit and other social facilities. A more educated farmer may be more inclined to adopt HYV because he has the appropriate knowledge and information about the potential benefits of such improved technology. Since most sampled rice farmers have less than primary education, and extension services are grossly inadequate, encouraging adult literacy education is a step in the right direction. Moreover, provision of more primary and secondary schools to most rural communities would afford farmers' children basic education which may have multiplier effects on their parents' farming practices. Above all, there is the need to review the existing extension services to aid the dissemination of agricultural innovation among farmers.

In conclusion, in developing agricultural technological innovation targeted at farmers', specific attention should not only be giving to farmers' specific factors but also spatial characteristics *viz-a-viz* risk avoidance and impatience. More focus should be on the micro-economic issues such as provision of subsidized inputs (improved seeds, agrochemicals and credit) to rice farmers. Lastly, incentives like accessible roads, schools, and adequate information through extension services should be provided to farmers to encourage the adoption of improved rice technology. In the face of inadequate extension services, farmers may be encouraged to strengthen their existing social networks and streamline these toward, not only helping one another to access adequate information about improved farm techniques but also to cooperatively harness the opportunities associated with cooperation and social networks.

7.3 Contributions, Limitations and Suggestions for Further Research

7.3.1 Contributions to Knowledge

This study does not only make contributions to the field of Agricultural, Food and Environmental Economics but is also novel in the decision-making literature. The primary objective of introducing improved agricultural technology such as rice varieties to farmers is to increase yield and income. Therefore, examining rice farmers' attitudes toward risk and time as well as the spatial heterogeneity in decision-making becomes imperative. The roles of risk aversion in technology adoption are well acknowledged and documented in the literature. Rice farmers' aversion to risk and bias towards the present may be spatially correlated with consequential effects on decisions to adopt improved agricultural technology. This may have negative consequences on economic development. Yet studies linking experimental decisions with observed agricultural data or decisions are very few. This study fills this deficiency and contributes to the literature in many ways.

First, many attempts have been made to identify factors determining the level of individual farmers' risk aversion in both the developed and developing countries. None of these studies examine the roles of spatial dependence in risky decision making. It was demonstrated in this study that farmers' willingness to risk taking is spatially correlated or related. This suggests that past studies have omitted key variable that may explain reasons for the heterogeneity in decision making among individuals or farmers especially in the developing countries.

Second, few studies in both developed and developing countries have elicited farmers' risk attitudes with the assumption that behaviour is homogenous, that is, only one utility parameter (risk aversion) explains attitude. In other words, studies that considered risk aversion in their analyses assume behaviour is homogenous while those examining heterogeneity in farmers' risk attitudes did not focus on adoption decisions. In this study, the homogeneity assumption is relaxed by eliciting rice farmers' risk preference using bi-dimensional panel lotteries. Indeed, this is the first study to apply panel lotteries to non-student subjects in the developing countries. Using this elicitation method allows this study to non-parametrically examine rice farmers' willingness to risk taking or risk attitudes across stakes and domains and show the implications for the adoption decisions.

Third, very few studies have attempted to identify the predictors of time preference or subjective discount rate among farmers in developing countries. These studies however ignored the role of spatial dependence in farmers' intertemporal decisions. It was demonstrated in this study that rice farmers' subjective discount rates are spatially correlated. Knowing how farmers behave in relation to space and time may guide policy for the development and acceptance of technological innovation. For instance, impatient rice farmers may be more spatially related or geographically clustered suggesting the same policy options may be targeted at and applied to these categories of farmers.

Fourth, literature suggests that risk aversion and spatial dependence are important determinants of farmers' adoption decisions. This relationship has however been independently examined in other studies. This study bridges this gap by incorporating spatial dependence into an adoption decision model through risk preferences. Specifically, the adoption models revealed that risk avoidance is endogenous in explaining adoption decisions. This endogeneity hypothesis has never been tested in the literature. Thus, this study affirms that both endogenous and exogenous variables are important in explaining the adoption of technological agricultural innovation. While the roles of observable farm and farmers' specific and institutional factors are not disputed in decision-making, this study shows that both the observed and latent variables matter in decision making among farmers.

Fifth, literature also suggests that impatience and spatial dependence determine farmers' adoption decisions yet this relationship has been independently examined. This study bridges this gap by incorporating spatial dependence into adoption decision model through time preferences. Specifically, the adoption models revealed that impatience is endogenous in explaining adoption decisions affirming that both endogenous and exogenous variables are important in explaining the adoption of technological agricultural innovation.

Sixth, several studies suggest that females are more risk averse relative to males. The finding of this study shows the contrary. Female rice farmers were found to be more willing to take risky decisions. This supports the argument that attitude or behaviour is not a fixed factor and thus not gender-specific. Attitude of individuals may depend on circumstances. It also suggests that attitude towards adoption of innovation may not be gender-specific as both gender may behave similarly or differently.

Lastly and specifically, in Nigeria past adoption studies did not only fail to examine the roles of risk and time preferences in improved farm technology adoption decisions but also failed to account for the role of spatial dependence in decision making. Examining the preferences of rice farmers in relation to risk and time provided information on the reasons why some farmers adopt HYV and others do not. In other words, it revealed the riskiness of the improved rice varieties relative to local varieties. Notwithstanding, decisions not to adopt such improved technology may translate to low income. Adoption is an investment decision that takes place over space and time, and as associated with a high degree of risk and future uncertainty. Time is not only necessary for decision-making relating to investment but is also important for future consumption decisions. Since most agricultural activities involve making input-commitment today with the expectation of future outcomes, it follows that how farmers weigh the future may determine their future economic status. Therefore, this study investigates how smallholder rice farmers' behave with respect to time in Nigeria which may affect their wealth accumulation.

7.3.2 Limitations and Suggestions for Further Research

This study has some few limitations that deserve future improvement and research.

First, the experiments conducted in this study are hypothetical due largely to lack of adequate funding and other logistics. The hypothetical experiment enables this study to deal with confounding but prevents non-rice farmers from participating in the experiments. Although some studies find no significant difference between real and hypothetical experiments, future research is required for confirmation. Incentivized experiments may be conducted in the future for comparison after designing other ways of preventing non-intended subjects from participating in the experiments.

Second, the risk experiment used in this study is adapted from the study previously conducted in the developed country. Thus, the coefficients of the curvature of utility obtained are rather strange and therefore not reported which partly suggests the introduction of the term 'risk avoidance'. Future study should seek for a better way of defining the payoffs in line with the existing economic reality of the intended subjects and country. This may require more efforts, yet its realization could produce comparable results with the present study. The other ways in which rice farmers risk attitudes could be explained, apart from utility theories, include pessimistic and optimistic. Therefore, this is a subject of future consideration.

Third, decision making is a complex concept which cuts across different domains and contexts. While the decision to limit this study to the risk preference and time preference is not a limitation on its own, future research should seek to elicit impulsiveness attitude as well as decision making for others (proxy decision). This may be important because at times, decisions are made by individuals without a deep thought about the consequences while local leaders or progressive farmers sometimes make decisions on behalf of other farmers. In other words, these forms of attitudes may have implications for day-to-day activities including decisions to invest in productive activities.

Fourth, the roles of ambiguity and uncertainty in the adoption of technological innovation are well acknowledged in the literature. However, these are not examined in this study. Consequently, future research should elicit these forms of behaviour and incorporate them into adoption decisions' models.

Fifth, as revealed in the spatial and adoption decisions' models, further research should focus on identifying the unobservable factors that may influence rice farmers' decision-making. The scope of such is beyond this study. Addressing this may provide more insights into the endogenous and exogenous variables that may strengthen the understanding and reasons for the acceptance and rejection of improved agricultural technology in the developing countries. Consequently, identification of such factors would guide effective planning by both researchers and policy makers.

Lastly, this study is constrained by finance and time. In other words, more geographical coverage suggests more financial and time commitments. Thus, the conclusions reached in this study regarding spatial dependence and adoption decisions could be subjected to further tests by covering a wider geographical location for example, from state-wide (which this study is limited to) to country-wide.

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Appendix A: Additional Tables

Table 31: Effects of Spatial Dependence on Risk attitudes (OLS estimates)

Variables	SG1	SG2	LG1	LG2
Spatial Dependence				
Spatial lags	0.0015*** (0.0002)	0.0018*** (0.0002)	0.0018*** (0.0002)	0.0018*** (0.0002)
Farmers' specific factors				
Age	0.0034*** (0.0009)	0.0024*** (0.0007)	0.0026*** (0.0008)	0.0022*** (0.0008)
Education	0.0049** (0.0023)	0.000558 (0.0020)	0.0040* (0.0023)	0.0040* (0.0022)
Christian	0.0559*** (0.0198)	0.0550*** (0.0172)	-0.0202 (0.0193)	0.0262 (0.0185)
Family size	0.0017 (0.0039)	0.002281 (0.0034)	0.001217 (0.0038)	2.58E-05 (0.0036)
Farm size	-0.0171** (0.0074)	-0.00505 (0.0064)	-0.0160** (0.0072)	-0.0078 (0.0069)
Male	0.0487** (0.0234)	0.0459** (0.0199)	0.0564** (0.0224)	0.0540** (0.0214)
Married	0.3086*** (0.0447)	0.2229*** (0.0387)	0.3093*** (0.0433)	0.2140*** (0.0414)
Location				
Bad road	0.1141*** (0.0205)	0.0578*** (0.0178)	0.1156*** (0.0199)	0.0621*** (0.0191)

Diagnostic statistics:

SG1: R-squares = 0.95, Adjusted R-squares = 0.95, F-value = 700 (DF=9, 319) (p<2.2E-16)
SG2: R-squares = 0.94, Adjusted R-squares = 0.94, F-value = 595 (DF =9,319) (p<2.2E-16)
LG1: R-squares = 0.95, Adjusted R-squares = 0.95, F-value = 635 (DF = 9, 319) (p<2.2E-16)
LG2: R-squares = 0.93, Adjusted R-squares = 0.92, F-value = 448 (DF = 9, 319) (p<2.2E-16)

Number of observation (N = 328)

Source: Data Analysis, 2017

Table 32: Effect of Risk Preference on HYV Adoption Decisions (Binary Probit)

Variables	SG1	SG2	LG1	LG2
Risk Preference				
Risk avoidance	-0.894	-0.787	-4.316**	-8.648***
	(1.644)	(2.182)	(1.977)	(2.588)
Farm and Farmer Specific Factor				
Age	-0.008	-5.39E-03	-1.8E-02	4.56E-04
	(0.028)	(0.026)	(0.026)	(0.029)
Education	2.2E-01***	0.208***	0.221***	0.280***
	(0.080)	(0.081)	(0.085)	(0.078)
Christian	-0.319	-0.360	-0.441	-0.342
	(0.425)	(0.451)	(0.476)	(0.519)
Household size	-0.154*	-0.158*	-0.166*	-0.225**
	(0.086)	(0.085)	(0.086)	(0.104)
Farm size	0.401***	0.408***	0.338***	0.272
	(0.119)	(0.122)	(0.124)	(0.294)
Male	-2.029***	-1.987***	-2.322***	-2.235***
	(0.731)	(0.653)	(0.795)	(0.772)
Married	-0.564	-0.639	-0.519	-0.710
	(0.846)	(0.901)	(0.821)	(0.922)
Upland	-0.224	-0.206	1.205	1.010
	(0.789)	(0.841)	(1.136)	(1.023)
Locations				
Ikenne	-4.168***	-4.359***	-4.661***	-4.935***
	(0.972)	(0.931)	(1.155)	(1.154)
Ijebu-Ode	-2.302**	-2.484**	-1.397	-2.301***
	(0.901)	(1.068)	(1.045)	(0.892)
Ilaro	0.126	0.0317	0.121	1.066*
	(0.735)	(0.679)	(0.688)	(0.618)
Institutional and Community Factors				
Extension contact	-0.011	-0.026	-0.039	-0.068
	(0.073)	(0.072)	(0.083)	(0.099)
Friends	-0.320	-0.201	-0.643	-0.781
	(0.496)	(0.464)	(0.558)	(0.589)
Perceptions of Technology Attributes				
High yield	-0.166	-0.193	-0.211	-0.199
	(0.244)	(0.223)	(0.293)	(0.351)
Long stem	-0.691**	-0.736**	-0.938***	-1.138***
	(0.290)	(0.298)	(0.348)	(0.409)
Short duration	-1.383***	-1.370***	-1.324***	-1.959***
	(0.429)	(0.398)	(0.446)	(0.465)
Good tiller	-1.274***	-1.282***	-1.502***	-1.723***
	(0.391)	(0.328)	(0.393)	(0.384)
Constant	11.493***	11.582***	14.821***	18.573***
	(2.856)	(2.680)	(3.368)	(3.622)

SG1: Wald chi2 (18) = 75.37 (P > 0.000), Log-likelihood = -22.799, Pseudo R^2 = 0.7728
SG2: Wald chi2 (18) = 72.56 (P > = 0.000), Log-likelihood = -22.839, Pseudo R^2 = 0.7724
LG1: Wald chi2 (18) = 62.65 (P > 0.000), Log likelihood = -20.920, Pseudo R^2 = 0.7915
LG2: Wald chi2 (18) = 54.99 (P > 0.000), Log likelihood = -17.690, Pseudo R^2 = 0.8237
*,**,*** imply significant at 10 percent, 5 percent and 1 percent respectively
Number of observation (N=328)

Source: Data Analysis, 2017

Table 33: Effect of Time Preference on Adoption Decisions (Binary Probit)

Variables	Coefficients	Standard Error	Z-value	P-value	Marginal Effects
Time Preference					
Impatience	-8.545**	3.659	-2.33	0.02	-0.298
Age	-0.011	0.030	-0.36	0.717	-0.000
Education	0.193**	0.081	2.37	0.018	0.007
Christian	-0.540	0.450	-1.2	0.231	-0.019
Family size	-0.212**	0.085	-2.47	0.014	-0.007
Farm size	0.420***	0.135	3.11	0.002	0.015
Male	-1.977***	0.673	-2.94	0.003	-0.069
Married	0.097	0.825	0.12	0.907	0.003
Upland	0.064	0.791	0.08	0.936	0.002
Locations/Agricultural Zones					
Ikenne	-3.673***	0.931	-3.94	0.000	-0.128
Ijebu-Ode	-1.426*	0.858	-1.66	0.097	-0.050
Ilaro	0.781	0.838	0.93	0.351	0.027
Institutional and Community Factors					
Extension contact	-0.019	0.074	-0.25	0.799	-0.001
Friends	-0.316	0.643	-0.49	0.623	-0.011
Perceptions about Technology Attributes					
High yield	-0.140	0.245	-0.57	0.569	-0.005
Long stem	-0.683**	0.311	-2.19	0.028	-0.024
Short duration	-1.335***	0.427	-3.12	0.002	-0.047
Good tiller	-1.366***	0.379	-3.59	0.000	-0.048
Constant	13.804***	2.859	4.83	0.000	

Log likelihood = -21.14, Wald Chi2 (18) = 79.02 (p<0.000), Pseudo R-squares = 79
Number of observation (N= 329)

Source: Data Analysis, 2017

Appendix B: Questionnaire

SURVEY QUESTIONNAIRE ON:
RICE FARMERS' PREFERENCES FOR RISK AND TIME AND ADOPTION DECISIONS

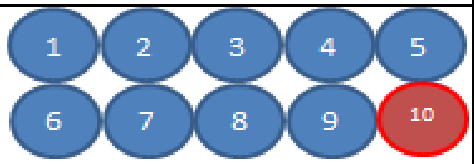
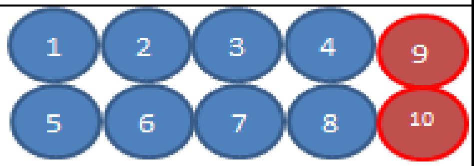
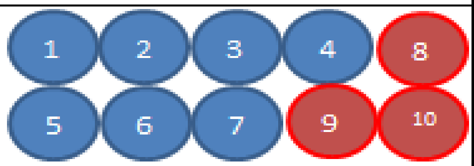
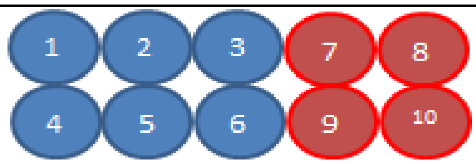
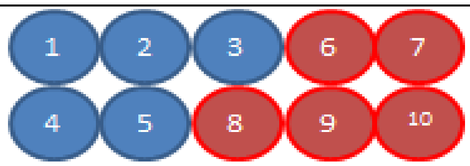
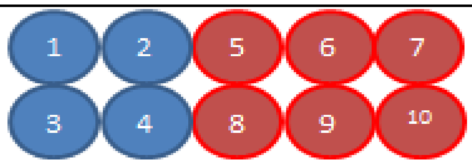
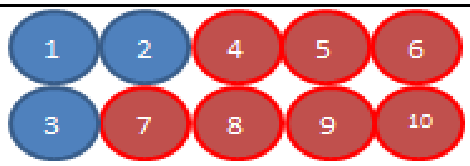
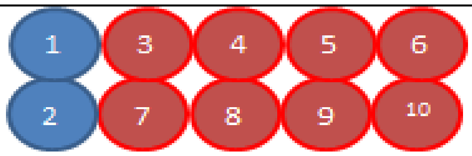
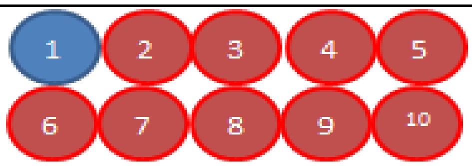
Dear Respondents,
The purpose of this survey is to obtain information on preferences for risk and time as well as other factors that may affect decisions to adopt improved rice varieties in Ogun State Nigeria. Only the household head that is responsible for decision making on rice production is eligible for interview. This survey will last for one and half hours only. Your time and honesty in answering the questions are highly appreciated. Be assured that your responses would be treated with confidentiality and only be used for research purpose. Thank you.

SECTION 1: RISK AND TIME EXPERIMENTS' RECORD SHEETS

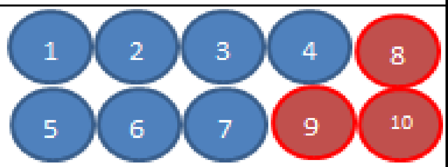
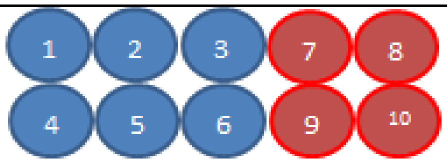
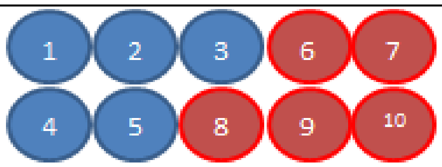
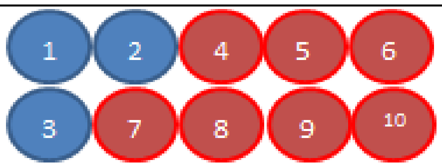
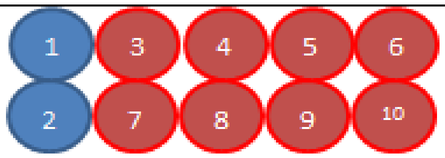
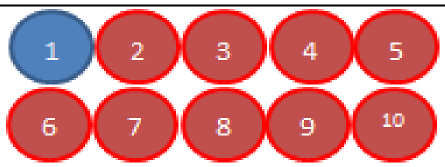
Thank you for agreeing to participate in the experiments. There are two independent experiments (tasks). Experiments one relates to risk attitude while experiment two examines your preference to time. The payoffs associated with the two experiments are presented below. Detailed instructions are given in Section **3.2.3 Data** Collection Methods and Experimental Instructions**).**

The Risk Experiment Record Sheets:

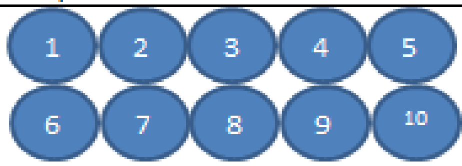
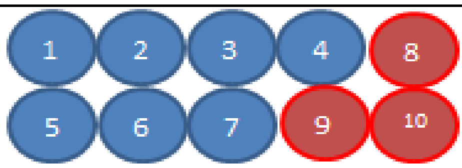
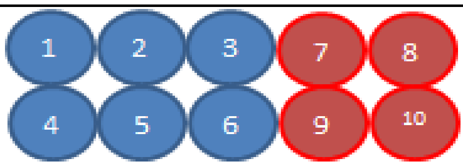
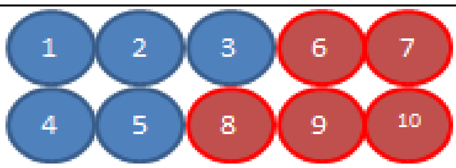
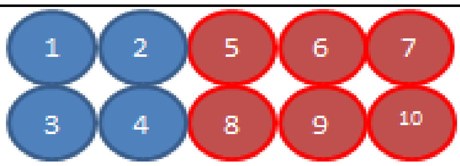
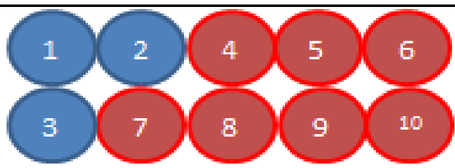
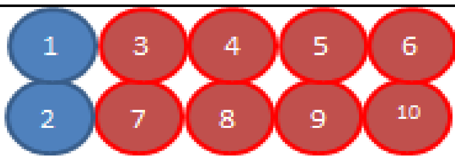
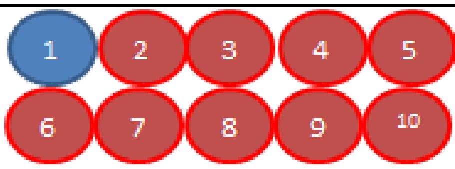
SG1 Panel 1

Row	Blue Balls =WIN, Red Balls = LOSE		Amount (₦)	Choose 1
1	10 blue balls win		225	
2	9 blue balls win		251	
3	8 blue balls win		282	
4	7 blue balls win		322	
5	6 blue balls win		376	
6	5 blue balls win		451	
7	4 blue balls win		563	
8	3 blue balls win		751	
9	2 blue balls win		1,126	
10	1 blue ball win		2,251	

SG1 Panel 2

Row	Blue Balls =WIN, Red Balls = Lose		Amount (₦)	Choose 1
1	10 blue balls win		225	
2	9 blue balls win		251	
3	8 blue balls win		282	
4	7 blue balls win		322	
5	6 blue balls win		376	
6	5 blue balls win		451	
7	4 blue balls win		564	
8	3 blue balls win		753	
9	2 blue balls win		1,129	
10	1 blue ball win		2,259	

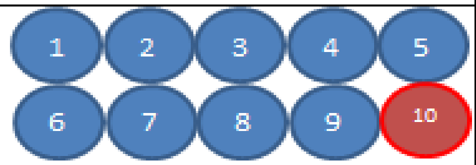
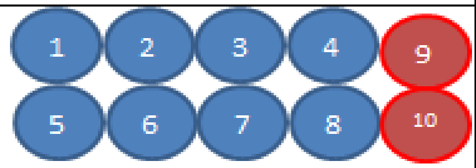
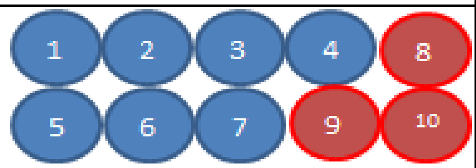
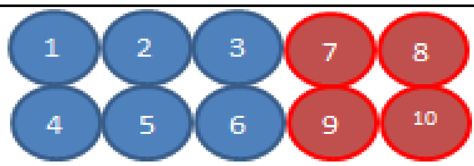
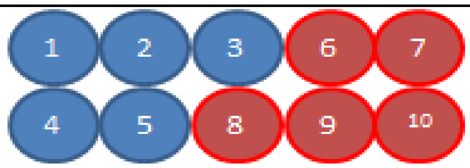
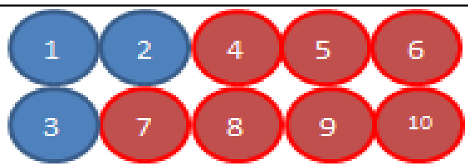
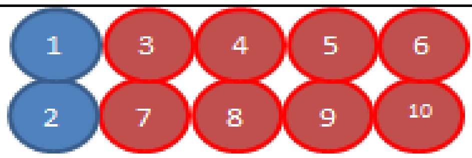
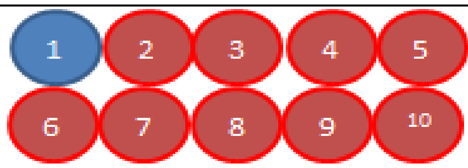
SG1 Panel 3

Row	Blue Balls =WIN, Red Balls = Lose		Amount (₦)	Choose 1
1	10 blue balls win		225	
2	9 blue balls win		251	
3	8 blue balls win		283	
4	7 blue balls win		324	
5	6 blue balls win		379	
6	5 blue balls win		455	
7	4 blue balls win		570	
8	3 blue balls win		762	
9	2 blue balls win		1,145	
10	1 blue ball win		2,295	

SG1 Panel 4

Row	Blue Balls =WIN, Red Balls = LOSE	Amount (₦)	Choose 1
1	10 blue balls win 1 2 3 4 5 6 7 8 9 10	225	
2	9 blue balls win 1 2 3 4 5 6 7 8 9 10	252	
3	8 blue balls win 1 2 3 4 9 5 6 7 8 10	284	
4	7 blue balls win 1 2 3 4 8 5 6 7 9 10	326	
5	6 blue balls win 1 2 3 7 8 4 5 6 9 10	382	
6	5 blue balls win 1 2 3 6 7 4 5 8 9 10	460	
7	4 blue balls win 1 2 5 6 7 3 4 8 9 10	578	
8	3 blue balls win 1 2 4 5 6 3 7 8 9 10	774	
9	2 blue balls win 1 3 4 5 6 2 7 8 9 10	1,165	
10	1 blue ball win 1 2 3 4 5 6 7 8 9 10	2,340	

SG2 Panel 1

Row	Blue Balls = WIN, Red Balls = LOSE		Amount (₦)	Choose 1
1	10 blue balls win		0	
2	9 blue balls win		26	
3	8 blue balls win		57	
4	7 blue balls win		97	
5	6 blue balls win		151	
6	5 blue balls win		226	
7	4 blue balls win		338	
8	3 blue balls win		526	
9	2 blue balls win		901	
10	1 blue ball win		2,026	

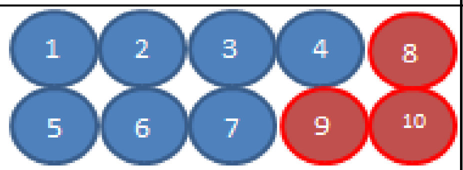
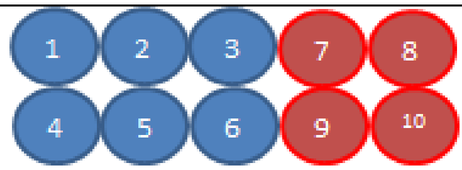
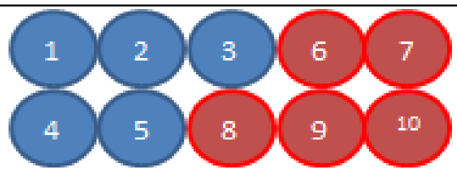
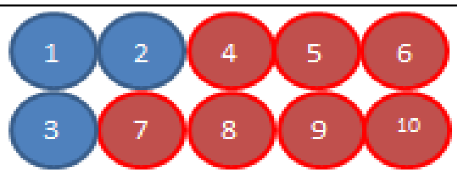
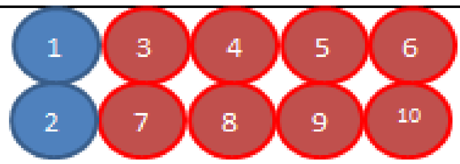
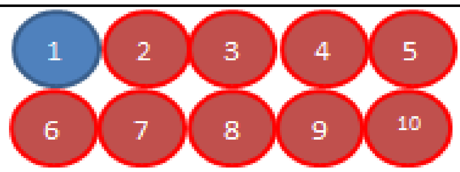
SG2 Panel 2

Row	Blue Balls =WIN, Red Balls = LOSE		Amount (₦)	Choose 1
1	10 blue balls win	1 2 3 4 5 6 7 8 9 10	0	
2	9 blue balls win	1 2 3 4 5 6 7 8 9 10	26	
3	8 blue balls win	1 2 3 4 9 5 6 7 8 10	57	
4	7 blue balls win	1 2 3 4 8 5 6 7 9 10	97	
5	6 blue balls win	1 2 3 7 8 4 5 6 9 10	151	
6	5 blue balls win	1 2 3 6 7 4 5 8 9 10	226	
7	4 blue balls win	1 2 5 6 7 3 4 8 9 10	339	
8	3 blue balls win	1 2 4 5 6 3 7 8 9 10	528	
9	2 blue balls win	1 3 4 5 6 2 7 8 9 10	904	
10	1 blue ball win	1 2 3 4 5 6 7 8 9 10	2,034	

SG2 Panel 3

Row	Blue Balls =WIN, Red Balls = LOSE	Amount (₦)	Choose 1
1	10 blue balls win	0	
2	9 blue balls win	26	
3	8 blue balls win	58	
4	7 blue balls win	99	
5	6 blue balls win	154	
6	5 blue balls win	230	
7	4 blue balls win	345	
8	3 blue balls win	537	
9	2 blue balls win	920	
10	1 blue ball win	2,070	

SG2 Panel 4

Row	Blue Balls =WIN, Red Balls = LOSE		Amount (₦)	Choose 1
1	10 blue balls win		0	
2	9 blue balls win		27	
3	8 blue balls win		59	
4	7 blue balls win		101	
5	6 blue balls win		157	
6	5 blue balls win		235	
7	4 blue balls win		353	
8	3 blue balls win		549	
9	2 blue balls win		940	
10	1 blue ball win		2,115	

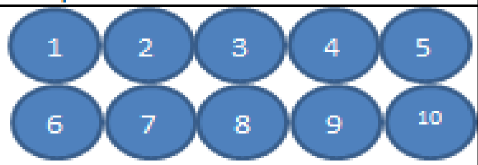
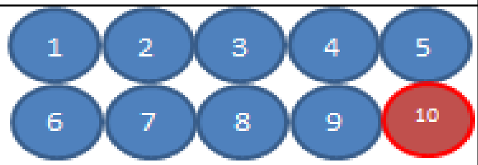
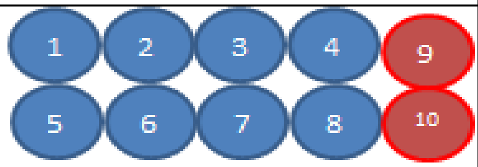
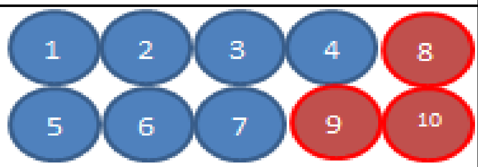
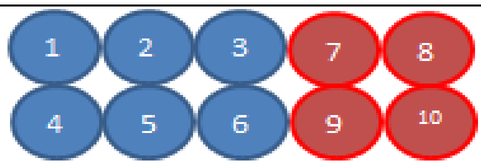
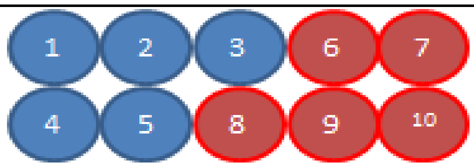
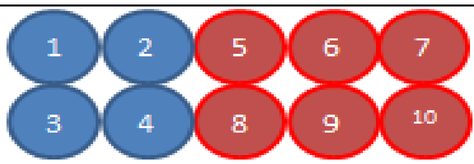
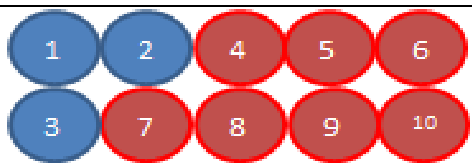
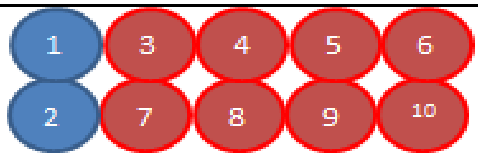
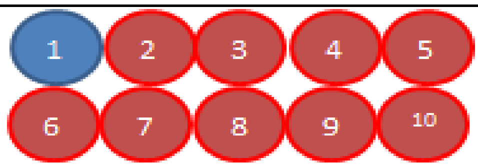
LG1 Panel 1

Row	Blue Balls =WIN, Red Balls = LOSE	Amount (₦)	Choose 1
1	10 blue balls win 1 2 3 4 5 6 7 8 9 10	22, 500	
2	9 blue balls win 1 2 3 4 5 6 7 8 9 10	25,002	
3	8 blue balls win 1 2 3 4 9 5 6 7 8 10	28,128	
4	7 blue balls win 1 2 3 4 8 5 6 7 9 10	32,148	
5	6 blue balls win 1 2 3 7 8 4 5 6 9 10	37,507	
6	5 blue balls win 1 2 3 6 7 4 5 8 9 10	45,010	
7	4 blue balls win 1 2 5 6 7 3 4 8 9 10	56,265	
8	3 blue balls win 1 2 4 5 6 3 7 8 9 10	75,024	
9	2 blue balls win 1 3 4 5 6 2 7 8 9 10	112,540	
10	1 blue ball win 1 2 3 4 5 6 7 8 9 10	225,090	

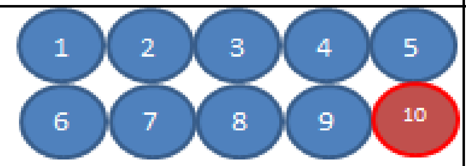
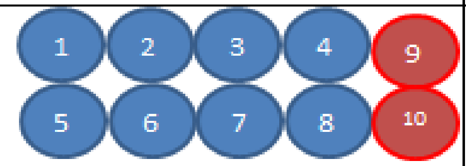
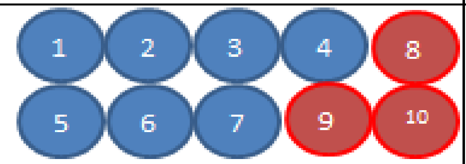
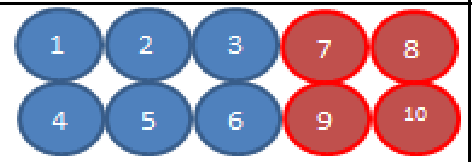
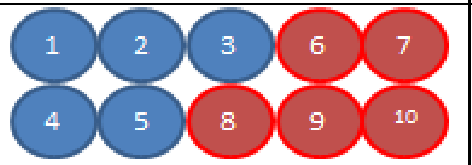
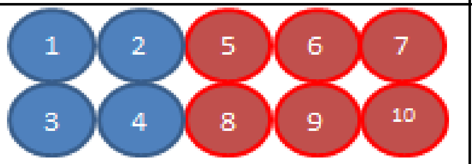
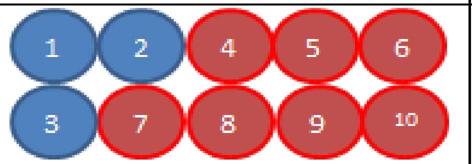
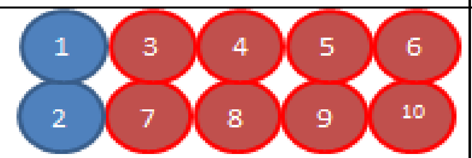
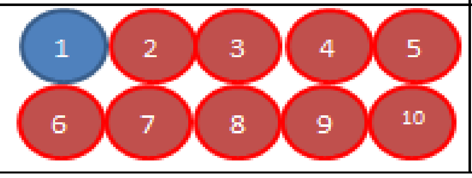
LG1 Panel 2

Row	Blue Balls =WIN, Red Balls = LOSE	Amount (₦)	Choose 1
1	10 blue balls win 1 2 3 4 5 6 7 8 9 10	22,500	
2	9 blue balls win 1 2 3 4 5 6 7 8 9 10	25,012	
3	8 blue balls win 1 2 3 4 9 5 6 7 8 10	28,150	
4	7 blue balls win 1 2 3 4 8 5 6 7 9 10	32,186	
5	6 blue balls win 1 2 3 7 8 4 5 6 9 10	37,567	
6	5 blue balls win 1 2 3 6 7 4 5 8 9 10	45,100	
7	4 blue balls win 1 2 5 6 7 3 4 8 9 10	56,400	
8	3 blue balls win 1 2 4 5 6 3 7 8 9 10	75,234	
9	2 blue balls win 1 3 4 5 6 2 7 8 9 10	112,900	
10	1 blue ball win 1 2 3 4 5 6 7 8 9 10	225,900	

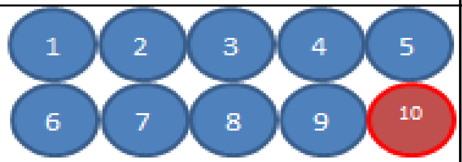
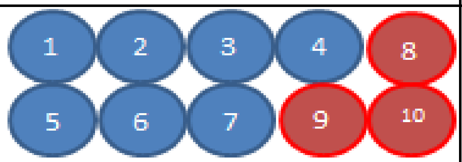
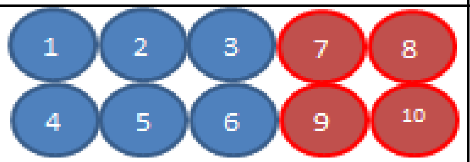
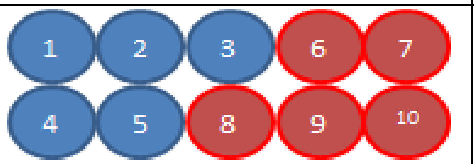
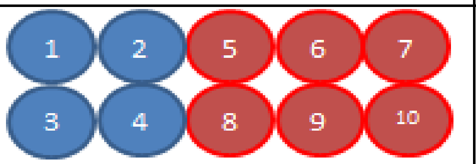
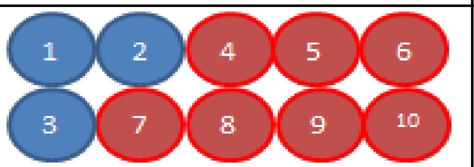
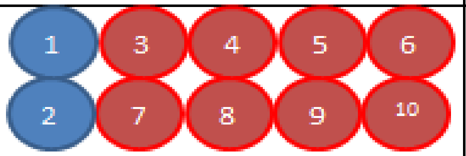
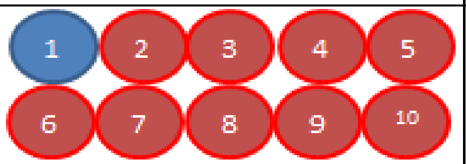
LG1 Panel 3

Row	Blue Balls =WIN, Red Balls = LOSE	Amount (₦)	Choose 1
1	10 blue balls win 	22,500	
2	9 blue balls win 	25,056	
3	8 blue balls win 	28,250	
4	7 blue balls win 	32,358	
5	6 blue balls win 	37,834	
6	5 blue balls win 	45,500	
7	4 blue balls win 	57,000	
8	3 blue balls win 	76,167	
9	2 blue balls win 	114,500	
10	1 blue ball win 	229,500	

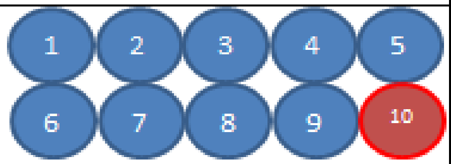
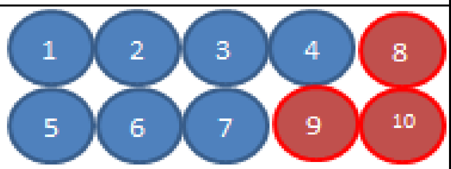
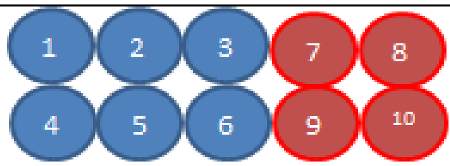
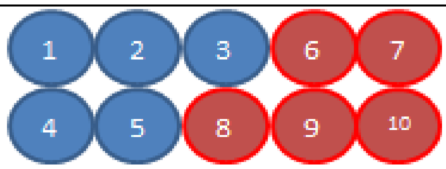
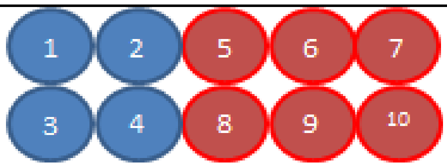
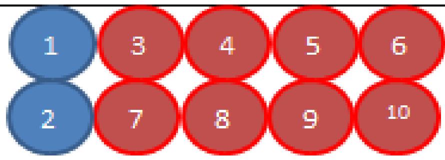
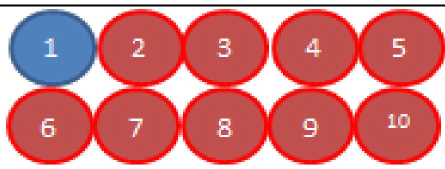
LG1 Panel 4

Row	Blue Balls =WIN, Red Balls = LOSE		Amount (₦)	Choose 1
1	10 blue balls win		22,500	
2	9 blue balls win		25,112	
3	8 blue balls win		28,375	
4	7 blue balls win		32,572	
5	6 blue balls win		38,167	
6	5 blue balls win		46,000	
7	4 blue balls win		57,750	
8	3 blue balls win		77,334	
9	2 blue balls win		116,500	
10	1 blue ball win		234,000	

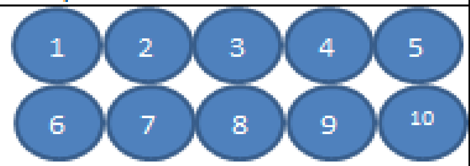
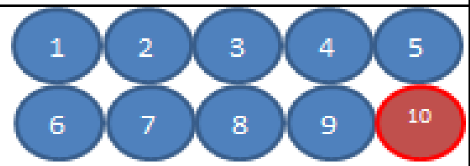
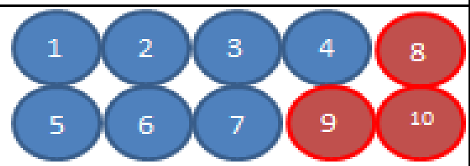
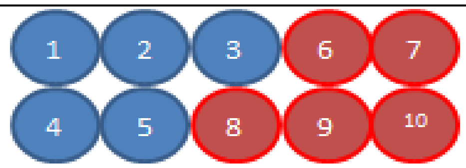
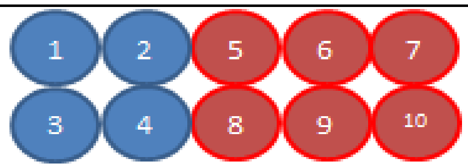
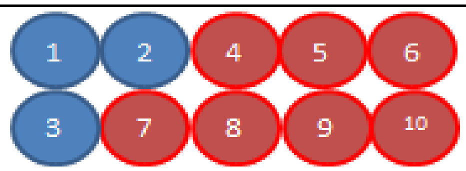
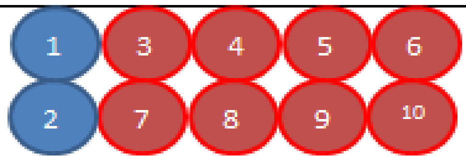
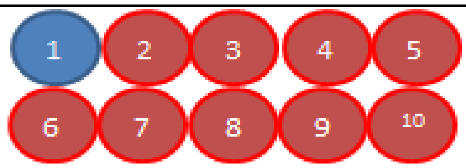
LG2 Panel 1

Row	Blue Balls =WIN, Red Balls = LOSE		Amount (₦)	Choose 1
1	10 blue balls win		0	
2	9 blue balls win		2,502	
3	8 blue balls win		5,628	
4	7 blue balls win		9,648	
5	6 blue balls win		15,007	
6	5 blue balls win		22,510	
7	4 blue balls win		33,765	
8	3 blue balls win		52,524	
9	2 blue balls win		90,040	
10	1 blue ball win		202,590	

LG2 Panel 2

Row	Blue Balls =WIN, Red Balls = LOSE		Amount (₦)	Choose 1
1	10 blue balls win		0	
2	9 blue balls win		2,512	
3	8 blue balls win		5,650	
4	7 blue balls win		9,686	
5	6 blue balls win		15,067	
6	5 blue balls win		22,600	
7	4 blue balls win		33,900	
8	3 blue balls win		52,734	
9	2 blue balls win		90,400	
10	1 blue ball win		203,400	

LG2 Panel 3

Row	Blue Balls =WIN, Red Balls = LOSE	Amount (₦)	Choose 1
1	10 blue balls win 	0	
2	9 blue balls win 	2,556	
3	8 blue balls win 	5,750	
4	7 blue balls win 	9,858	
5	6 blue balls win 	15,334	
6	5 blue balls win 	23,000	
7	4 blue balls win 	34,500	
8	3 blue balls win 	53,667	
9	2 blue balls win 	92,000	
10	1 blue ball win 	207,000	

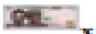
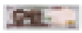
LG2 Panel 4

Row	Blue Balls =WIN, Red Balls = LOSE		Amount (₦)	Choose 1
1	10 blue balls win	1 2 3 4 5 6 7 8 9 10	0	
2	9 blue balls win	1 2 3 4 5 6 7 8 9 10	2,612	
3	8 blue balls win	1 2 3 4 9 5 6 7 8 10	5,875	
4	7 blue balls win	1 2 3 4 8 5 6 7 9 10	10,072	
5	6 blue balls win	1 2 3 7 8 4 5 6 9 10	15,667	
6	5 blue balls win	1 2 3 6 7 4 5 8 9 10	23,500	
7	4 blue balls win	1 2 5 6 7 3 4 8 9 10	35,250	
8	3 blue balls win	1 2 4 5 6 3 7 8 9 10	54,834	
9	2 blue balls win	1 3 4 5 6 2 7 8 9 10	94,000	
10	1 blue ball win	1 2 3 4 5 6 7 8 9 10	211,500	

The Time Experiment record sheet follows:

SERIES 1

Row 1

PLAN A (₦10,000 TODAY)			PLAN B (₦12,000 in 2 MONTHS)		
 x10 Today	1 Month	2 Months	Today	1 Month	 x12 2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 2

PLAN A (₦10,000 TODAY)			PLAN B (₦14,000 in 2 MONTHS)		
 x10 Today	1 Month	2 Months	Today	1 Month	 x14 2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

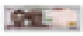
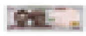
TICK A ☐ OR TICK B ☐

Row 3

PLAN A (₦10,000 TODAY)			PLAN B (₦16,000 in 2 MONTHS)		
 x10 Today	1 Month	2 Months	Today	1 Month	 x16 2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 4

PLAN A (₦10,000 TODAY)			PLAN B (₦18,000 in 2 MONTHS)		
 x10 Today	1 Month	2 Months	Today	1 Month	 x18 2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

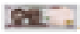
SERIES 2

Row 5

PLAN A (₦8,000 TODAY)			PLAN B (₦18,000 in 2 MONTHS)		
 x8 Today	1 Month	2 Months	Today	1 Months	 x18 2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 6

PLAN A (₦6,000 TODAY)			PLAN B (₦18,000 in 2 MONTHS)		
 x6 Today	1 Month	2 Months	Today	1 Months	 x18 2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

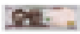
TICK A ☐ OR TICK B ☐

Row 7

PLAN A (₦4,000 TODAY)			PLAN B (₦18,000 in 2 MONTHS)		
 x4 Today	1 Month	2 Months	Today	1 Months	 x18 2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 8

PLAN A (₦2,000 TODAY)			PLAN B (₦18,000 in 2 MONTHS)		
 x2 Today	1 Month	2 Months	Today	1 Months	 x18 2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

SERIES 3

Row 9

PLAN A (₦10,000 in 4 MONTHS)			PLAN B (₦12,000 in 6 MONTHS)		
Today	1 Months	2 Months	Today	1 Month	2 Months
3 Months	x10 4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	x12 6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 10

PLAN A (₦10,000 in 4 MONTHS)			PLAN B (₦14,000 in 6 MONTHS)		
Today	1 Months	2 Months	Today	1 Month	2 Months
3 Months	x10 4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	x14 6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 11

PLAN A (₦10,000 in 4 MONTHS)			PLAN B (₦16,000 in 6 MONTHS)		
Today	1 Month	2 Months	Today	1 Month	2 Months
3 Months	x10 4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	x16 6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 12

PLAN A (₦10,000 in 4 MONTHS)			PLAN B (₦18,000 in 6 MONTHS)		
Today	1 Months	2 Months	Today	1 Month	2 Months
3 Months	x10 4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	x18 6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

SERIES 4

Row 13

PLAN A (₦8,000 in 4 MONTHS)			PLAN B (₦18,000 in 6 MONTHS)		
Today	1 Months	2 Months	Today	1 Month	2 Months
3 Months	 x8 **4 Months**	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x18 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 14

PLAN A (₦6,000 in 4 MONTHS)			PLAN B (₦18,000 in 6 MONTHS)		
Today	1 Months	2 Months	Today	1 Month	2 Months
3 Months	 x6 **4 Months**	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x18 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

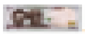
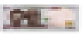
TICK A ☐ OR TICK B ☐

Row 15

PLAN A (₦4,000 in 4 MONTHS)			PLAN B (₦18,000 in 6 MONTHS)		
Today	1 Months	2 Months	Today	1 Month	2 Months
3 Months	 x4 **4 Months**	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x18 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 16

PLAN A (₦2,000 in 4 MONTHS)			PLAN B (₦18,000 in 6 MONTHS)		
Today	1 Months	2 Months	Today	1 Month	2 Months
3 Months	 x2 **4 Months**	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x18 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

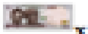
TICK A ☐ OR TICK B ☐

SERIES 5
Row 17

PLAN A (₦10,000 TODAY)			PLAN B (₦11,000 in 1 MONTH)		
 x10 Today	1 Month	2 Months	Today	 x11 1 Month	2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 18

PLAN A (₦10,000 TODAY)			PLAN B (₦12,000 in 1 MONTH)		
 x10 Today	1 Month	2 Months	Today	 x12 1 Month	2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 19

PLAN A (₦10,000 TODAY)			PLAN B (₦13,000 in 1 MONTH)		
 x10 Today	1 Month	2 Months	Today	 x13 1 Month	2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 20

PLAN A (₦10,000 TODAY)			PLAN B (₦14,000 in 1 MONTH)		
 x10 Today	1 Month	2 Months	Today	 x14 1 Month	2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

SERIES 6

Row 21

PLAN A (₦9,000 TODAY)			PLAN B (₦14,000 in 1 MONTH)		
x9 Today	1 Month	2 Months	Today	x14 1 Month	2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 22

PLAN A (₦8,000 TODAY)			PLAN B (₦14,000 in 1 MONTH)		
x8 Today	1 Month	2 Months	Today	x14 1 Month	2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 23

PLAN A (₦7,000 TODAY)			PLAN B (₦14,000 in 1 MONTH)		
x7 Today	1 Month	2 Months	Today	x14 1 Month	2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

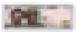
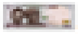
Row 24

PLAN A (₦5,000 TODAY)			PLAN B (₦14,000 in 1 MONTH)		
x5 Today	1 Month	2 Months	Today	x14 1 Month	2 Months
3 Months	4 Months	5 Months	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	6 Months	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

SERIES 7

Row 25

PLAN A (₦10,000 in 5 MONTHS)			PLAN B (₦11,000 in 6 MONTHS)		
Today	1 Month	2 Months	Today	1 Month	2 Months
3 Months	4 Months	 x10 **5 Months**	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x11 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 26

PLAN A (₦10,000 in 5 MONTHS)			PLAN B (₦12,000 in 6 MONTHS)		
Today	1 Month	2 Months	Today	1 Month	2 Months
3 Months	4 Months	 x10 **5 Months**	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x12 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

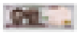
TICK A ☐ OR TICK B ☐

Row 27

PLAN A (₦10,000 in 5 MONTHS)			PLAN B (₦13,000 in 6 MONTHS)		
Today	1 Month	2 Months	Today	1 Month	2 Months
3 Months	4 Months	 x10 **5 Months**	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x13 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 28

PLAN A (₦10,000 in 5 MONTHS)			PLAN B (₦14,000 in 6 MONTHS)		
Today	1 Month	2 Months	Today	1 Month	2 Months
3 Months	4 Months	 x10 **5 Months**	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x14 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

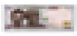
SERIES 8

Row 29

PLAN A (₦9,000 in 5 MONTHS)			PLAN B (₦14,000 in 6 MONTHS)		
Today	1 Month	2 Months	Today	1 Month	2 Months
3 Months	4 Months	 x9 **5 Months**	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x14 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

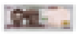
TICK A ☐ OR TICK B ☐

Row 30

PLAN A (₦8,000 in 5 MONTHS)			PLAN B (₦14,000 in 6 MONTHS)		
Today	1 Month	2 Months	Today	1 Month	2 Months
3 Months	4 Months	 x8 **5 Months**	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x14 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

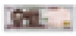
TICK A ☐ OR TICK B ☐

Row 31

PLAN A (₦7,000 in 5 MONTHS)			PLAN B (₦14,000 in 6 MONTHS)		
Today	1 Month	2 Months	Today	1 Month	2 Months
3 Months	4 Months	 x7 **5 Months**	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x14 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

Row 32

PLAN A (₦5,000 in 5 MONTHS)			PLAN B (₦14,000 in 6 MONTHS)		
Today	1 Month	2 Months	Today	1 Month	2 Months
3 Months	4 Months	 x5 **5 Months**	3 Months	4 Months	5 Months
6 Months	7 Months	8 Months	 x14 **6 Months**	7 Months	8 Months
9 Months	10 Months	11 Months	9 Months	10 Months	11 Months

TICK A ☐ OR TICK B ☐

SECTION 2: FACTORS AFFECTING ADOPTION DECISIONS

In this Section, you would be asked questions relating to your farm, household, rice varieties planted, as well as institutional and community factors.

A. Farms and Farmers' Specific Factors

1. What is your age in years? i. < 25 ( ), ii. 25-34 ( ), iii. 35-44 ( ), iv. 45-54 ( ), v. 55-64 ( ), vi > 64 ( ). Kindly indicate your actual age (if known) _________years
2. How many **years** of formal education do you have? ________
3. Indicate your educational qualification: i. No formal education ( ), ii. Primary school completed ( ), iv. Incomplete secondary ( ), v. Secondary school completed ( ), vi. Technical/Vocational Education ( ), vii. NCE/ND ( ), viii. BSc. ( ), ix. Post Graduate ( ), x. Others (specify)____________
4. Your gender: Male ( ), Female ( )
5. What is your religion? i. Christianity ( ), ii. Islam ( ), iii. Traditional ( ), iv. Others (specify) __________
6. What is your marital status: i. Single ( ), ii. Married ( ), iii. Divorced/Separated ( )
7. What is the total number of your household? Number of children less than 18 years_______. Number of adults who are 18 years or over_________
8. What other economic activities do you engaged in? i. Trading ( ), ii. Artisanship ( ), iii. Transportation ( ), iv. Fishing ( ), v. Civil service ( ), vi. Others (specify) ________
9. Kindly give your total years of farming experience: ______.
10. Kindly give your total years of experience in rice farming ______.
11. On average, how many times do you plant rice per year? i. ( ), ii ( ), iii. ( ), iv. ( )
12. Do you grow other crops? Yes ( ), No ( )
13. If yes, kindly name the total number of other crops grown in the last production season. i. __________ ii. ____________. iii. __________. iv. ____________
14. Kindly indicate the types of rice grown (rice system). MULTIPLE ANSWERS ALLOWED. i. Upland ( ), ii Lowland ( ), iii Upland and Lowland ( ), iv. Irrigated lowland ( ), v. Irrigated upland ( ), Irrigated upland and lowland ( ), Hydromorphic ( )
15. What is your source of land for rice production? i. Inheritance ( ), ii. Rented ( ), iii. Purchase ( ), iv. Communal arrangement ( ), v. Gift ( ), vi. Others (specify) __________
16. Have you ever planted HYV? Yes ( ) or No ( )
17. If yes, what year did you first grow/plant HYV? _______
18. Are you currently growing/planting HYV? Yes ( ), No ( )
19. What types/varieties of HYV have you planted so far? e.g NERICA 1, Please name all:
____
20. What is the size of your total farm area? ______ hectares or ______acres or ________plots.
21. What is the total farm size planted to rice? ______hectares or ______acres or ________plots

22. What are your sources of labour for rice production? i. family ( ), ii hired ( ), rotational ( )

23. Kindly indicate the number of household aged 18 years and above involved in rice production________

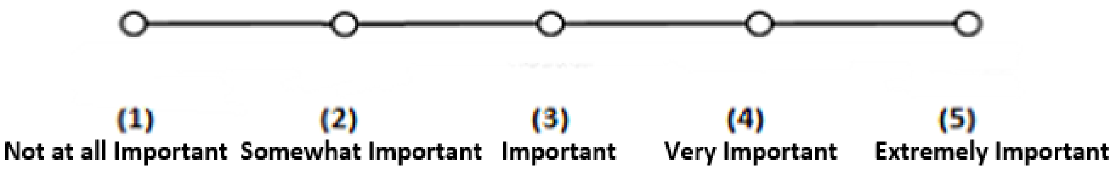
24. Do you experience short fall of labour in rice production? Yes ( ), No ( )

B. Perceptions about HYV Technology Attributes:

25. How important are the following attributes when considering adopting HYV?

Attributes	**Extremely important (5)**	**Very Important (4)**	**Important (3)**	**Somewhat important (2)**	**Not at all important (1)**
High yield					
Stem Height					
Early maturity					
Tiller capacity					
Grain size					
Grain colour					
Taste					

*the perceptual question is illustrated to farmers using the scale below



C. Institutional and Community Factors

26. What are your primary sources of information about HYV? i. Extension agent ( ), ii. Cooperative society ( ), iii. Community news ( ), iv. Friends/Neighbours ( ), v. vi. No much information/awareness ( ). Others (specify) ______.

27. How often do you have contact with extension agents? i. Daily ( ), ii. Weekly ( ), iii. Fortnightly ( ), iv. Monthly ( ), v. Once in two months ( ), vi. Once in three months ( ),viii. No contact ( ) ix. Others (specify) __________.

28. Are you a member of any community association? Yes ( ), No ( ).

29. Are you a member of cooperative organization? Yes ( ), No ( ).

30. What are your sources of credit? i. Personal savings ( ), ii. Agricultural Banks ( ), iii. Commercial Banks ( ), iv. Cooperatives ( ) v. Others (specify) ___________.

31. What are the constraints to HYV seed access? i. _________________________ ii.______________________iii._____________________iv.________________

32. How do you process your seeds? i. Manual ( ), ii. Machine ( ), iii. Others (specify) ______________

33. How do you package your processed rice? i. Manual ( ), ii. Machine ( ).

34. What is the present road condition in your community? i. Tarred ( ), ii. Untarred ( ), iii. Tarred but non-accessible ( ), iv. Untarred accessible ( ), v. Untarred non-accessible ( ).

35. Kindly record the ADP zone. i. Abeokuta ( ), ii. Ilaro ( ), iii. Ikenne ( ), iv. Ijebu-Ode ( ).